Lecture on Graphs and Algorithms (Master 1 and 2)

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Abstract

These are lecture notes of the course I gave, at Master 1 (Parts I-III) and Master 2 (Parts IV-...) level. The main goal of this lecture is to present some ways/techniques/methods to design efficient algorithms (and their analysis) to solve (NP-hard or not) optimization problems (mainly in the graph context).

Chapters 1 to 8 are mostly dedicated to the course I give at Master 1 level. Note that Chapter 8 is (a bit) beyond the scope of this lecture (especially Section 8.5 that is presented rather in an informal way) but aims at going further into algorithmic graph theory.

Chapters 9 and further are dedicated to the continuation of this course in Master 2.

Contents

I Introduction 3

1 Informal Introduction 3

2 Basics on Graphs [2, 5] 4

2.1 $P$ vs. $NP$-hard, a first example: Eulerian vs. Hamiltonian 6

2.2 Trees, subgraphs and spanning trees (Kruskal’s algorithm) 7

2.3 Matching and Vertex Cover in graphs 8

2.3.1 Matchings in bipartite graphs (Hall’s theorem, Hungarian’s method) 10

2.3.2 Vertex Cover in graphs (König’s theorem and 2-approximation) 11


3 Introduction to Approximation Algorithms: Load balancing 13

3.1 Definition of an Approximation Algorithm 13

3.2 The Load Balancing Problem 14

3.2.1 Greedy 2-Approximation (least loaded processor) 15

3.2.2 Greedy $\frac{3}{2}$-Approximation (least loaded processor and ordered tasks) 16

4 Traveling Salesman Problem (TSP) 17

4.1 Different variants and exact dynamic programming algorithm 17

4.2 2-Approximation (using minimum spanning tree) 19

4.3 $\frac{3}{2}$-Approximation (Christofides’algorithm) 20

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5 Set Cover
5.1 Relationship with Graphs: Dominating Set and Vertex Cover .................................. 21
5.2 Greedy $O(\log n)$-approximation ................................................................. 22

6 Knapsack and (F)PTAS 24
6.1 (Pseudo-polynomial) Exact Algorithm via dynamic programming ................. 24
6.2 Greedy 2-Approximation and PTAS ............................................................ 26

7 Introduction to Parameterized Algorithms (with Vertex Cover as toy example) 28
7.1 First Approach: deciding if $\text{vc}(G) \leq k$? ........................................ 28
7.2 Fixed Parameter Tractable (FPT) Algorithms and Kernelization ................. 30
7.3 A first Kernelization Algorithm for Vertex Cover ..................................... 31
7.4 Iterative Compression technique: example of Vertex Cover ...................... 31

8 Toward tree-decompositions, Graph Minor Theory and beyond 34
8.1 Minimum (weighted) Vertex Cover in trees ........................................... 34
8.2 2-trees ......................................................... 35
8.3 $k$-trees ................................................... 38
8.4 Brief introduction to treewidth and tree-decompositions .......................... 39
8.5 Graph Minor theory ........................................ 45

IV Linear Programming for graphs 47
9 Linear Programming in a nutshell [8] 48
9.1 Definition of a Linear Programme ....................................................... 48
9.2 A few words on how to solve a Linear Programme ................................. 49
9.3 Integer Linear Programming ................................................................. 50

10 Model graph problems using ILP 52
10.1 Minimum Vertex Cover ................................................................. 52
10.2 Maximum Independent Set ............................................................. 53
10.3 Maximum Clique ................................................................. 53
10.4 Proper 3-coloring ................................................................. 54
10.5 Minimum Spanning Tree ............................................................. 55
10.6 Shortest path ................................................................. 56
10.7 Minimum Hamiltonian cycle ....................................................... 56
10.8 Maximum flow ................................................................. 56
10.9 Back to Shortest paths and Minimum spanning trees .......................... 58

11 A second Kernelization Algorithm for Vertex Cover (using LP) 59

V Shortest Path Problem 60
12 Dijkstra’s algorithm 61
Part I
Introduction

1 Informal Introduction

This introduction is only meant to be an intuition of what will be addressed in the lecture (most of the concepts mentioned here will be more formally defined and exemplified later).

Tradeoff between time complexity and quality of the solution. What is an efficient algorithm? Some problems have a unique solution (e.g., sorting a list of integer), some other problems have several valid (≈ correct) solutions but only some of them are optimal (e.g. finding a shortest path between two vertices in a graph: there may be many paths, but only few of them may be shorter).

Here, we measure the efficiency as a tradeoff between the “time” to get a valid/correct solution (time-complexity) and the “quality” of a valid solution (how “far” is it from an optimal solution?).
Difficult vs. Easy Problems. We assume here that readers are familiar with basics on time complexity of algorithms. If not, see [3] or here (in french, on polynomial-time algorithms) for prerequisite background.

Very informally, problems may be classified into

**P.** Class of problems for which we know a Polynomial-time algorithm (polynomial in the size of the input) to solve them.

**NP.** Class of problems for which we know a Non-deterministic Polynomial-time algorithm to solve them. Equivalently, it can be checked in (deterministic) polynomial-time whether a solution to such problem is valid/correct. (Clearly, \( P \subseteq NP \))

**NP-hard.** Class of problems that are “as hard as the hardest problems in \( NP \)”. I don’t want to give a formal definition of it here. Informally, you should understand this class of problems as the ones for which nobody currently knows a deterministic polynomial-time algorithm to solve them (related to the question whether \( P = NP \), a question that worths 1.000.000 dollars). Intuitively (not formally correct), the best known algorithms for solving such problems consist of trying all possibilities...

In what follows, I refer to problems in \( P \) as “easy” and to \( NP\)-hard problems as “difficult”.

The main question I try to address in this lecture is how to deal with difficult problems. We probably (unless \( P = NP \)) cannot solve them “efficiently” (in polynomial time)... so, should we stop trying solving them? NO !!! there are many ways to tackle them and the goal of this lecture is to present some of these ways. Roughly, we will speak about:

2. Approximation algorithms. Design poly-time algo. for computing solution (not necessarily optimal) with “quality’s guaranty” (“not far from the optimal”) [9]
3. Restricted graph classes. “Use specificities of inputs” [4, 9]
4. Parameterized algorithms. (formal definition will be given later) [4]

First, I want to give some basics on graph theory. The main reasons for it is that: (1) graphs are a natural (and nice) mathematical model to describe many real-life problems, and (2), we will then mainly consider graph problems as examples (so, we need a common background on graphs structural results and algorithms). Then, this lecture will try to address several techniques (mentioned above) to deal with difficult problems (mostly in graphs).

## 2 Basics on Graphs [2, 5]

A graph \( G \) is a pair \( G = (V,E) \) where \( V \) is a set\(^1\) of elements and \( E \subseteq V \times V \) is a relationship on \( V \). Any element of \( V \) is called vertex. Two vertices \( u, v \in V \) are “linked” by an edge \( \{u,v\} \) if \( \{u,v\} \in E \), in which case \( u \) and \( v \) are said adjacent or neighbors. So \( V \) is the set of vertices and \( E \) is the set of edges.\(^2\)

**Intuition.** It can be useful (actually, IT IS!!) to draw graphs as follows: each vertex can be depicted by a circle/point, and an edge between two vertices can be drawn as a curve (e.g., a (straight) line) linking the corresponding circles/points.

\(^1\)In what follows, we always assume that \( V \) is finite, i.e., \( |V| \) is some integer \( n \in \mathbb{N} \).

\(^2\)Technical remark. Unless stated otherwise, in what follows, we only consider simple graphs, i.e., there are no loops (i.e., no vertex is linked with itself, i.e., \( \{v,v\} \notin E \) for every \( v \in V \)) nor parallel edges (i.e., there is at most one edge between two vertices).
Graphs are everywhere. As examples, let us consider a graph where vertices are: cities, proteins, routers in the Internet, people,... and where two vertices are linked if they are: linked by a road (road networks), by some chemical interaction (biological networks), by optical fiber (computer networks/Internet), by friendship relationship (social networks: Facebook, Twitter...).

Notation. For \( v \in V \), let \( N(v) = \{ w \in V \mid \{v, w\} \in E \} \) be the neighborhood of \( v \) (set of its neighbors) and \( N[v] = N(v) \cup \{v\} \) be its closed neighborhood. The degree of a vertex \( v \in V \) is the number \( \deg(v) = |N(v)| \) of its neighbors. Given a graph \( G \), if \( V \) and \( E \) are not specified, let \( E(G) \) denote its edge-set and let \( V(G) \) denote its vertex-set.

Proposition 1 Let \( G = (V, E) \) be any simple graph: \( |E| \leq \frac{|V|(|V|-1)}{2} \) and \( \sum_{v \in V} \deg(v) = 2|E| \).

Proof. We prove that \( \sum_{v \in V} \deg(v) = 2|E| \) by induction on \( |E| \). If \( |E| = 1 \), then \( G \) must have two vertices with degree 1, and all other with degree 0. So the result holds. Assume by induction that the result holds for \( |E| \leq k \) and let assume that \( |E| = k + 1 \). Let \( \{a, b\} \in E \) and let \( G' = (V, E \setminus \{a, b\}) \) be the graph obtained from \( G \) by removing the edge \( \{a, b\} \). By induction, \( \sum_{v \in V} \deg_{G'}(v) = 2|E(G')| = 2(|E| - 1) \). Since \( \sum_{v \in V} \deg_{G}(v) = \sum_{v \in V} \deg_{G'}(v) + 2 \) (because the edge \( \{a, b\} \) contributes for 2 in this sum), the result holds. Let \( n = |V| \).

Since each vertex has degree at most \( n - 1 \), \( 2|E| = \sum_{v \in V} \deg(v) \leq \sum_{v \in V} (n - 1) = n(n - 1) \). ■

A Walk in a graph \( G = (V, E) \) is a sequence \((v_1, \cdots, v_k)\) of vertices such that two consecutive vertices are adjacent (i.e., for every \( 1 \leq i < k \), \( \{v_i, v_{i+1}\} \in E \)). A Trail is a walk where no edges are repeated. A trail is a Tour if the first and last vertex are equal. A tour is Eulerian if it uses each edge of \( G \) exactly once.

A Path is a walk with no repeated vertex. Finally, a Cycle is a tour with no repeated vertex (except that the first and last vertices are equal). A cycle is Hamiltonian if it meets every vertex of \( G \) exactly once.

Note that, a path is a trail, and a trail is a walk (but not all walks are trails, not all trails are paths). Similarly, a cycle is a tour, and a tour is a walk (not all walks are tours, not all tours are cycles).

Exercise 1 Give examples of graphs that are

- Eulerian (that admits a Eulerian tour) AND Hamiltonian (admits an Hamiltonian cycle);
- not Eulerian AND Hamiltonian;
- Eulerian AND not Hamiltonian;
- not Eulerian AND not Hamiltonian.

At a first glance, the problem of deciding whether a graph is Eulerian and the problem of deciding whether a graph is Hamiltonian look very similar. From the complexity point of view it seems they are quite different.

\[ ^{3} \text{Formally, a graph reduced to a single vertex is a pathological case of a graph with both a Eulerian cycle and an Hamiltonian cycle (both reduced to this single vertex). Try to find examples with more vertices.} \]
2.1 $P$ vs. $NP$-hard, a first example: Eulerian vs. Hamiltonian

A graph $G = (V, E)$ is connected if, for every two vertices $u, v \in V$, there is a path connecting $u$ to $v$. Note that, to admit a Eulerian or Hamiltonian cycle, a graph must be connected. So, in what follows, we only focus on connected graphs. Given $v \in V$, the connected component of $G$ containing $v$ is the graph $(V_v, E \cap (V_v \times V_v))$ where $V_v$ is the set of all vertices reachable from $v$ in $G$.

The following algorithm decides whether a graph is Hamiltonian. For this purpose, it considers one after the other every permutation of $V$ (all possible ordering of the $n$ vertices) and checks if this permutation corresponds to a cycle.

**Algorithm 1** Naive algorithm for Hamiltonicity

**Require:** A connected graph $G = (V, E)$.

**Ensure:** Answers Yes is $G$ is Hamiltonian and No otherwise.

1: for each permutation of $V$ do
2: if the permutation corresponds to a cycle then
3: return Yes.
4: end if
5: end for
6: return No

There are $n!$ permutations of $V^4$ so, in the worst case, there are $n!$ iterations of the for-loop. At each iteration, the algorithm checks $n$ edges to verify if the current permutation is a cycle. Overall, the time-complexity is then $O(n \cdot n!)$. In this course, we will see other (much better) algorithms for this problem, but all have at least exponential time-complexity. Roughly, the only way we know is to try all possibilities. Indeed, it can be proved (I will not do it here) that the problem of deciding whether a graph is Hamiltonian is $NP$-hard! [7]

The other problem is very different.

**Theorem 1 [Euler 1736]** A graph admits an Eulerian cycle iff all vertices have even degree.

Before proving this theorem, let us look at its consequence.

**Algorithm 2** Algorithm for deciding of a graph is Eulerian

**Require:** A connected graph $G = (V, E)$.

**Ensure:** Answers Yes is $G$ is Eulerian and No otherwise.

1: for every $v \in V$ do
2: if $v$ has odd degree then
3: return No.
4: end if
5: end for
6: return Yes

There are $n$ iterations and each of them just checks the degree of one vertex. Overall, the complexity is $O(\sum_{v \in V} \text{deg}(v))$ which is $O(|E|)$ by proposition above. Therefore, the problem of deciding whether a graph has an Eulerian cycle is in $P$.

**Proof.**[Sketch of proof of Th. 1] Assume that $G$ is Eulerian and let $v \in V$. Each time the cycle reaches $v$ by some edge, it must leave by another (not used yet) edge. Hence, $v$ has even degree.

---

4For any set with $n$ elements, there are $n!$ orderings of these elements. Indeed, there are $n$ choices for the first element, $n-1$ for the 2nd one, $n-2$ for the 3rd one, and so on, so $n(n-1)(n-2)\cdots2\cdot1 = n!$ in total.
Now, let us assume that every vertex has even degree. The proof is constructive (it produces a Eulerian cycle). Let us sketch a recursive algorithm that computes an Eulerian cycle.

1. First, start from any vertex \( v \) and greedily progress along the edges. Each time a new vertex is reached, it is possible to leave it since its degree is even (and so it remains at least one non-used edge). Since a graph is finite, eventually, this greedy walk reaches a vertex that has already been visited and so, we found a cycle \( C = (v_1, \cdots, v_r) \).

2. Let \( G' \) be the graph obtained by removing from \( G \) every edge of \( C \). Let \( G'_1, \cdots, G'_k \) be the connected components of \( G' \). Removing the edges of \( C \), every vertex of \( C \) has its degree reduced by exactly two. So, for every \( i \leq k \), every vertex of \( G'_i \) has even degree and, by induction on the number of edges, \( G'_i \) has a Eulerian cycle. By applying recursively the algorithm on \( G'_i \), let \( C'_i \) be the Eulerian cycle obtained for \( G'_i \).

3. A Eulerian cycle of \( G \) is obtained by starting from \( v_1 \), following \( C \) and, each time it meets a vertex \( v_j \) (\( j \leq r \)), it follows the Eulerian cycle of the connected component of \( G' \) that contains \( v_j \) (if not yet met). Prove that it is actually a Eulerian cycle.

Note that this algorithm has roughly time-complexity \( O(|E||V|) \) (finding a cycle takes time \( O(|V|) \) and, in the worst case, has size 3 and so decreases by 3 the number of edges).

Note that, previous proof shows that, not only it can be decided if a graph is Eulerian in polynomial-time, but also an Eulerian cycle (if any) can be found in polynomial-time.

### 2.2 Trees, subgraphs and spanning trees (Kruskal’s algorithm)

A Tree is any acyclic (with no cycle) connected graph.

A Subgraph of \( G \) is any graph that can be obtained from \( G \) by removing some edges and some vertices. Hence, a subgraph of \( G = (V, E) \) is any graph \( H = (V', E') \) with \( V' \subseteq V \) and \( E' \subseteq E \cap (V' \times V') \). If \( V' = V \), then \( H \) is a spanning subgraph. A spanning tree of \( G \) is a spanning subgraph which is a tree.

**Exercise 2** Let \( G = (V, E) \) be any graph. Show that:

- if \( G \) is a tree, there is a unique path between any two vertices of \( G \);
- if \( G \) is a tree, then \( |E| = |V| - 1 \);
- \( G \) admits a spanning tree if and only if \( G \) is connected;
- deduce from previous items that, \( G \) is connected \( \Rightarrow |E| \geq |V| - 1 \);
- if \( G \) is acyclic and \( |E| = |V| - 1 \), then \( G \) is a tree;
- if \( G \) is connected and \( |E| = |V| - 1 \), then \( G \) is a tree;

Given \( X \subseteq V \), the subgraph (of \( G \)) induced by \( X \) is the subgraph \( G[X] = (X, E \cap (X \times X)) \). If \( F \subseteq E \), the graph induced by \( F \) is \( G[F] = (\bigcup_{\{u,v\} \in F} \{u,v\}, F) \).

Let \( w : E \rightarrow \mathbb{R}^+_\ast \) be a weight function on the edges. The weight of a subgraph \( G[F] \) induced by \( F \subseteq E \) is \( \sum_{e \in F} w(e) \). The goal of this section is the computation of a connected spanning subgraph with minimum weight.

**Exercise 3** Let \( (G, w) \) be a graph with an edge-weight function. Show that any minimum-weight spanning connected subgraph is a spanning tree.
Proof. Let $H$ be a minimum spanning connected subgraph. If $H$ contains no cycle, it is a tree. Otherwise let $C$ be a cycle in $H$ and let $e \in E(C)$ be any edge of $E$. Show that $(V(H), E(H) \setminus \{e\})$ is a connected spanning subgraph of $G$. Conclusion? ■

Above exercise somehow justifies the interest of minimum spanning tree in a practical point of view. For instance, assume you want to connect some elements of a network (cities connected by roads, buildings connected by electrical cables, etc.) and that weights on the links represent the price of building them. Then, a minimum spanning tree will be the cheapest solution.

Let’s compute it!

Algorithm 3: Kruskal’s Algorithm (1956)

Require: A (non-empty) connected graph $G = (V, E)$ and $w : E \to \mathbb{R}^+$.  
Ensure: A minimum spanning tree $T$ of $G$. 
1: Order $E$ in non-decreasing order: $w(e_1) \leq w(e_2) \leq \cdots \leq w(e_m)$. 
2: Let $v \in V$ and $T = (\{v\}, \emptyset)$. 
3: for $i$ from 1 to $m$ do 
4: if $T$ is connected and spanning then 
5: return $T$. 
6: end if 
7: Let $e_i = \{u, v\}$. 
8: if $(V(T) \cup \{u, v\}, E(T) \cup \{e_i\})$ is acyclic then 
9: $T \leftarrow (V(T) \cup \{u, v\}, E(T) \cup \{e_i\})$. 
10: end if 
11: end for 

The first step (ordering the edges) takes time $O(m \log m)^5$. Then there are at most $m$ iterations of the for-loop. Each iteration takes time $O(1)$ (by using suitable data structure such as Union-Find). Overall, the time-complexity of the algorithm of Kruskal is $O(m \log m)$.

Theorem 2 The Kruskal’s algorithm returns a minimum spanning tree of $G$.

Proof. Let $T$ be the spanning tree computed by the algorithm. Let $(e_{i_1}, e_{i_2}, \cdots, e_{i_{n-1}})$ be the edges of $T$ ordered in non-decreasing order of their weights. Let $T^*$ be a minimum spanning tree minimizing $|E(T^*) \cap E(T)|$. If $T^* = T$, we are done. Otherwise, let $j < n$ be the minimum index such that $e_{i_j} \in E(T) \setminus E(T^*)$ (why it exists?). Note that $E(T^*) \cap \{e_1, e_2, \cdots, e_{i_j}\} = \{e_{i_1}, e_{i_2}, \cdots, e_{i_{j-1}}\}$ by def. of $j$ and of the algorithm. Let $e_{i_j} = \{u, v\}$ and let $P$ be the unique path from $u$ to $v$ in $T^*$ (why it exists?). Show that $P$ contains an edge $f \notin E(T)$ such that $w(f) \geq w(e_{i_j})$. Show that $(T^* \setminus \{f\}) \cup \{e_{i_j}\}$ is a minimum spanning tree of $G$. Conclusion? ■

As we will see in the following of the lecture, computing a minimum spanning tree of a graph is one important basic blocks of many graph algorithms!!

2.3 Matching and Vertex Cover in graphs

Graphs are a very useful tool to deal with allocation problems. For instance, consider a set of students that have to choose an internship among a set of proposals. Each student and proposal may be modeled as vertices of a graph and a student is linked to a proposal if it has some interest for it. How to assign internships to students so that at most one student is assigned to each proposal and every student gets an internship that interests him/her? Say differently, how to match internships and students? This is the topic of this subsection.

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5Recall that ordering a set of $n$ elements takes time $O(n \log n)$ (e.g., merge-sort)
Let $G = (V, E)$ be a graph. A matching in $G$ is a set $M \subseteq E$ of edges such that $e \cap f = \emptyset$ for every $e \neq f \in M$. That is, a matching is a set of edges pairwise disjoint.

A matching $M$ is perfect if all vertices are matched, i.e., for every vertex $v$, there is an edge $e \in M$ such that $v \in e$.

**Exercise 4** Show that a graph has a perfect matching only if $|V|$ is even.

Give a connected graph with $|V|$ even but no perfect matching.

**Exercise 5** Show that every maximum matching is maximal.

Give examples of maximal matchings that are not maximum.

**Algorithm 4** Algorithm for Maximal Matching

**Require:** A graph $G = (V, E)$.

**Ensure:** A maximal matching $M$ of $G$.

1. $G' \leftarrow G$ and $M \leftarrow \emptyset$.
2. while $E(G') \neq \emptyset$ do
3.   Let $e = \{u, v\} \in E(G')$ // so, $e$ is any (arbitrary) edge of $G'$
4.   $M \leftarrow M \cup \{e\}$ and $G' \leftarrow G'[V(G') \setminus \{u, v\}]$.
5. end while
6. return $M$.

**Exercise 6** Prove that above algorithm computes a maximal matching in time $O(|E|)$.

**Proof.** Three things to be proved: $M$ is a matching, $M$ is maximal, and the time-complexity.

Now, we focus on computing maximal matchings in graphs. Let $G = (V, E)$ be a graph and $M \subseteq E$ be a matching in $G$. A vertex $v \in V$ is covered by $M$ if there is $e \in M$, $v \in e$ (i.e., if $v$ “touches” one edge of the matching). Let $k \geq 2$. A path $P = (v_1, \cdots, v_k)$ is $M$-alternating if, for any two consecutive edges $e_{i-1} = \{v_{i-1}, v_i\}$ and $e_i = \{v_i, v_{i+1}\}$ ($1 < i < k$), exactly one of $e_{i-1}$ and $e_i$ is in $M$. The path $P$ is $M$-augmenting if $P$ is alternating and $v_1$ and $v_k$ are not covered by $M$. Note that, in that case, $v_2, \cdots, v_{k-1}$ are all covered by $M$ and $k$ is even.

**Theorem 3 (Berge 1957)** Let $G = (V, E)$ be a graph and $M \subseteq E$ be a matching in $G$. $M$ is maximum matching if and only if there are no $M$-augmenting paths.

**Proof.** First, let us assume that there is an $M$-augmenting path $P$. Show that $M' = (M \setminus E(P)) \cup (E(P) \setminus M)$ (“switch” the edges in $P$) is a matching and that $|M'| = |M| + 1$ and so, $M$ is not maximum. For this purpose, first show that $M'$ is a matching. Then, show that $P$ has odd length, i.e., $2k + 1$ edges, and that $k$ edges of $P$ are in $M$ and $k + 1$ are not in $M$. Conclude.

Now, assume that there are no $M$-augmenting paths. Recall that the symmetric difference $A \Delta B$ between two sets $A$ and $B$ equals $(A \cup B) \setminus (A \cap B) = (A \setminus B) \cup (B \setminus A)$. Let $M^*$ be a maximum matching in $G$ and let $X = G[M \Delta M^*]$. So, $X$ is the subgraph of $G$ induced by the edges that are in $M$ or $M^*$ but not in both.
Show that every vertex has degree at most two (in X) in any connected component of X. Deduce that the connected components of the graph X consist of paths and cycles (we say that X is the disjoint union of paths and cycles).

So the connected components of X consist of cycles $C_1, \ldots, C_k$ and paths $P_1, \ldots, P_t$. Show that, for every $i \leq k$, $C_i$ has even size. Deducing that $|E(C_i) \cap M| = |E(C_i) \cap M^*|$, let $j \leq \ell$. Show that, because there are no M-augmenting path, $|E(P_j) \cap M^*| \leq |E(P_j) \cap M|$. Therefore, $|M^*| = |M \cap M^*| + \sum_{i=1}^{k} |E(C_i) \cap M^*| + \sum_{j=1}^{\ell} |E(P_j) \cap M^*| \leq |M \cap M^*| + \sum_{i=1}^{k} |E(C_i) \cap M| + \sum_{j=1}^{\ell} |E(P_j) \cap M| = |M|$. So $|M^*| \leq |M|$ and $M$ is a maximum matching (since $M^*$ is maximum).

Theorem 3 suggests (actually proves) that, to compute a maximum matching in a graph, it is sufficient to follow the following greedy algorithm. The key point is that the order in which augmenting paths are considered is not relevant! (see [Bensmail et al. 2017] for different behavior).

Algorithm 5 Algorithm for Maximum Matching

Require: A graph $G = (V, E)$.
Ensure: A maximum matching $M$ of $G$.
1: $M \leftarrow \emptyset$.
2: while there is an $M$-augmenting path $P$ do
3: $M \leftarrow (M \setminus E(P)) \cup (E(P) \setminus M)$.
4: end while
5: return $M$.

The time-complexity of previous algorithm relies on the time needed to find an $M$-augmenting path (condition in the While-loop). This can actually be done in polynomial-time using the Blossom algorithm [Edmonds 1965]. This algorithm has been improved and a maximum matching in any graph $G = (V, E)$ can be found in time $O(\sqrt{|V||E|})$ [Micali, Vazirani 1980]. Computing matching in graphs is a basic block of many graph algorithms as we will see below.

In what follows, we focus on a restricted graphs' class, namely bipartite graphs.

2.3.1 Matchings in bipartite graphs (Hall’s theorem, Hungarian’s method)

Given a graph $G = (V, E)$, a set of $I \subseteq V$ is an independent set (or stable set) if, $\{u, v\} \notin E$ for every $u, v \in I$ (the vertices of I are pairwise not adjacent in G). A graph $G = (V, E)$ is bipartite if $V$ can be partitioned into two stable sets $A$ and $B$.

Exercise 7 Show that any tree is bipartite.

Show that a graph $G$ is bipartite iff $G$ has no cycle of odd size.

Proof. Show that, if there is an odd cycle in $G$, then it is not bipartite.

Otherwise, let $v$ be any vertex and consider a Breadth First Search (BFS) from $v$. Set $A$ to be the vertices at even distance from $v$ and $B = V \setminus A$.

Let $G = (A \cup B, E)$ be a bipartite graph$^7$. W.l.o.g., $|A| \leq |B|$. Clearly (prove it), a maximum matching $M$ in $G$ is such that $|M| \leq |A|$. A set $S \subseteq A$ is saturated by a matching $M$ of $G$ is all vertices of $S$ are covered by $M$ (in which case $|M| = |A|$). For any graph $G = (V, E)$, given

$^6$Please see [3] or [5] if you don’t know what a BFS is.

$^7$Implicitly (or say, by notation), $A$ and $B$ are stable sets.
Algorithm 6: Hungarian method [Kuhn 1955]

Require: A bipartite graph $G = (A \cup B, E)$.
Ensure: A matching $M$ saturating $A$ or a set $S \subseteq A$ such that $|S| > |N(S)|$.

1. $M \leftarrow \emptyset$.
2. while $A$ is not saturated by $M$ do
   3. Let $a_0 \in A$ be any vertex not covered by $M$. Set $X = \{a_0\}$.
   4. Let $Continue = True$.
   5. while $N(X)$ saturated by $M$ and $Continue$ do
      6. $Y \leftarrow \{a_0\} \cup \{a \mid \exists b \in N(X), \{a, b\} \in M\}$.
      7. if $X \subset Y$ then
         8. $X \leftarrow Y$
      9. else
         10. $Continue = False$.
      11. end if
   12. end while
   13. if $\exists b_0 \in N(X)$ not covered by $M$ then
      14. Let $P$ be an $M$-augmenting path between $a_0$ and $b_0$;
      15. $M \leftarrow (M \setminus E(P)) \cup (E(P) \setminus M)$.
   16. else
      17. return $X$
   18. end if
   19. end while
20. return $M$.

Let $S \subseteq V$, let us denote $N(S) = \{u \in V \setminus S \mid \exists v \in S, \{u, v\} \in E\} = \bigcup_{v \in S}(N(v) \setminus S)$. That is, $N(S)$ is the set of vertices not in $S$ that are neighbor of some vertex in $S$.

**Theorem 4 (Hall 1935)** Given a bipartite graph $G = (A \cup B, E)$, $|A| \leq |B|$, there is matching saturating $A$ iff, for all $S \subseteq A$, $|S| \geq |N(S)|$.

**Proof.** If there is $S \subseteq A$ such that $|S| > |N(S)|$ then no matching can saturates $S$. The reverse implication can be proved by induction on $|A|$. Algorithm 6 is a constructive proof.

Prove the correctness of this algorithm (In particular, prove that, in the last Else case, $|X| = |N(X)| + 1$).

Note that above algorithm, known as the Hungarian method [Kuhn 1955], can be used to find augmenting paths in polynomial-time in bipartite graphs (just try every uncovered vertex as starting point), and so it allows to compute a maximum matching in bipartite graphs.

Understanding why this algorithm requires the graph to be bipartite would be an instructive exercise.

### 2.3.2 Vertex Cover in graphs (König’s theorem and 2-approximation)

On the “practical” point of view, consider a city (buildings are vertices that are linked with streets/edges). We aim at placing, say, as few as possible (because it is expansive) fire-stations in buildings so that each building it adjacent to at least one fire-station.

This problem is modeled as follows. Given a graph $G = (V, E)$, a set $K \subseteq V$ is a vertex cover if $K \cap e \neq \emptyset$ for every $e \in E$. Let $vc(G)$ be the smallest size of a vertex cover in $G$. The problem of computing a minimum vertex cover in a graph is $NP$-hard in general graphs [7].

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11
When you are facing an NP-hard problem (or, even, any problem), you must have the reflex to think to any “naive” algorithm to solve it (e.g., trying all feasible solutions and keep a best one). Precisely, imagine any feasible solution (e.g., prove that $V$ is a vertex cover for any graph $G = (V, E)$) and try to improve it.

Algorithm 7 Naive Algorithm for Minimum Vertex Cover

Require: A graph $G = (V, E)$.
Ensure: A minimum Vertex Cover of $G$.

1: $K \leftarrow V$.
2: for every $S \subseteq V$ do
3: if $S$ is a vertex cover of $G$ and $|S| < |K|$ then
4: $K \leftarrow S$.
5: end if
6: end for
7: return $K$

In the above algorithm, there are $2^{|V|}$ iterations of the For-loop (number of subsets of $V$), and each iteration requires to check if a set of vertices is a vertex cover (check if all edges are touched), i.e., each iteration requires time $O(|E|)$. Overall, for any $G = (V, E)$, the problem of computing $vc(G)$ can be solved in time $O(|E| \cdot 2^{|V|})$.

Again, the goal of this lecture is to learn how/when to solve such a problem (that, unless $P = NP$, cannot be solved in polynomial-time) in more efficient ways...

Now, we show that the Min. Vertex Cover problem is “easy” (can be solved in polynomial-time) in bipartite graphs. Then we show that finding a vertex cover that is “not too large” is not difficult in any graph.

Lemma 1 Let $K$ be any vertex cover and $M$ be any matching of any graph $G$. Then $|M| \leq |K|$.

Proof. For every edge $e \in M$, $K \cap e \neq \emptyset$ by definition of a vertex cover. Moreover, for every $v \in K$, there is at most one edge $e \in M$ such that $v \in e$ (by definition of a matching). So $|M| \leq |K|$ (each edge of $M$ is touched by at least one vertex of $K$ and each vertex of $K$ touches at most one edge of $M$).

Theorem 5 (König-Egerváry 1931) For any bipartite graph $G = (A \cup B, E)$, the size of a minimum vertex cover $vc(G)$ equals the size of a maximum matching $\mu(G)$.

Proof. The fact that $\mu(G) \leq vc(G)$ follows from Lemma 1.

Let $M$ be a maximum matching of $G$, i.e., $M$ is a matching of $G$ and $|M| = \mu(G)$. If $A$ is saturated by $M$ then $|M| = |A|$ and, because $G$ is bipartite, $A$ is a vertex cover and the result follows. Assume $A$ is not saturated by $M$ and let $U \subseteq A$ be the uncovered vertices in $A$. Let $X$ be the set of vertices linked to some vertex in $U$ by a $M$-alternating path. Let $X_A = X \cap A$ and $X_B = X \cap B$. Note that $X_B$ is saturated (since otherwise, there is a $M$-augmenting path contradicting that $M$ is maximum by Th. 3). Moreover, $X_A = N(X_B)$. Prove that $Y = X_B \cup (A \setminus X_A)$ is a vertex cover of size $|M|$ (take any edge $e \in E$ and show that at least one of its ends is in $Y$ and prove that $|Y| = |M|$). So, $vc(G) \leq |Y| = |M| = \mu(G)$.

Note that the proof of Theorem 5 is constructive: it allows to compute, from a maximum matching in a bipartite graph, a minimum vertex cover in polynomial-time.

Theorem 6 Let $M$ be any maximal matching of a graph $G$. Then, $|M| \leq vc(G) \leq 2|M|$.
Proof. The left inequality follows from Lemma 1.

Let $M$ be a maximal matching. Then $Y = \bigcup_{(u,v) \in M} \{u, v\}$ is a vertex cover. Indeed, if not, there is $f = \{x, y\} \in E$ such that $Y \cap \{x, y\} = \emptyset$, and so $M \cup \{f\}$ is a matching, contradicting that $M$ is maximal. Hence, $vc(G) \leq |Y| = 2|M|$.

Recap. on Min. Vertex Cover. Let us consider the problem that takes a graph $G = (V, E)$ as input and aims at computing a set $K \subseteq V$, which is a vertex cover of minimum size in $G$. As mentioned above the corresponding decision problem is $NP$-complete in general graphs and can be (naively) solved in time $O(|E| \cdot 2^{|V|})$. The goal of this lecture is to explain how/when we can improve this time-complexity. In the introduction, we mentioned four possible ways to go through the “$P$ vs. $NP$ barrier”. In the current subsection, we gave two different answers in the specific case of the Min. Vertex Cover Problem (MVCP):

Restrict inputs: By Th. 5 and algorithm of [Micali, Vazirani 1980], the MVCP can be solved in time $O(\sqrt{|V||E|})$ in bipartite graphs, i.e., MVCP is in $P$ when restricted to bipartite graphs!!

First Approximation Algorithm: Consider the following algorithm: compute $M$ a maximal matching of $G$ (can be done in time $O(|E|)$ by Alg. Maximal Matching) and return $V(M) = \{v \mid \exists e \in M, v \in M\}$. By the proof of Th. 6, $V(M)$ is a vertex cover of $G$. Moreover, $|V(M)| = 2 \cdot |M| \leq 2 \cdot vc(G)$ (because $|M| \leq vc(G)$ by Th. 6). So, in polynomial-time $O(|E|)$, it is possible to compute a vertex cover $X$ of any graph $G$ that is “not too bad” ($|X|$ is at most twice the size of a minimum vertex cover).

Exercise 8 Give an example of graph for which the algorithm of previous paragraph gives a vertex cover of size twice the optimal.

Note that last proposition relies on the following facts. We are able to compute in polynomial-time some feasible solution (here $M$) and to bound on both sides (lower and upper bound) the size of any optimal solution in the size of $M$!!

Roughly, these are the key points of approximation algorithms as we formalize them in next section.

Part II

Approximation Algorithms [9]

3 Introduction to Approximation Algorithms: Load balancing

In this section, we formally define the notion of approximation algorithm (efficient algorithm that computes a “not too bad” solution) and exemplify this notion via the Load Balancing problem. For this problem we design and analyze two approximation algorithms, the second algorithm improving the first one.

3.1 Definition of an Approximation Algorithm

The following definition is not really formal since I do not want to give the formal definition of an optimization problem here. I think/hope this will be sufficient for our purpose.

Let us consider an optimization problem II and let $w$ be the function evaluating the quality (or cost) of a solution. Let $k \geq 1$. An algorithm $A$ is a $k$-approximation for II if each of the following three conditions is satisfied. For any input $I$ of II:
• A computes an output \( O \) in \textbf{polynomial-time} (in the size of \( I \));
• this output \( O \) is a \textbf{valid} solution for \( I \), i.e., satisfies the constraints defined by \( \Pi \), and
  • if \( \Pi \) is a \textit{minimization problem} (aims at finding a valid solution with minimum cost),
    then \( w(O) \leq k \cdot w(O^*) \) where \( O^* \) is an optimal (i.e., with minimum cost) valid solution for \( I \).
  • if \( \Pi \) is a \textit{maximization problem} (aims at finding a valid solution with maximum cost),
    then \( w(O^*) \leq k \cdot w(O) \) where \( O^* \) is an optimal (i.e., with maximum cost) valid solution for \( I \).

For instance, if \( \Pi \) is the minimum vertex cover studied in previous section, the goal is, given a graph \( G = (V,E) \), to compute a set \( K \subseteq V \) with the constraint that it is a vertex cover (i.e., every edge is touched by some vertex in \( K \)), and the cost function is the size \( |K| \) of the set.

\textbf{Exercise 9} Show that the algorithm that consists in computing a maximal matching \( M \) in \( G \) and returning \( V(M) \) is a \( 2 \)-approximation for the minimum vertex cover problem.

\textbf{Remark.} In previous definition, we have assumed that \( k \) is a constant. This definition can be generalized by considering \( k \) as a function \( f \) of the size of the input. For instance, a \( f(n) \)-approximation is an algorithm that, given an input of size \( n \), computes in polynomial-time a valid solution of cost at most \( f(n) \) times the cost of an optimal solution for a minimization problem (resp., of cost at least \( \frac{1}{f(n)} \) times the cost of an optimal solution for a maximization problem).

\section{3.2 The Load Balancing Problem}

For once, let us not speak about graphs...

Let us consider a set of \( m \in \mathbb{N} \) identical processors, and a set of \( n \in \mathbb{N} \) jobs described by the \( n \)-tuple \( (t_1, \cdots, t_n) \) where \( t_i \) is the time required by a processor to execute job \( i \), for every \( 1 \leq i \leq n \). Each processor can treat only one job at a time. Moreover, we assume that each job is unbreakable, i.e., it cannot be shared between several processors. The goal of the \textit{Load Balancing} Problem is to assign each job to one processor in order to minimize the overall completion time.

More formally, the goal of the Load Balancing problem is to compute a partition \( S = \{A_1, \cdots, A_m\} \) of the jobs, i.e., \( \bigcup_{1 \leq i \leq m} A_i = \{1, \cdots, n\} \) and \( A_i \cap A_j = \emptyset \) for every \( 1 \leq i < j \leq m \) (this corresponds to an assignment of the jobs to the processors. Note that any \( A_i \) may be \( \emptyset \)) minimizing \( \max_{1 \leq i \leq m} \sum_{j \in A_i} t_j \). Given an assignment \( S = \{A_1, \cdots, A_m\} \), the \textit{load} \( L_i(S) \) of the processor \( i \) (\( 1 \leq i \leq m \)) is \( \sum_{j \in A_i} t_j \) and \( \max_{1 \leq i \leq m} L_i(S) \) is called the \textit{makespan} of \( S \). So the Load Balancing problem consists in finding an assignment minimizing the makespan.

\textbf{Load Balancing Problem (LBP)}:

\textbf{Input}: \( m \in \mathbb{N} \) and \( (t_1, \cdots, t_n) \in (\mathbb{R}^+)^n \).

\textbf{Output}: A partition \( \{A_1, \cdots, A_m\} \) of \( \{1, \cdots, n\} \) such that \( \max_{1 \leq i \leq m} \sum_{j \in A_i} t_j \) is minimum.

The LBP is a classical \textit{NP}-complete problem \cite{7}.

As usual, let us first think to what could be a (naive) algorithm: try all possibilities!! Each of the \( n \) jobs can be assigned to any of the \( m \) processors, which give \( m^n \) possibilities :(
Hence, we aim at designing approximation algorithms for solving it. An approximation algorithm requires to be able to evaluate the quality of the solution it returns with respect to the quality $OPT$ of an optimal solution. Since, in general, we don’t know the cost of an optimal solution, it is important to have reliable lower (in case of minimization problems) bounds on the cost of an optimal solution (resp., upper bound for maximization problems). Indeed, consider a minimization problem (the case of a maximization problem is similar, prove it). If we know a lower bound $LB \leq OPT$ of the cost of an optimal solution and that we can relate the cost $c$ of any solution computed by our algorithm to $LB$ (e.g., say $c \leq k \cdot LB$ for some constant $k$), this will be an indirect way to relate $c$ and $OPT$: $LB \leq OPT \leq c \leq k \cdot LB \leq k \cdot OPT$.

3.2.1 Greedy 2-Approximation (least loaded processor)

For the LBP, there are two easy lower bounds:

**Lemma 2** Let $(m, (t_1, \cdots, t_n))$ be an instance of the LBP and let $OPT$ be the minimum makespan over all assignments. Then $\max_{1 \leq i \leq n} t_i \leq OPT$ and $\frac{1}{m} \sum_{1 \leq i \leq n} t_i \leq OPT$.

**Proof.** The first statement is obvious. The 2nd statement follows the pigeonhole principle. ■

**Exercise 10** Prove that, if $n \leq m$, an optimal solution is to assign each job to exactly one processor, and that $\max_{1 \leq i \leq n} t_i = OPT$.

Hence, let us assume that $n > m$. Let us consider the intuitive simple greedy algorithm\footnote{Roughly, an algorithm is greedy if each of its steps is guided by a simple local (i.e., depending on the current state) rule.}.

**Algorithm 8** : 2-Approximation for Load Balancing Problem

Require: $n > m \in \mathbb{N}$ and $(t_1, \cdots, t_n) \in (\mathbb{R}^+)^n$.

Ensure: A partition $\{A_1, \cdots, A_m\}$ of $\{1, \cdots, n\}$.

1: $\{A_1, \cdots, A_m\} \leftarrow \{\emptyset, \cdots, \emptyset\}$.
2: for $i = 1$ to $n$ do
3: \hspace{1cm} $A_1 \leftarrow A_1 \cup \{i\}$.
4: \hspace{1cm} Reorder the $A_i$’s such that $\sum_{j \in A_1} t_j \leq \sum_{j \in A_2} t_j \leq \cdots \leq \sum_{j \in A_m} t_j$.
5: end for
6: return $\{A_1, \cdots, A_m\}$.

**Theorem 7** Algorithm 8 is a 2-approximation for the LBP, with time-complexity $O(n \log m)$.

**Proof.** There are 3 properties to be proved! First, it returns a valid solution, i.e., here the computed solution $\{A_1, \cdots, A_m\}$ is a partition of $\{1, \cdots, n\}$. This is obvious (I hope?). Second, it has polynomial-time complexity. Indeed, there are $n$ iterations of the For-loop, and each of them requires to re-sort an already sorted list of $m$ elements where only one has changed, which takes $O(\log m)$ time per iteration (see, e.g., [3]).

The third property, i.e., that the makespan $L = \max_{1 \leq i \leq m} \sum_{j \in A_i} t_j$ of the computed partition $\{A_1, \cdots, A_m\}$ is at most twice the optimal makespan $OPT$, is the most “difficult” to prove. For any $i \leq m$, let $L_i = \sum_{j \in A_i} t_j$. 
Let \( x \leq m \) be such that \( L = L_x = \max_{1 \leq i \leq m} L_i \) (i.e., Processor \( x \) is one of the most loaded in the computed solution). Note that \( OPT \leq L \).

Let \( j \leq n \) be the last job assigned to \( A_x \), i.e., \( j \) is the maximum integer in \( A_x \). Note that \( t_j \leq OPT \) by the first statement of Lemma 2.

For every \( 1 \leq y \leq m \), let \( L'_i \) be the load of Processor \( i \) when \( t_j \) is assigned to \( P_x \) (i.e., after iteration \( j - 1 \) of the For-loop). Then, \( L_x - t_j \leq L'_i \) for every \( i \leq m \) (indeed, it is obvious for \( i = x \), and if there is \( y \in \{1, \cdots, m\} \setminus \{x\} \) with \( L_x - t_j > L'_y \), the job \( j \) would have been assigned to Processor \( y \) by the definition of Algorithm 8). Since, for every \( 1 \leq i \leq m \), the load of Processor \( i \) is not decreasing during the algorithm, this implies that \( L_x - t_j \leq L_i \) for every \( i \leq m \).

Therefore, \( m(L_x - t_j) \leq \sum_{1 \leq i \leq m} L_i = \sum_{1 \leq i \leq n} t_i \). Hence, \( L_x - t_j \leq \frac{1}{m} \sum_{1 \leq i \leq n} t_i \leq OPT \) where the last inequality is given by the second statement of Lemma 2.

Hence, by previous paragraphs, we have \( t_j \leq OPT \) and \( L_x - t_j \leq OPT \).

To conclude, \( L = L_x = (L_x - t_j) + t_j \leq OPT + OPT = 2 \cdot OPT \).

Note that, sometimes, the algorithm is better than we can expect from its analysis. For instance, previous theorem proves that Algorithm 8 is a 2-approximation for the LBP. The next question is whether Algorithm 8 is a \( c \)-approximation for the LBP for some \( c < 2 \). Note that the latter is not true if we can find an instance for which Algorithm 8 computes a solution of cost exactly twice the optimal.

**Exercise 11** Let \( m \in \mathbb{N} \) and \( n = (m-1)m+1 \). Apply Algorithm 8 to the input \((m, (t_1, \cdots, t_n))\) where \( t_1 = \cdots = t_{n-1} = 1 \) and \( t_n = m \). Conclusion (let \( m \) tend to \( \infty \))?

Hence, to expect a \( c \)-approximation for the LBP with \( c < 2 \), we need another algorithm.

### 3.2.2 Greedy \( \frac{3}{2} \)-Approximation (least loaded processor and ordered tasks)

**Algorithm 9** : \( \frac{3}{2} \)-Approximation for Load Balancing Problem

Require: \( n > m \in \mathbb{N} \) and \((t_1, \cdots, t_n) \in (\mathbb{R}^+)^n \).

Ensure: A partition \( \{A_1, \cdots, A_m\} \) of \( \{1, \cdots, n\} \).

1. Order the jobs in non decreasing order of their completion time, i.e. \( t_1 \geq \cdots \geq t_n \).
2. \( \{A_1, \cdots, A_m\} \leftarrow \{\emptyset, \cdots, \emptyset\} \).
3. for \( i = 1 \) to \( n \) do
4. \( A_1 \leftarrow A_1 \cup \{i\} \).
5. Reorder the \( A_i \)'s such that \( \sum_{j \in A_1} t_j \leq \sum_{j \in A_2} t_j \leq \cdots \leq \sum_{j \in A_m} t_j \).
6. end for
7. return \( \{A_1, \cdots, A_m\} \).

Note that Algorithm 9 only differs from Algorithm 8 by its first step that consists in ordering the jobs by non-decreasing completion time. However, it offers us the opportunity to use a new lower bound (proved by pigeonhole principle).

**Lemma 3** Let \( n > m \), \((m, (t_1, \cdots, t_n))\) be an instance of the LBP with \( t_1 \geq \cdots \geq t_n \) and let \( OPT \) be the minimum makespan over all assignments. Then \( OPT \geq 2 \cdot t_{m+1} \).

**Theorem 8** Algorithm 9 is a \( \frac{3}{2} \)-approximation for the LBP, with time-complexity \( O(n \log n) \).
Proof. Again, Algorithm 9 computes a valid solution (a partition) \( \{ A_1, \ldots, A_m \} \). Moreover, the bottleneck for the time-complexity is the first step that takes time \( O(n \log n) \). It only remains to prove the approximation ratio.

For any \( i \leq m \), let \( L_i = \sum_{j \in A_i} t_j \) and let \( x \leq m \) be such that \( L = L_x = \max_{1 \leq i \leq m} L_i \) (i.e., Processor \( x \) is one of the most loaded in the computed solution). Note that \( OPT \leq L \).

Let \( j \leq n \) be the last job assigned to \( A_x \), i.e., \( j \) is the maximum integer in \( A_x \). Then, \( j \geq m + 1 \) and \( 2 \cdot t_j \leq OPT \) by Lemma 3 and because \( t_j \leq t_m + 1 \). As in the proof of previous theorem, \( L_x - t_j \leq OPT \). Hence, \( L_x = (L_x - t_j) + t_j \leq OPT + OPT/2 = \frac{3}{2} \cdot OPT \). \[ \blacksquare \]

4 Traveling Salesman Problem (TSP)

4.1 Different variants and exact dynamic programming algorithm

A salesman has to visit several cities but aims at minimizing the length (or cost) of his journey. The TSP aims at computing a best possible route for the salesman.

More formally, let \( K_n \) be the complete graph (or clique) with \( n \) vertices, i.e., the graph with all possible edges between the \( n \) vertices. Recall that the weight of a subgraph \( H \) is \( \sum_{e \in E(H)} w(e) \).

Given the clique \( K_n \) with edge-weight \( w : E(K_n) \to \mathbb{R}^+ \), the Traveling Salesman Problem (TSP) aims at computing a Hamiltonian cycle of minimum weight in \( (K_n, w) \).

Note that the problem is restricted to complete graphs to ensure that there exists a Hamiltonian cycle. However, the TSP is equivalent to the problem of computing a minimum-weight walk\(^9\) passing through all vertices and going back to the initial vertex in any graph. Indeed, let \( G = (V, E) \) be a graph with edge-weight \( \ell : E \to \mathbb{R}^+ \). The distance between 2 vertices \( u, v \in V \), denoted by \( dist_G(u, v) \), is the minimum weight of a path from \( u \) to \( v \) in \( (G, \ell) \). Let \( w : V \times V \to \mathbb{R}^+ \) that assigned to every pair \((u, v)\) of vertices the weight \( w(u, v) = dist_G(u, v) \).

Exercise 12 Show that there exists a Hamiltonian cycle in \((K_n, w)\) of weight \( \leq k \in \mathbb{R}^+ \) if and only if there exists a walk passing through all vertices and going back to the initial vertex, in \( G \), with weight \( \leq k \).

Given \((K_n, w)\) and \( k \in \mathbb{R}^+ \), the problem of deciding whether there exists a Hamiltonian cycle of weight at most \( k \) is \( \text{NP}\)-complete [7]. The algorithm proposed in Section 2.1 to decide if a graph has a Hamiltonian cycle can be directly adapted to solve the TSP in time \( O(n \cdot n!) \). Here, we show how to improve the time complexity by presenting a dynamic programming algorithm.

Let \( v_1 \in V(K_n) \) and let \( S \subseteq V(K_n) \setminus \{ v_1 \} \) be a non-empty set of vertices and \( v \in S \). Let \( OPT[S, v] \) denote the minimum weight of a path that starts in \( v_1 \) and visits exactly all vertices in \( S \), ending in \( v \). Clearly, for every \( v \neq v_1 \), \( OPT[\{v\}, v] = w(v_1, v) \).

Lemma 4 Let \( S \subseteq V(K_n) \setminus \{ v_1 \} \) with \( |S| \geq 2 \) and let \( v \in S \).

\[ OPT[S, v] = \min_{u \in S \setminus \{v\}} OPT[S \setminus \{v\}, u] + w(u, v). \]

Proof. The proof is by double inequalities.

First, let \( P \) be a path from \( v_1 \) to \( v \), with \( V(P) = S \cup \{ v_1 \} \) and with weight \( OPT[S, v] \). Let \( x \) be neighbor of \( v \) in \( P \) and let \( P' \) be the subpath of \( P \) from \( v_1 \) to \( x \). Then, \( OPT[S, v] = w(P') + w(x, v) \geq OPT[S \setminus \{v\}, x] + w(x, v) \geq \min_{u \in S \setminus \{v\}} OPT[S \setminus \{v\}, u] + w(u, v) \).

\(^9\)The weight of a walk \((v_1, \ldots, v_k)\) is \( \sum_{1 \leq i < k} w(v_i, v_{i+1}) \), i.e., the multiplicity of edges is taken into account.
Conversely, let \( x \in S \setminus \{ v_1 \} \) be such that \( \text{OPT}[S \setminus \{ v \}, x] + w(x, v) \) is minimum. Let \( P' \) be a path from \( v_1 \) to \( x \), with \( V(P) = (S \setminus \{ v \}) \cup \{ v_1 \} \) and with weight \( \text{OPT}[S \setminus \{ v \}, x] \). Let \( P \) be the path from \( v_1 \) to \( v \) obtained from \( P' \) by adding to it the edge \( \{ x, v \} \). Then, \( \min_{u \in S \setminus \{ v \}} \text{OPT}[S \setminus \{ v \}, u] + w(u, v) = \text{OPT}[S \setminus \{ v \}, x] + w(x, v) = w(P) \geq \text{OPT}[S, v]. \)


**Require:** Complete graph \( K_n = (V, E) \) with \( w : E \to \mathbb{R}^+ \).

**Ensure:** The minimum weight of a Hamiltonian cycle.

1. Let \( v_1 \in V \).
2. for \( v \in V \setminus \{ v_1 \} \) do
3. \( \text{OPT}[\{ v \}, v] = w(v_1, v) \).
4. end for
5. for \( S \subseteq V \setminus \{ v_1 \} \) with \( |S| \geq 2 \) in non-decreasing size order do
6. for \( v \in V \setminus \{ v_1 \} \) do
7. \( \text{OPT}[S, v] = \min_{u \in S \setminus \{ v \}} \text{OPT}[S \setminus \{ v \}, u] + w(u, v) \).
8. end for
9. end for
10. return \( \min_{v \in V \setminus \{ v_1 \}} \text{OPT}[V \setminus \{ v_1 \}, v] + w(v, v_1) \).

**Theorem 9 (Bellman-Held-Karp 1962)** Algorithm 10 computes the minimum weight of a Hamiltonian cycle (and can be easily adapted to compute a minimum-weight Hamiltonian cycle) in time \( O(n^2 \cdot 2^n) \).

**Proof.** The time complexity comes from the fact that there are \( O(2^n) \) sets \( S \) to be considered. For each set \( S \), and for each of the \( O(n) \) vertices in \( V \setminus \{ v_1 \} \), the algorithm must find a minimum value among \( O(n) \) values, so each iteration of the main For-loop takes time \( O(n^2) \).

The correctness follows the fact that, after the last “EndFor”, the values \( \text{OPT}[V \setminus \{ v_1 \}, v] \) are known for every \( v \in V \setminus \{ v_1 \} \) (by Lemma 4). To conclude, let \( C^* \) be an optimal Hamiltonian cycle and let \( \text{OPT} \) be its weight. The proof is by double inequalities.

Let \( x \) be a neighbor of \( v_1 \) in \( C^* \) and let \( P \) be the path obtained from \( C^* \) by removing the edge \( \{ v_1, x \} \). Then, \( \text{OPT} = w(P) + w(v_1, x) \geq \text{OPT}[V \setminus \{ v_1 \}, x] + w(x, v_1) \geq \min_{v \in V \setminus \{ v_1 \}} \text{OPT}[V \setminus \{ v_1 \}, v] + w(v, v_1) \). Finally, let \( x \in V \setminus \{ v_1 \} \) minimizing \( \text{OPT}[V \setminus \{ v_1 \}, x] + w(x, v_1) \) and let \( P \) be a spanning path from \( v_1 \) to \( x \) with weight \( \text{OPT}[V \setminus \{ v_1 \}, x] \). Then adding the edge \( \{ x, v_1 \} \) to \( P \) leads to a Hamiltonian cycle \( C \) and so, \( \min_{v \in V \setminus \{ v_1 \}} \text{OPT}[V \setminus \{ v_1 \}, v] + w(v, v_1) = \text{OPT}[V \setminus \{ v_1 \}, x] + w(x, v_1) = w(C) \geq \text{OPT} \).

No algorithm for solving TSP in time \( O(c^n) \) is known for any \( c < 2 \). Moreover,

**Theorem 10** If \( P \neq \text{NP} \), there is no \( c \)-approximation algorithm for solving TSP, for any constant \( c \geq 1 \).

So the TSP problem is difficult and it is even difficult to approximate it. To overcome this difficulty, there may be several options. Here, we discuss two of them: simplifying the problem and/or restricting the instances. To simplify the problem, we may allow repetitions of vertices and edges. So, let \( TSP^r \) be the problem that, given a weighted \( K_n \), must compute a closed \(^{10} \) walk, passing through all vertices, and with minimum weight. On the other hand, we may restrict the instances of the TSP. Since considering a complete graph is important

\(^{10} \) “Closed” means that the starting and final vertices are the same.
because it ensures the existence of a Hamiltonian cycle, let us restrict the weight function. A weight function \( w : V \times V \to \mathbb{R}^+ \) satisfies the triangular inequality if, for every \( a, b, c \in V \), \( w(a, b) \leq w(a, c) + w(c, b) \). Let \( TSP_\delta \) be the problem that, given a weighted \((K_n, w)\) where \( w \) satisfies the triangular inequality, must compute a Hamiltonian cycle with minimum weight. Finally, let \( TSP_\delta^r \) be the problem that, given a weighted \((K_n, w)\) where \( w \) satisfies the triangular inequality, must compute a closed walk, passing through all vertices, and with minimum weight.

**Lemma 5** Any \( c \)-approximation algorithm for one problem in \{\( TSP^r, TSP_\delta, TSP_\delta^r \)\} can be turned into a \( c \)-approximation algorithm for any problem in \{\( TSP^r, TSP_\delta, TSP_\delta^r \)\}.

**Proof.** Any solution for \( TSP_\delta \) is a solution for \( TSP_\delta^r \) (with same weight). Similarly, any solution for \( TSP^r \) is a solution for \( TSP_\delta^r \) (with same weight).

Let \( W = (v_1, \ldots, v_k) \) be a solution for \( TSP_\delta^r \). If no vertex is repeated, then \( W \) is a solution of \( TSP_\delta \). Otherwise, let us assume that there are \( 1 \leq i < j < k \) such that \( v_i = v_j \), then \( W' = (v_1, \ldots, v_{j-1}, v_{j+1}, \ldots, v_k) \) is a solution and the weight of \( W' \) is not larger than the weight of \( W \) by the triangular inequality. Repeating this process sequentially until no vertex is repeated leads to a solution of \( TSP_\delta \) (without increasing the weight).

Finally, let \((K_n = (V, E), w)\) be an instance of \( TSP^r \). Let \( dist_{K_n} : E \to \mathbb{R}^+ \) be the distance function with respect to \( w \). Prove that \( dist_{K_n} \) satisfies the triangular inequality. Then, \((K_n, dist_{K_n})\) is an instance of \( TSP_\delta \). Following Exercise 12, any solution of \((K_n, dist_{K_n})\) for \( TSP_\delta \) leads to a solution (with same weight) of \((K_n, w)\) for \( TSP^r \).

Prove that above arguments allow to prove the lemma.

### 4.2 2-Approximation (using minimum spanning tree)

Let us now show that these problems \((TSP^r, TSP_\delta, TSP_\delta^r)\) admit “good” approximation algorithms. Precisely, let us first consider the problem \( TSP^r \). Since repetitions of edges/vertices are allowed, we may consider any connected graph (rather than complete graphs) since closed walk passing through every vertex always exists in any connected graph. Recall the notion of Depth First Search (DFS) of a tree [3].

As usual, the design (and analysis) of an approximation algorithm for solving some optimization problem \( \Pi \) requires some lower bound (if possible, that can be computed in polynomial time) on the quality of an optimal solution of \( \Pi \).

**Lemma 6** Let \( G = (V, E) \) be a connected graph and \( w : E \to \mathbb{R}^+ \). Let \( w^* \) be the minimum weight of a closed walk passing through all vertices in \( V \). Let \( t^* \) be the minimum weight of a spanning tree in \( G \). Then, \( t^* \leq w^* \).

**Proof.** Let \( W \) be any closed walk passing through all vertices in \( V \) and with minimum weight \( w(W) = w^* \). Then, \( E(W) \) induces a connected spanning subgraph \( H \) of \( G \) with weight \( w(H) \leq w(W) \) (the difference between \( w(H) \) and \( w(W) \) is that, in \( w(H) \), each edge is counted only once). Let \( T \) be any minimum spanning tree of \( G \). By Exercise 3, the weight \( t^* = w(T) \) of \( T \) is at most the weight of any connected spanning subgraph. Hence, \( t^* \leq w(T) \leq w(H) \leq w(W) = w^* \).

**Theorem 11** Algorithm 11 is a 2-approximation algorithm for the problem \( TSP^r \).

**Proof.** The fact that Algorithm 11 returns a valid solution is trivial. Its time-complexity follows from the one of the problem of computing a minimum spanning tree which can be done in polynomial-time (Th. 2). Finally, the weight of the computed walk \( W \) is twice the minimum weight \( t^* \) of the computed spanning tree \( T \) (because \( W \) follows a DFS of \( T \), each edge of \( T \) is crossed exactly twice in \( W \)). Hence, \( w(W) = 2t^* \leq 2w^* \) where \( w^* \) is the weight of an optimal closed spanning walk (by Lemma 6).
Algorithm 11: 2-approximation for TSP

**Require:** A connected graph $G = (V,E)$ with $w: E \to \mathbb{R}^+$.

**Ensure:** A closed walk passing through every vertex in $V$.

1. Let $T$ be a minimum spanning tree of $G$.
2. **return** the closed walk defined by any DFS-traversal of $T$.

4.3 $\frac{3}{2}$-Approximation (Christofides’ algorithm)

Let us conclude this section by an even better approximation algorithm. To simplify the presentation, let us consider the TSP.

**Lemma 7** Let $K_n$ with $w: E \to \mathbb{R}^+$ satisfying the triangular inequality, and let $w^*$ be the minimum weight of a Hamiltonian cycle. Let $V' \subseteq V(K_n)$ with $|V'|$ even. Finally, let $M$ be a minimum weight perfect matching of $V'$. Then, $w(M) \leq w^*/2$.

**Proof.** Let $C$ be an optimal Hamiltonian cycle of $K_n$ and let $C'$ be the cycle spanning $V'$ obtained by short-cutting $C$. By triangular inequality, $w(C') \leq w(C) = w^*$. Moreover, $E(C')$ can be partitioned into two perfect matchings $M_1$ and $M_2$ of $V'$. Since $w(C') = w(M_1) + w(M_2)$, w.l.o.g., $w(M_1) \leq w(C')/2$. Finally, $w(M) \leq w(M_1) \leq w(C')/2 \leq w(C)/2 = w^*/2$.

Algorithm 12: 3/2-approximation for TSP_{ti} [Christofides 1976]

**Require:** A complete graph $K_n = (V,E)$ with $w: E \to \mathbb{R}^+$ satisfying the triangular inequality.

**Ensure:** A Hamiltonian cycle.

1. Let $T^*$ be a minimum spanning tree of $G$.
2. Let $O$ be the set of vertices with odd degree in $T^*$.
3. Let $M$ be a perfect matching, with minimum weight, between the vertices in $O$.
4. Let $H$ be the graph induced by $E(T^*) \cup M$ (possibly, $H$ has parallel edges) and $C$ be an eulerian cycle in $H$.
5. **return** the Hamiltonian cycle obtained by considering the vertices in the order they are met for the first time in $C$.

**Theorem 12 (Christofides 1976)** Algorithm 12 is a $3/2$-approximation algorithm for the problem TSP_{ti}.

**Proof.** Note that, by Proposition 1, $O$ has even size and then, it is easy to see that $M$ is well defined (because $|O|$ is even and we are in a clique) and can be computed in polynomial time. By construction, every vertex has even degree in $H$ and so $C$ is well defined and can be computed in polynomial time (Th. 1). Finally, the Hamiltonian cycle returned by the algorithm has weight at most $w(C)$ by the triangular inequality. Hence, Algorithm 12 computes, in polynomial time, a Hamiltonian cycle with weight at most $w(C) = w(T^*) + w(M)$. The result follows from Lemmas 6 and 7.

5 Set Cover

To continue with approximation algorithms, let us consider that a new problem that is not (directly) related to graphs.
The **Set Cover** problem takes as inputs a ground set (a *universe*) \( U = \{e_1, \ldots, e_n\} \) of elements, a set \( S = \{S_1, \ldots, S_m\} \subseteq 2^U \) of subsets of elements and \( k \in \mathbb{N} \). The goal is to decide if there exists a set \( K \subseteq \{1, \ldots, m\} \) such that \( \bigcup_{j \in K} S_j = U \) and \( |K| \leq k \). In “optimization” words, the Set Cover problem aims at computing a minimum number of sets in \( S \) covering all elements in \( U \).

As an example, consider a set of persons, each one speaking only its own language (English, French, Spanish...) and a set of translators, each one speaking several languages (the first translator knows French, Chinese and Russian, the second one knows French and Spanish...). What is the minimum number of translators required to be able to communicate with all persons?

**Exercise 13** Formalize the above paragraph in terms of Set Cover problem (define \( U \) and \( S \)). Invent another application of the Set Cover problem.

Without surprise (given the topic of this course), the Set Cover problem is NP-complete [7].

### 5.1 Relationship with Graphs: Dominating Set and Vertex Cover

Before trying to solve the Set Cover problem, let us discuss its relationship with graphs. This subsection aims at getting a better understanding of Set Cover problem by considering it by different points of view (related to graphs).

Given a graph \( G = (V, E) \), a *dominating set* \( D \subseteq V \) is a set of vertices such that \( N[D]\)\(^\text{11} = V \). The minimum size of a dominating set in \( G \) is denoted by \( \gamma(G) \).

**Exercise 14** Show that, for any graph \( G = (V, E) \), \( \gamma(G) \leq \text{vc}(G) \) (recall that \( \text{vc}(G) \) is the minimum size of a vertex cover in \( G \)). That is, prove that any vertex cover is a dominating set.

Give a graph \( G \) in which \( \gamma(G) < \text{vc}(G) \).

The **minimum Dominating Set** (MDS) problem takes a graph \( G = (V, E) \) and \( k \in \mathbb{N} \) as inputs, and asks whether \( \gamma(G) \leq k \). The MDS problem is actually “related” to the Set Cover problem. Precisely, we show below that, any polynomial-time algorithm solving the MDS problem in bipartite graphs may be used to solve the Set Cover problem in polynomial-time.

Let \( (U = \{e_1, \ldots, e_n\}, \mathcal{S} = \{S_1, \ldots, S_m\}, k) \) be an instance of the Set Cover problem. Let us define the bipartite graph \( G(U, \mathcal{S}) = (A \cup B, E) \) as follows. Let \( A = U \setminus \{r\} \) and \( B = \mathcal{S} \cup \{r'\} \). Let us add an edge between \( r \) and every vertex in \( B \), and an edge \( \{r, r'\} \). Then, for every \( u \in U = A \setminus \{r\} \) and \( s \in B = \mathcal{S} \), there is an edge \( \{u, s\} \in E \) if and only if \( u \in s \).

**Lemma 8** Let \( k \in \mathbb{N} \). There exists a Set Cover of \((U, \mathcal{S})\) of size \( \leq k \) iff there exists a dominating set of \( G(U, \mathcal{S}) \) of size \( \leq k + 1 \).

**Proof.** Let \( K \subseteq \mathcal{S} \) be a set cover of \((U, \mathcal{S})\). Then, it is easy to check that \( K \cup \{r\} \) is a dominating set in \( G(U, \mathcal{S}) \).

Let \( D \subseteq V(G(U, \mathcal{S})) \) be a dominating set in \( G(U, \mathcal{S}) \). Prove that either \( r \) or \( r' \) belongs to \( D \), and that, if \( r' \in D \), then \( (D \setminus \{r'\}) \cup \{r\} \) is a dominating set with size no larger than \( |D| \). Hence, we may assume that \( r \in D \) and \( r' \notin D \). Now, if there is \( u \in D \cap U \), let \( s \in \mathcal{S} \) such that \( \{u, s\} \in E(G(U, \mathcal{S})) \) (i.e., \( u \in s \)). Show that \( (D \setminus \{u\}) \cup \{s\} \) is a dominating set with size no larger than \( |D| \). Hence, we may assume that \( r \in D \) and \( D \subseteq \mathcal{S} \cup \{r\} \). Finally, show that \( D \setminus \{r\} \) is a set cover of \((U, \mathcal{S})\). \( \blacksquare \)

\(^{11}\)In a graph \( G = (V, E) \) and given \( X \subseteq V \), \( N(X) = \{u \in V \setminus X \mid \exists v \in X, \{u, v\} \in E\} \) and \( N[X] = N(X) \cup X \).
On the other hand, Set Cover is “related” to the Vertex Cover problem. Precisely, any polynomial-time algorithm solving the Set Cover problem can be used to solve the Vertex Cover problem in polynomial-time. For every graph $G = (V, E)$ and, for every $v \in V$, let $E_v = \{uv \in E | u \in V\}$ be the set of edges adjacent to $v$.

**Exercise 15** Let $G = (V, E)$ be a graph. For any $K \subseteq V$, $\{E_v \mid v \in K\}$ is a Set Cover of $(E, \{E_v \mid v \in V\})$ if and only if $K$ is a vertex cover of $G$.

**Remark.** The following goes beyond this course (since, I voluntary do not want to go into more details about NP-hardness). However, let us mention that above paragraphs actually consist of reductions leading to hardness proofs. If you already know what it is about, there is no need for more details, otherwise let us just state the following consequence.

Since the Set Cover problem is NP-hard and, since building $G(U, S)$ can be done in polynomial-time, Lemma 8 leads to the following corollary.

**Corollary 1** The Minimum Dominating Set problem is NP-hard even if the input graphs are restricted to the class of bipartite graphs.

Similarly, since the Vertex Cover problem is NP-hard and, since building $(E, \{E_v \mid v \in V\})$ can be done in polynomial-time, Exercise 15 leads to the following corollary.

**Corollary 2** The Set Cover problem is NP-hard even if the input $(U, S)$ is such that every element of $U$ is in at most 2 sets in $S$.

### 5.2 Greedy $O(\log n)$-approximation

Let $(U = \{e_1, \cdots, e_n\}, S = \{S_1, \cdots, S_m\} \subseteq 2^U)$ be an instance of the Set Cover problem. Moreover, we consider a cost function $c : S \rightarrow \mathbb{R}^+$ over the sets. This section is devoted to the computation of a minimum-cost solution.

**Exercise 16** Give a “naive” algorithm that computes a set $K \subseteq \{1, \cdots, m\}$ such that $\bigcup_{j \in K} S_j = U$ and of minimum cost in time $O^*(2^m)^{12}$.

Next, let us present a greedy algorithm for the Set Cover problem that, while very simple, appears to be an approximation algorithm with best asymptotic approximation ratio. More precisely, the greedy algorithm sequentially adds to the set cover, while the set cover does not cover all elements, a new set with minimum effective cost defined as follows. Given $F \subseteq \{1, \cdots, m\}$, $X_F = \bigcup_{i \in F} S_i$ and $j \in \{1, \cdots, m\} \setminus F$ such that $S_j \setminus X_F \neq \emptyset$, let the effective cost of $S_j$, denoted by $c_{eff}(S_j, F)$, be $\frac{c(S_j)}{|S_j \setminus X_F|}$ (i.e., the cost of $S_j$ is shared among the elements that are not covered by $F$). Note that, if $c(S_i) = 1$ for all $i \leq m$, a set $S_j$ has minimum effective cost with respect to $F$ iff $S_j$ is a set covering the maximum number of elements uncovered by $F$.

The intuition behind this algorithm can be stated as follows. At each iteration, when a new set $S_i$ is added in the solution, its effective cost is equally distributed to each element that $S_i$ allows to cover. Precisely, for every element $e \in U$, let us assume that $e$ is covered for the first time when a set $S_i$ is added to the current solution $K$ (i.e., consider the value of $K$ before $S_i$ is added to it). Let us say that this element $e$ receives $\text{price}(e) = c_{eff}(S_i, \bigcup_{j \in K} S_j) = \frac{c(S_i)}{|S_i \setminus \bigcup_{j \in K} S_j|}$.

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$^{12}$A function $f(n) = O^*(g(n))$ if there exists $c > 0$ such that $f(n) = O(g(n)n^c)$, i.e., $O^*$ omits polynomial factors.
Theorem 13 (Chvátal 1979) Algorithm 13 is a $O(\log n)$-approximation algorithm for the Set Cover problem (with $n$ being the size of the ground-set/universe $U$).

Proof. Algorithm 13 clearly returns a valid solution in polynomial-time. Let us focus on the approximation ratio.

Let $K = \{j_1, \ldots, j_k\} \subseteq \{1, \ldots, m\}$ be a solution returned by the above algorithm. For every $1 \leq i \leq k$, let $X_i = \bigcup_{\ell < i} S_\ell$ be the set of elements already covered before the $i$th iteration of the While-loop.

Let $K^*$ be an optimal solution for the Set Cover problem and let $OPT = \sum_{j \in K^*} c(S_j)$. For every $1 \leq i \leq k$, let $F_i \subseteq K^*$ such that, for every $j \in F_i$, $S_j$ is needed to cover some vertex in $E \setminus X_i$ (i.e., for all $j \in F_i$, $\bigcup_{\ell \in F_i \setminus \{j\}} S_\ell$ does not cover $U \setminus X_i$). By the pigeonhole principle:

Claim 2 For every $1 \leq i \leq k$, there is $j \in F_i$ such that $c_{\text{eff}}(S_j, X_i) \leq \frac{OPT}{n - |X_i|}$.

Proof of Claim. First, let us show that the total cost $\sum_{j \in F_i} c(S_j)$ of the sets in $F_i$ is distributed to the elements in $U \setminus X_i$ (by considering the effective costs of these sets and the prices of elements in $U \setminus X_i$ as in above claim).

Precisely, let us set $\{S_j \mid j \in F_i\} = \{S_{i1}^*, \ldots, S_{|F_i|}^*\}$ and assume that these sets are “added” to the optimal solution in this order. Hence, for all $j \leq |F_i|$, the effective cost $c_{\text{eff}}(S_j^*, X_i \cup \bigcup_{\ell < j} S_\ell^*) = \frac{c(S_j^*)}{|S_j^* \setminus (X_i \cup \bigcup_{\ell < j} S_\ell^*)|}$ (Note that, because $K^*$ is an optimal solution, for every $j \in F_i$, there is at least one element covered only by $S_j$, and so this effective cost is well defined) is equally distributed among the elements in $S_j^* \setminus (X_i \cup \bigcup_{\ell < j} S_\ell^*)$. Hence, the total cost $\sum_{j \in F_i} c(S_j) = \sum_{j \leq |F_i|} c(S_j^*) \leq OPT$ is distributed over the elements of $U \setminus X_i$. 

23
By the pigeonhole principle, some element must receive a price at most \( \sum_{j \in F_i} \frac{c(S_j)}{|U \setminus X_i|} \leq \frac{OPT}{|U \setminus X_i|} \). Hence, the set \( S'_j, j \leq |F_i| \), associated to this element has effective cost at most \( \frac{OPT}{n-|X_j|} \).

Let us go back to the solution computed by Algorithm 13. Let us assume that all elements of \( U \) are covered in the following order \( (e_1, \cdots, e_n) \).

Let \( j \leq n \) and assume that the element \( e_j \in U \) is covered when the set \( S_{j_i} \) (for some \( j_i \leq k \)) is added to the solution. By claim above, there is \( t \in F_i \) such that \( c_{eff}(S_t, X_i) \leq \frac{OPT}{n-|X_i|} \). By the definition of the algorithm, this implies that \( c_{eff}(S_{j_i}, X_i) \leq \frac{OPT}{n-|X_i|} \). Moreover, \( X_i \subseteq \{e_1, \cdots, e_{j-1}\} \) (since \( e_j \) is not covered before \( S_{j_i} \) is added and so \( e_j, \cdots, e_n \notin X_i \)) and, therefore, \( |X_i| \leq j - 1 \) and so, \( price(e_j) = c_{eff}(S_j, X_i) \leq \frac{OPT}{n-j+1} \).

It follows that \( \sum_{j \in K} \sum_{1 \leq j \leq n} c(S_j) \leq \sum_{1 \leq j \leq n} \frac{OPT}{n-j+1} = OPT \). Hence, \( \sum_{1 \leq j \leq n} \frac{1}{j} = O(\log n) \cdot OPT \).

It can be proved that no \( o(\log n) \)-approximation algorithm exists (unless \( P = NP \)) for the Set Cover problem [9]. That is, Algorithm 13 is asymptotically optimal in terms of approximation ratio (as a function of \( n \)). However, if the input \( (U, S) \) is such that every element of \( U \) appears in at most \( f \geq 2 \) sets in \( S \), better performances may be achieved (e.g., Vertex Cover, where \( f = 2 \)). For instance, rounding of linear programming relaxation allows the design of a \( O(f) \)-approximation (e.g., see here).

6 Knapsack and (F)PTAS

The Knapsack problem takes a set of integers \( S = \{w_1, \cdots, w_n\} \) and an integer \( b \) as inputs. The objective is to compute a subset \( T \subseteq \{1, \cdots, n\} \) of items such that \( \sum_{i \in T} w_i \leq b \) and \( \sum_{i \in T} w_i \) is maximum. That is, we want to fill our knapsack without exceeding its capacity \( b \) and putting the maximum total weight in it.

6.1 (Pseudo-polynomial) Exact Algorithm via dynamic programming

Recall that Dynamic Programming is a generic algorithmic method that consists in solving a problem by combining the solutions of sub-problems.

As an example, the Simple Knapsack Problem consists in computing an optimal solution for an instance \( S = \{w_1, \cdots, w_n\} \) and an integer \( b \). Let \( OPT(S, b) \) denote such a solution. We will compute it using solutions for sub-problems with inputs \( S_i = \{w_1, \cdots, w_i\} \) and \( b' \in \mathbb{N} \), for any \( i \leq n \) and \( b' < b \). That is, we will compute \( OPT(S, b) \) from all solutions \( OPT(S_i, b') \) for \( i \leq n \) and \( b' < b \).

**Theorem 14** Algorithm 14 computes a optimal solution for the Knapsack problem in time \( O(n \cdot b) \).

**Proof.** Algorithm 14 consists in two imbricated loops, the first one with \( O(n) \) iterations and the second one with \( O(b) \) iterations. “Inside” the second loop, there are a constant number of operations (tests, comparisons, arithmetical operations). Hence, its time-complexity is \( O(nb) \).

To prove the correctness of Algorithm 14, let us first understand the meaning of \( OPT(S_i, b') \) \( (i \leq n, b' \leq b) \). The set \( OPT(S_i, b') \) is a combination (a choice/a subset) of elements in \( \{1, \cdots, i\} \) that maximizes the weight of the chosen elements such that it does not exceed \( b' \).
That is $OPT(S_i, b') \subseteq \{1, \ldots, i\}$ is such that $opt(S_i, b') = \sum_{j \in OPT(S_i, b')} w_j \leq b'$ and, for every $T \subseteq \{1, \ldots, i\}$ with $w(T) = \sum_{j \in T} w_j \leq b'$, then $w(T) \leq opt(S_i, b')$. The key point is that,

**Claim 3** For every $1 \leq i \leq n$ and $b' \leq b$, $opt(S_i, b') = \max\{opt(S_{i-1}, b'), w_i + opt(S_{i-1}, b' - w_i)\}$.

*Proof of Claim.* Clearly, $OPT(S_i, b')$ is obtained either by not taking the $i^{th}$ element, in which case a solution is $OPT(S_{i-1}, b')$, or by taking the $i^{th}$ element (with weight $w_i$) and adding to it $OPT(S_{i-1}, b' - w_i)$. Formally prove this claim by “mimicking” the proof of Theorem 4. $\diamond$

Then, the correctness easily follows by induction. Indeed, by Lines 1-2, $OPT[0, b'] = OPT(S_0, b') = \emptyset$ and $opt\_cost[0, b'] = opt(S_0, b') = 0$ for every $b' \leq b$ (setting $S_0 = \emptyset$). Then, by induction on $i \leq n$, let us assume that, for every $b' \leq b$, $OPT[i, b'] = OPT(S_i, b')$ and $opt\_cost[i, b'] = opt(S_i, b')$. Then, by Lines 5-10, $opt\_cost[i + 1, b'] = \max\{opt\_cost[i, b'], w_i + opt\_cost[i, b' - w_i]\}$. By the induction hypothesis, $opt\_cost[i, b'] = opt(S_i, b')$ and $opt\_cost[i, b' - w_i] = opt(S_i, b' - w_i)$. By the claim, $opt(S_{i+1}, b') = \max\{opt(S_i, b'), w_i + opt(S_i, b' - w_i)\}$. Hence, $opt\_cost[i + 1, b'] = opt(S_{i+1}, b')$ and similarly, $OPT[i + 1, b'] = OPT(S_{i+1}, b')$.

So, the algorithm returns $OPT[n, b] = OPT(S_n, b)$ which is, by definition, an optimal solution. $\blacksquare$

**Exercise 17** Explain that we may assume that $\max_i w_i \leq b$ and $b \leq \sum_i w_i$ since, otherwise, the instance may be simplified.

Prove that, if $\max_i w_i \leq b \leq \sum_i w_i$, Algorithm 14 proceed in polynomial-time if $\max_i w_i$ is polynomial in $n$ but exponential if $\max_i w_i$ is exponential in $n$.

Actually, the Knapsack Problem is an example of Weakly NP-hard (roughly, it can be solved in polynomial-time if the weights are polynomial). Typically (informally), a weakly NP-hard problem takes a set of $n$ integers as inputs and can be solved in time polynomial in the number of integers ($n$) and in the maximum value of the integers (pseudo-polynomial algorithm) but, if the values of the integers are exponential in the number $n$ of integers, we do not know any polynomial-time (in $n$) algorithm to solve it.
6.2 Greedy 2-Approximation and PTAS

**Algorithm 15** Greedy 2-approximation for Knapsack

**Require:** A set of integers $S = \{w_1, \cdots, w_n\}$ and $b \in \mathbb{N}$.

**Ensure:** A subset $T \subseteq \{1, \cdots, n\}$ of items such that $\sum_{i \in T} w_i \leq b$

1: $T = \emptyset$
2: total_weight $= 0$
3: Sort $S$ such that $w_1 \geq w_2 \geq \cdots \geq w_n$.
4: for $i = 1$ to $n$ do
5: \hspace{1em} if total_weight $+ w_i \leq b$ then
6: \hspace{2em} Add $i$ to $T$
7: \hspace{1em} Add $w_i$ to total_weight
8: \hspace{1em} end if
9: \hspace{1em} end for
10: return $T$

Note that Algorithm 15 proceeds in a greedy way: it takes one by one the possible items (in non increasing order of their weights) and simply add them if they fit in the sack.

**Theorem 15** Algorithm 15 is a 2-approximation algorithm for the Knapsack problem.

**Proof.** In line 3, there is a sorting of $n$ integers (time $O(n \log n)$), then there is a loop with $n$ iterations with, for each iteration, a constant number of operations. Hence, the algorithm has complexity $O(n \log n)$. Moreover, it clearly computes a valid solution. Hence, it only remains to prove the approximation ratio. Let $OPT = \sum_{i \in S^*} w_i$ be the value of an optimal solution $S^* \subseteq \{1, \cdots, n\}$. Note that, in contrast with previous examples, this is a maximization problem. Hence, we aim at proving that $\frac{OPT}{2} \leq ValueOfComputedSolution \leq OPT$.

To prove the approximation ratio, let $T \subseteq \{1, \cdots, n\}$ be the computed solution and let $\sum_{i \in T} w_i = SOL$ be its value. Clearly, $\sum_{1 \leq i \leq j} w_i \leq SOL \leq OPT \leq b$. Let $j \geq 1$ be the smallest integer such that $j + 1$ is NOT in $T$. By definition of the algorithm, $\sum_{1 \leq i \leq j+1} w_i = w_{j+1} + \sum_{1 \leq i \leq j} w_i > b$ and, because the $w_i$’s are ordered, $w_{j+1} \leq \min_{1 \leq i \leq j} w_i = w_j$. Finally, $\min_{1 \leq i \leq j} w_i \leq \sum_{1 \leq i \leq j} w_i$ (because the average of $w_1, \cdots, w_j$ cannot be less than the minimum $w_i$).

It follows that $\sum_{1 \leq i \leq j} w_i \leq SOL \leq OPT \leq b < w_{j+1} + \sum_{1 \leq i \leq j} w_i \leq (1 + 1/j) SOL \leq 2SOL$ (because $j \geq 1$) and obviously $2SOL \leq 2OPT$.

Summing up, $OPT \leq 2SOL \leq 2OPT$, i.e., $\frac{OPT}{2} \leq SOL \leq OPT$.

A polynomial-time approximation scheme (PTAS) is a family of algorithms which take an instance of an optimization problem and a parameter $\epsilon > 0$ and, in polynomial time in the size of the instance (not necessarily in $\epsilon$), produces a solution that is within a factor $1 + \epsilon$ of being optimal.

That is, when $\epsilon$ tends to 0, the solution tends to an optimal one, while the complexity increases (generally, the complexity is of the form $O(n^{f(1/\epsilon)})$ for some function $f$).

We now present a PTAS algorithm for the Knapsack Problem. Algorithm 16 generalizes the previous greedy algorithm. Instead of computing a greedy solution “from scratch”, Algorithm 16 depends on some fixed integer $k = \lceil 1/\epsilon \rceil$. For every subset $X$ of size at most $k$, Algorithm 16 starts from $X$ and uses the greedy algorithm to complete (try to improve) $X$.  

26
Then, Algorithm 16 keeps the best solution that it met in this way. Intuitively, Algorithm 16 aims at using the greedy algorithm but starting from a “best” partial solution (since it checks all subsets of size \( \leq k \), in particular, there is one iteration for which it will consider the heaviest \( k \) elements of an optimal solution, and it will only need to improve this “already good” partial solution “not too badly”). Hence, the larger \( k \) (the smaller \( \epsilon \)), the better will be the obtained solution (the approximation ratio) but the higher will be the time-complexity (since we need at least to check all subsets of size at most \( k \)).

**Algorithm 16** PTAS for the Knapsack Problem

**Require:** A set of integers \( S = \{w_1, \ldots, w_n\}, b \in \mathbb{N} \) and a real \( \epsilon > 0 \).

**Ensure:** A subset \( T \subseteq \{1, \ldots, n\} \) of items such that \( \sum_{i \in T} w_i \leq b \)

1: best = \( \emptyset \)
2: best\_cost = 0
3: \( k = \lceil 1/\epsilon \rceil \)
4: Sort \( S \) such that \( w_1 \geq w_2 \geq \cdots \geq w_n \).
5: for Any subset \( X \subseteq S \) of size at most \( k \) do
6: //Complete \( X \) using the Greedy Algorithm. That is:
7: Let \( T = X \) and \( k' = |X| \leq k \).
8: Let total\_weight = \( \sum_{i \in X} w_i \)
9: Up to renaming the elements in \( S \setminus X \), let us assume that \( S \setminus X = \{w_1, \ldots, w_{n-k'}\} \) with \( w_1 \geq w_2 \geq \cdots \geq w_{n-k'} \).
10: for \( i = 1 \) to \( n-k' \) do
11: if total\_weight + \( w_i \leq b \) then
12: Add \( i \) to \( T \)
13: Add \( w_i \) to total\_weight
14: end if
15: end for
16: if total\_weight > best\_cost then
17: Replace best by \( T \)
18: end if
19: end for
20: return \( T \)

**Theorem 16** Algorithm 16 is a PTAS for the Knapsack problem.

**Proof.** Algorithm 16 computes a valid solution in time-complexity \( O(n^{1/\epsilon}+1) \). Indeed, there are \( O(n^k) \) subsets of size at most \( k \) in a ground-set with \( n \) elements.

Then, Algorithm 16 is a \((1+\epsilon)\)-approximation algorithm for the Knapsack problem. Indeed, consider an optimal solution \( OPT \) and let \( X^* = \{i_1, \ldots, i_k\} \) be the \( k \) items with largest weight in \( OPT \) (show that, if \( OPT \) consists of less than \( k \) items, then Algorithm 16 computes an optimal solution). Consider the iteration of Algorithm 16 when it considers \( X^* \). The proof is a (not difficult) adaptation of the proof of Theorem 15.

Actually, we can do better. Indeed, the Knapsack Problem admits a fully polynomial-time approximation scheme (FPTAS) algorithm, that is an algorithm that computes a solution that is within a factor \( 1 + \epsilon \) of being optimal in time polynomial both in the size of the instance AND in \( 1/\epsilon \).
Part III
Parameterized Algorithms [4]

7 Introduction to Parameterized Algorithms (with Vertex Cover as toy example)

Until now, we have evaluated the “quality/efficiency” of algorithms (resp., the “difficulty” of problems we have met) in function of the size $s$ (generally, in graph’s problems, the number of vertices and/or edges) of the instances. Very roughly, a problem is considered as “easy” if there exists an algorithm for solving it in time polynomial in $s$. If no such algorithm is known (all known algorithms are exponential in $s$), the problem is said “difficult” ($NP$-hard).

On the other hand, we have seen that problems that are “difficult” in general may be “easy” in some particular classes of instances. For instance, the Vertex Cover problem is $NP$-hard in general graphs but can be solved in polynomial-time when restricted to bipartite graphs (Theorem 5).

Very roughly, the Parameterized Complexity aims at evaluating the complexity (here we only focus on time-complexity) of an algorithm/a problem not only as a function of the size of the input but also as a function of other parameters of the instance/problem. For instance, in graphs, appropriated parameters may be the diameter, the maximum degree, the minimum vertex cover (i.e., in the case of the Vertex Cover problem, the size of the solution itself), etc.

7.1 First Approach: deciding if $vc(G) \leq k$?

Recall that a vertex cover $K \subseteq V$ of a graph $G = (V, E)$ is a subset of vertices such that $K \cap e \neq \emptyset$ for all $e \in E$. Moreover, recall that $vc(G)$ denotes the minimum size of a Vertex Cover in $G$. In Section 2.3, we have already seen that the following algorithm computes a minimum-size Vertex Cover in time $O^*(2^{|V|})$.

Algorithm 7 Naive Algorithm for Minimum Vertex Cover (reminder)

Require: A graph $G = (V, E)$.
Ensure: A minimum Vertex Cover of $G$.
1: $K \leftarrow V$.
2: for every $S \subseteq V$ do 
3: if $S$ is a vertex cover of $G$ and $|S| < |K|$ then
4: $K \leftarrow S$.
5: end if
6: end for
7: return $K$

Let us (slightly) simplify the question. Let $k \in \mathbb{N}$ be a fixed parameter. Instead of looking for $vc(G)$ (or a Vertex Cover of minimum size), let us “only” ask whether $G$ has some Vertex Cover of size $\leq k$ (we may also ask to compute a minimum Vertex Cover of $G$ given that we already know that $vc(G) \leq k$).

Exercise 18 Show that Algorithm 17 has time-complexity $O^*(|V|^k)$.

Compare $O^*(|V|^k)$ and $O^*(2^{|V|})$ when, for instance, $|V| = 10^4$ and $k = 10$. 

28
**Algorithm 17** 1st Algorithm to decide if \( vc(G) \leq k \), where \( k \in \mathbb{N} \) is a fixed parameter.

**Require:** A graph \( G = (V, E) \).

**Ensure:** A minimum Vertex Cover of \( G \) (if \( vc(G) \leq k \)) or \( V \) (if \( vc(G) > k \)).

1. \( K \leftarrow V \).
2. **for** every \( S \subseteq V, |S| \leq k \) **do**
3.   **if** \( S \) is a vertex cover of \( G \) and \( |S| < |K| \) **then**
4.     \( K \leftarrow S \).
5.   **end if**
6. **end for**
7. **return** \( K \)

Hence, if we \textit{a priori} know that the graph into consideration has “small” vertex cover (at most \( k \)), the above algorithm is much more efficient than the previous one. We show below that even better algorithm can be designed. For this purpose, we need the following lemma:

**Lemma 9** Let \( G = (V, E) \) be a graph and \( \{x, y\} \in E \). \( vc(G) = \min\{vc(G \setminus x), vc(G \setminus y)\} + 1 \)

**Intuition:** for any edge \( xy \), any minimum vertex cover contains at least one of \( x \) or \( y \)

**Proof.** Let \( S \subseteq V \) be any vertex cover of \( G \setminus x \). Then \( S \cup \{x\} \) is a vertex cover of \( G \). Hence \( vc(G) \leq vc(G \setminus x) + 1 \) (symmetrically for \( G \setminus y \)).

Let \( S \subseteq V \) be any vertex cover of \( G \). At least one of \( x \) or \( y \) is in \( S \). If \( x \in S \) then \( S \setminus x \) vertex cover of \( G \setminus x \). Hence \( vc(G \setminus x) \leq vc(G) - 1 \). Otherwise, if \( y \in S \), then \( S \setminus y \) vertex cover of \( G \setminus y \) and \( vc(G \setminus y) \leq vc(G) - 1 \).

**Algorithm 18** Branch & Bound Algo. to decide if \( vc(G) \leq k \), where \( k \in \mathbb{N} \) is a fixed parameter.

**Require:** A graph \( G = (V, E) \) and an integer \( \ell \leq k \).

**Ensure:** The minimum size of a Vertex Cover of \( G \) if \( vc(G) \leq \ell \) or \( \infty \) otherwise.

1. **if** \( \ell = 0 \) and \( |E| > 0 \) **then**
2.   **return** \( \infty \)
3. **else**
4.   **if** \( |E| = 0 \) **then**
5.     **return** \( 0 \)
6. **else**
7.   **Let** \( \{u, v\} \in E \) be any edge
8.   **Let** \( x = \text{Algorithm 18}(G \setminus u, \ell - 1) \) and \( y = \text{Algorithm 18}(G \setminus v, \ell - 1) \)
9.   **return** \( \min\{x, y\} + 1 \)
10. **end if**
11. **end if**

**Exercise 19** Using Lemma 9, prove the correctness of Algorithm 18. Show that the recursive depth is at most \( k \). Deduce that Algorithm 18 has time-complexity \( O(2^k|E|) \).

Adapt Algorithm 18 to return a minimum vertex cover of \( G \) if \( vc(G) \leq k \).

**Lemma 10** Let \( G = (V, E) \) be any simple graph. If \( vc(G) \leq k \), then \( |E| \leq k(|V| - 1) \).

**Proof.** Let \( K \subseteq V \) be a vertex cover with \( |K| \leq k \). Note that \( G - K \) induces a stable set. Hence, every edge of \( G \) is incident to a vertex in \( K \) (it is the definition of a vertex cover). Finally, each vertex in \( K \) is adjacent to at most \( |V| - 1 \) edges.

It follows that:

**Corollary 3** Algorithm 18 has time-complexity $O(k^2k \cdot |V|)$.

Hence, Algorithm 18 is linear in the order of the graph! Note that Vertex Cover is NP-hard, but we proved that the combinatorial complexity does not come from the order of the graph but from its structure. That is, the Vertex Cover problem can be solved in linear time (in the size of the input) in the class of graphs with bounded (fixed) minimum size of a vertex cover. Compare the complexity of Algorithm 18 with the complexity of Algorithm 17 when, for instance, $|V| = 10^4$ and $k = 10$.

The key difference between the time-complexity of Algorithm 17, $O(|E| |V|^k)$, and the one of Algorithm 18, $O(k^2k \cdot |V|)$, that are both polynomial in $|V|$ and exponential in $k$, is that, in the latter case, the polynomial on $|V|$ does not depend on $k$. That is, in Algorithm 18, the dependencies in $k$ and $|V|$ are “separated”. Such an algorithm is called a **Fixed Parameter Tractable (FPT)** algorithm, parameterized by the size of the solution (the size of the vertex cover).

### 7.2 Fixed Parameter Tractable (FPT) Algorithms and Kernelization

We don’t aim at giving a formal definition of parameterized complexity and refer to, e.g., [4] for more precise definition. As usual, we moreover focus on graphs.

Let $G$ be the set of all graphs. A **graph parameter** is any function $p : G \rightarrow \mathbb{N}$ (e.g., diameter, maximum degree, minimum size of a vertex cover, minimum size of a dominating set, etc.).

Roughly, a parameterized problem $(\Pi, p)$ is defined by a problem $\Pi$ (here on graphs) and a parameter $p$. The key point is to understand the behaviour of the time-complexity of an algorithm for solving $\Pi$ not only as a function of $n$, the size of the instance, but also as a function of the value of the parameter $p$.

An algorithm $A$ for solving $(\Pi, p)$ is said **Fixed Parameter Tractable (FPT)** if there exists a computable function $f : \mathbb{N} \rightarrow \mathbb{N}$, such that the time-complexity of $A$ can be expressed as $O(f(p(G))n^{O(1)})$, where $n$ is the size of the input graph $G$. Note that the polynomial in $n$ is independent on $p(G)$ and $f$ depends only on the parameter $p(G)$. A parameterized problem $(\Pi, p)$ is FPT if it admits a FPT algorithm, parameterized by $p$, for solving it.

For instance, Algorithm 18 shows that the Vertex Cover problem is FPT when parameterized by the size of the solution. Another example is any FPTAS algorithm, that can be seen as a FPT (approximation) algorithm parameterized by $1/\epsilon$.

To conclude this subsection, let us present a particular kind of FPT algorithms called **Kernelization** algorithms. A natural way to tackle difficult problems is to try to reduce the size of the input (e.g., in the case of graphs, to “limit” the problem to the connected components of a graph, or to its 2-connected components...).

Precisely, given a parameterized problem $(\Pi, p)$, a kernelization algorithm replaces an instance $(I, p(I))$ by a “reduced” instance $(I', p'(I'))$ (called **problem kernel**) such that

1. $p'(I') \leq g(p(I))$, $|I'| \leq f(p(I))$ for some computable functions $f$ and $g$ only depending on $p(I)$ (not on $|I|$)\(^{13}\),

2. $(I, p(I)) \in \Pi$ if and only if $(I', p'(I')) \in \Pi$, and

3. reduction from $(I, p(I))$ to $(I', p'(I'))$ has to be computable in polynomial time (in $|I| + p(I)$).

\(^{13}\)A kernel $G'$ is said linear (resp., quadratic, single exponential...) if $|G'| = O(k)$ (resp., $|G'| = O(k^2)$, $|G'| = O(2^k)$,...).
Hence, if a parameterized problem (Π, p) admits a Kernelization algorithm that transforms a n-node graph G and parameter p(G) = k into an equivalent graph G' with size f(n) (for some computable function f) and parameter k' = p'(G') ≤ g(k) (for some computable function g) in time (n + p(G))^{O(1)}, then (Π, k) admits a FPT algorithm with time complexity n^{O(1)} + O(2^{f(g(k))}): first reduce G to G' and then exhaustive search in G' with parameter k' ≤ g(k). Note the difference between this complexity and the one of Algorithm 18 (also FPT): in the latter one, the terms depending on k and n are multiplied, while here it is a sum. More generally, it is easy to prove (while a bit counter-intuitive) that:

**Theorem 17 (Bodlaender et al. 2009)*** A parameterized problem is FPT if and only if it is decidable and has a kernelization algorithm.

### 7.3 A first Kernelization Algorithm for Vertex Cover

We aim at improving Algorithm 18.

**Lemma 11** Let G = (V, E) be a graph and v ∈ V with degree > k. Then v belongs to every vertex cover K of size at most k

**Proof.** Indeed, if v ∉ K, all its neighbors must belong to it and |K| > k. ■

**Lemma 12** Let G = (V, E) be a graph. If vc(G) ≤ k and no vertex of G has degree > k. Then |E| ≤ k^2

**Proof.** Each of the ≤ k vertices of a Vertex Cover covers ≤ k edges (see proof of Lem. 9). ■

The following algorithm to decide if vc(G) ≤ k proceeds as follows. While there is a “high” degree node, add it to the solution. When there are no such nodes, either it remains too much edges to have a small vertex cover. Otherwise, apply brute force algorithm (e.g., Algorithm 18) to the remaining “small” graph.

**Exercise 20** Using Lemmas 11 and 12, prove the correctness of Algorithm 19. Show that Algorithm 19 has time-complexity O(2^k k^2 + k|V|). Adapt Algorithm 19 to return a minimum vertex cover of G if vc(G) ≤ k.

Note that previous algorithm relies on a quadratic kernel. Compare the complexity of Algorithm 19 with the complexity of Algorithm 18 when, for instance, |V| = 10^4 and k = 10.

### 7.4 Iterative Compression technique: example of Vertex Cover

This subsection is devoted to present a classical technique for designing FPT algorithms, namely Iterative Compression. Roughly, a Compression Routine is an algorithm that, given a problem instance and an initial feasible solution (not necessarily optimal), either calculates a smaller solution or proves that the given solution is of minimum size. The main idea of the Iterative Compression method is to repeatedly use a compression Routine: finding an optimal solution to the problem by iteratively building up the structure of the instance and compressing intermediate solutions.

As usual, we illustrate this technique with Minimum Vertex Cover Problem as example. Let k ∈ N be a fixed integer.
Algorithm 19 Kernelization Alg. to decide if \( vc(G) \leq k \), where \( k \in \mathbb{N} \) is a fixed parameter.

Require: A graph \( G = (V, E) \) and an integer \( \ell \leq k \).
Ensure: The minimum size of a Vertex Cover of \( G \) if \( vc(G) \leq \ell \) or \( \infty \) otherwise.

1. Let \( I \subseteq V \) be the set of isolated vertices in \( G \). Remove \( I \) from \( G \).
2. If \( |E| = 0 \) then
3. return 0
4. Else
5. If \( \ell = 0 \) then
6. return \( \infty \)
7. Else
8. If \( G \) has no vertex of degree \( > \ell \) and \( |E| > \ell^2 \) then
9. return \( \infty \)
10. Else
11. If \( G \) has no vertex of degree \( > \ell \) then
12. return Algorithm 18\((G, \ell)\)
13. Else
14. Let \( v \) be a vertex of degree \( > \ell \)
15. return Algorithm 19\((G \setminus v, \ell - 1) + 1\)
16. End if
17. End if
18. End if
19. End if

Routine Compression. The Compression Routine takes any Vertex Cover \( Q \geq V \) of a graph \( G = (V, E) \) as inputs, and it aims at using \( Q \) to find a solution of size at most \( k \) (if any). For this purpose, it will “check” all possible ways a vertex cover of size at most \( k \) can intersect \( Q \). More precisely, let \( Y \subseteq Q \) be any subset of \( Q \). We want to decide if there is a Vertex Cover \( X \) such that \( X \cap Q = Y \) and \( |X| \leq k \). Let \( N(Q \setminus Y) \) be the set of vertices that have a neighbor in \( Q \setminus Y \).

Algorithm 20 Compression Routine for \( k \)-Vertex Cover

Require: A graph \( G = (V, E) \) and any vertex cover \( Q \subseteq V \).
Ensure: A vertex cover of size \( \leq k \) if it exists, and \( No \) otherwise

1. For every \( Y \subseteq Q \) do
2. If there are no edges in \( G[Q \setminus Y] \) and \( |Y \cup N(Q \setminus Y)| \leq k \) then
3. return \( Y \cup N(Q \setminus Y) \)
4. End if
5. End for
6. return \( No \)

Lemma 13 If \( G \) admits a vertex cover of size at most \( k \), then Algorithm 20 (Compression Routine) returns a vertex cover of \( G \) of size \( \leq k \) in time \( O(|E|^2|Q|) \).

Proof. The time-complexity should be obvious (at most \( 2^{|Q|} \) iterations of the For-loop, each one checking \( O(|E|) \) edges). Let us prove the correctness.

First, let \( Y \subseteq Q \). Let us show that, if \( E(G[Q \setminus Y]) = \emptyset \), then \( Y \cup N(Q \setminus Y) \) is a vertex cover of \( G \). For purpose of contradiction, let us assume that \( uv \in E \) is not covered, i.e., \( u, v \notin Y \cup N(Q \setminus Y) \). By assumption, it is not possible that both \( u, v \in Q \setminus Y \) since \( E(G[Q \setminus Y]) = \emptyset \).
Moreover, it is not possible that one vertex in \{u, v\}, say v, belongs to \(Q \setminus Y\), since otherwise \(u \in N(Q \setminus Y)\). Hence, \(u, v \notin Q \setminus Y\). Since \(Q\) is a vertex cover of \(G\), then at least one of \(u\) and \(v\) belongs to \(Y\), a contradiction.

Hence, if Algorithm 20 does not return \(No\), then it returns a vertex cover of \(G\) with size at most \(k\).

Second, let us assume that \(G\) admits a vertex cover \(X \subseteq V\) with \(|X| \leq k\). Let \(Y_0 = Q \cap X \subseteq Q\). Let us show that \(E(G[Q \setminus Y_0]) = \emptyset\). For purpose of contradiction, let us assume that there exist \(uv \in E(G[Q \setminus Y_0])\). But, neither \(u\) nor \(v\) belong to \(X\), contradicting the fact that \(X\) is a vertex cover of \(G\). Hence, \(G[Q \setminus Y_0]\) has no edges. Moreover, let us show that \(N(Q \setminus Y_0) \subseteq X\).

Let \(v \in N(Q \setminus Y_0)\) and let \(u \in Q \setminus Y_0\) such that \(uv \in E\). Since \(u \notin X\), then \(v\) must be in \(X\) otherwise the edge \(uv\) would not be covered, contradicting that \(X\) is a vertex cover of \(G\). Hence, \(Y_0 \cup N(Q \setminus Y_0) \subseteq X\) and so \(|Y_0 \cup N(Q \setminus Y_0)| \leq |X| \leq k\).

Hence, if \(G\) has a vertex cover of size at most \(k\), Algorithm 20 will return \(Y \cup N(Q \setminus Y)\) for some \(Y \subseteq Q\) (at least during the iteration considering \(Y = Y_0\)), i.e., it returns a vertex cover of size at most \(k\).

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**Algorithm 21** FPT algorithm for \(k\)-VERTEX COVER using Iterative Compression

**Require:** A graph \(G = (V, E)\) with \(V = \{v_1, \ldots, v_n\}\).

**Ensure:** A vertex cover of \(G\) of size \(\leq k\) if it exists, and \(No\) otherwise

1. if \(n \leq k + 1\) then
   2. return \(V \setminus \{v_n\}\)
   3. end if
   4. \(Q_k \leftarrow \{v_1, \ldots, v_k\}\)
   5. for \(i = k + 1\) to \(n\) do
      6. \(Q_i = \text{Algorithm20}(G[\{v_1, \ldots, v_i\}], Q_{i-1} \cup \{v_i\})\)
   7. if \(Q_i = No\) then
      8. return \(No\)
   9. end if
10. end for
11. return \(Q\)

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**Theorem 18** [4] If \(G\) admits a vertex cover of size at most \(k\), then Algorithm 21 returns a vertex cover of \(G\) of size \(\leq k\) in time \(O(|E||V|2^{k+1})\).

**Proof.** The correctness is obvious if \(|V| \leq k + 1\) since, for every graph \(G = (V, E)\) and any vertex \(v \in V\), then \(V \setminus \{v\}\) is a vertex cover (Prove it). Let us assume that \(n > k + 1\) and that \(G\) admits a vertex cover of size at most \(k\).

Let us prove by induction on \(i \in \{k, \ldots, n\}\) that \(Q_i\) is a vertex cover of \(G_i = G[\{v_1, \ldots, v_i\}]\) of size at most \(k\). It is obvious for \(i = k\) since \(Q_k = V(G_k)\). Assume the induction hypothesis holds for \(i - 1 \in \{k, \ldots, n - 1\}\). Then, \(Q_{i-1} \cup \{v_i\}\) is a vertex cover of \(G_i\) of size at most \(k + 1\) (Prove it). By Lemma 13, then either \(Q_i\) is a vertex cover of \(G_i\) of size at most \(k\), or \(G_i\) has no vertex cover of size at most \(k\). In the latter case, \(Q_i = No\) and Algorithm 21 returns \(No\) but, if \(G_i\) has no vertex cover of size at most \(k\), then \(G\) neither (Prove it), a contradiction. Hence, after the iteration \(i\), \(Q_i\) is a vertex cover of \(G_i\) of size at most \(k\).

Since each of the \(O(|V|)\) iterations of the For-loop applies Algorithm 20 with a vertex cover \(Q = Q_{i-1} \cup \{v_i\}\) (of \(G_i\)) of size at most \(k + 1\), it takes time \(O(|E|2^{k+1})\) by Lemma 13. □

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33
8 Toward tree-decompositions, Graph Minor Theory and beyond

In this last section, we focus on particular graph classes. Precisely, we will start with trees, then generalize the proposed method to \( k \)-trees and then to graphs with bounded treewidth. We will then conclude with planar graphs and beyond. Along the way, we will continue to use our favorite problem, namely Vertex Cover, as an illustrative example.

8.1 Minimum (weighted) Vertex Cover in trees

Let us start with the problem of computing a minimum-size vertex cover (as it has been studied many times above). That is, given a tree \( T = (V,E) \), the goal is to compute a set \( K \subseteq V \), such that \( \forall e \in E, e \cap K \neq \emptyset \), and \(|K|\) is minimum subject to this property. Recall that \( \text{vc}(T) \) denotes the minimum size of a vertex cover in \( T \).

Prove that any tree is a bipartite graph (e.g., use a BFS). So, by Kőnig’s theorem (Th. 5) and, e.g., the Hungarian method (Th. 4), \( \text{vc}(T) \) can be computed in polynomial time in any tree \( T \). We aim at giving here a simpler algorithm in the case of trees. It is based on the following lemma whose proof is left to the reader.

**Lemma 14** Let \( G = (V,E) \) be any graph with a vertex \( v \) of degree 1. Let \( u \) be the unique neighbor of \( v \) and let \( K \) be a vertex cover of \( G \). Then, \( K \cap \{u,v\} \neq \emptyset \), and \( K' = (K \setminus \{v\}) \cup \{u\} \) is a vertex cover of \( G \) such that \( |K'| \leq |K| \).

**Notation.** Let \( T = (V,E) \) be a tree and \( r \in V \) be any vertex. Let us denote by \( T_r \) the tree rooted in \( r \). For any \( v \in V \), the children of \( v \) in \( T_r \) are the neighbors of \( v \) whose distance to \( r \) is greater than \( \text{dist}(r,v) \). The parent of \( v \) in \( T_r \) (if \( v \) is not the root \( r \)) is the unique neighbor of \( v \) that is not a children of \( v \). The descendants of \( v \) in \( T_r \) are all vertices \( u \) such that \( v \) is an internal vertex of the path between \( r \) and \( u \) in \( T \) (such a path is unique by Exercise 2). Finally, the subtree \( T_v \) rooted at \( v \) in \( T_r \) is the subtree induced by \( v \) and its descendants. A leaf in a rooted tree is any vertex \( v \neq r \) with degree 1.

**Algorithm 22** Greedy Algorithm for Minimum Vertex Cover in trees

**Require:** A tree \( T = (V,E) \) rooted in any arbitrary vertex \( r \in V \).

**Ensure:** A minimum Vertex Cover of \( T \).

1. if \( E = \emptyset \) then
2. \hspace{1em} return \( \emptyset \)
3. else
4. \hspace{1em} Let \( v \in V \) be any non-leaf vertex maximizing the distance with \( r \) (possibly \( r = v \)).
5. \hspace{1em} Let \( T' \) be the tree (rooted in \( r \)) obtained from \( T \) by removing \( v \) and all its children.
6. \hspace{1em} return \( \{v\} \cup \text{Algorithm 22}(T') \)
7. end if

**Theorem 19** Algorithm 22 computes a minimum Vertex Cover of any tree \( T \) in linear time.

**Proof.** Let us first prove its correctness. Let \( T_r \) be a rooted tree, \( v \) be a non-leaf maximizing the distance with \( r \) (possibly \( v = r \)) and \( T' \) be defined as in Algorithm 22 (i.e., \( T' \) is the tree rooted in \( r \) obtained from \( T \) by removing \( v \) and all its leaves neighbors). We claim that \( \text{vc}(T) = 1 + \text{vc}(T') \). Indeed, if \( K' \) is a minimum vertex cover of \( T' \), then \( K' \cup \{v\} \) is a vertex cover of \( T \).
cover of $T$ of size $|K'| + 1 = vc(T') + 1 \geq vc(T)$. On the other hand, let $K$ be a minimum vertex cover of $T$. By Lemma 14, we may assume that $v \in K$. Hence, $K' = K \setminus \{v\}$ is a vertex cover of $T'$ and so $|K'| = vc(T') - 1 \geq vc(T')$. By induction on $|V(T)|$, Algorithm 22 returns a vertex cover of size $1 + vc(T')$. By the claim, it is then an optimal vertex cover of size $vc(T)$. Hence, Algorithm 22 is correct.

For the time-complexity, there at most $|V(T)|$ recursive calls (since $|V(T')| < |V(T)|$). The main (most time consuming) step at each call consists in finding the vertex $v$.

Algorithm 23 computes a minimum weight Vertex Cover of any vertex-weighted tree $T$, where the weight of a vertex cover in $(T, w)$ is defined as the minimum weight of a vertex cover of $T$ containing $v$ (i.e., $vc(T_i, w)$ is the minimum weight of any vertex cover among all vertex covers of $(T_i, w)$ containing $v$).

From Lemma 15 and by induction on $|V(T)|$, the proof of next theorem easily follows.

**Theorem 20** Algorithm 23 computes a minimum weight Vertex Cover of any vertex-weighted tree $(T, w)$ in linear time.

### 8.2 2-trees

In the sequel, we will extend Algorithm 23 to some graph class generalizing trees (graphs with bounded treewidth). To make the next algorithms easier to understand, let us first go one step further. For this purpose, a key notion is the one of separators in graphs. Given a graph $G = (V, E)$ and $X, Y \subseteq V$, $X \cap Y = \emptyset$, a set $S \subseteq V \setminus (X \cup Y)$ is a $(X, Y)$-separator in $G$ if, for
Algorithm 23 Dynamic Programming Algorithm for Minimum weight Vertex Cover in trees

Require: A weighted tree \((T_r = (V, E), w : V \to \mathbb{R}^+)\) rooted in any arbitrary vertex \(r \in V \neq \emptyset\).
Ensure: \((K, K')\) where \(K\) is a minimum Vertex Cover of \((T_r, w)\) (of weight \(vc(T, w)\)) and \(K'\) is a minimum Vertex Cover of \((T_r, w)\) containing \(r\) (of weight \(vc'(T, w)\))

1: if \(V = \{r\}\) then
   2: return \((\emptyset, \{r\})\) \hspace{1cm} // of weight respectively 0 and \(w(r)\)
3: else
4: Let \(r_1, \ldots, r_d\) be the children of \(r\) and, for every \(1 \leq i \leq d\), let \(T_i\) be the subtree of \(T_r\) rooted in \(r_i\).
5: for \(i = 1\) to \(d\) do
6: \hspace{1cm} Let \((K_i, K'_i) = \text{Algorithm 23}(T_i, w|_{V(T)}))\)
   \hspace{1cm} //\(K_i\) is a minimum weight vertex cover of \(T_i\), i.e., of weight \(vc(T_i, w|_{V(T)}))\)
   \hspace{1cm} //\(K'_i\) is a minimum weight vertex cover of \(T_i\) containing \(r_i\), i.e., of weight \(vc'(T, w)\))
7: end for
8: Let \(K' = \{r\} \cup \bigcup_{1 \leq i \leq d} K_i\). \hspace{1cm} // Show it is a min. weight VC of \((T, w)\) containing \(r\)
9: Let \(K'' = \bigcup_{1 \leq i \leq d} K'_i\). \hspace{1cm} // Show it is a min. weight VC of \((T, w)\) not containing \(r\)
10: Let \(K \in \{K', K''\}\) such that \(w(K) = \min \{w(K'), w(K'')\}\).
    \hspace{1cm} // Show it is a min. weight VC of \((T, w)\)
11: return \((K, K')\).
12: end if

every \(u \in X\) and \(v \in Y\), every \(u, v\)-path goes through a vertex in \(S\) (equivalently, \(u\) and \(v\) are in distinct connected components of \(G[V \setminus S]\)). A set \(S \subset V\) is a separator in \(G\) if there exist \(u, v \in V \setminus S\) such that \(S\) is a \((\{u\}, \{v\})\)-separator (or \(u, v\)-separator).

The class of 2-trees is defined recursively as follows. A complete graph (clique) \(K_3\) with 3 vertices (triangle) is a 2-tree. Given any 2-tree \(H\) with some edge \((u, v) \in E(H)\), the graph obtained from \(H\) by adding a new vertex \(x\) adjacent to \(u\) and \(v\) is a new 2-tree. The recursive construction of a 2-tree naturally leads to the definition of a corresponding “building tree”.

Given a 2-tree \(G = (V, E)\), a tree-decomposition \((T, \mathcal{X} = \{X_t \mid t \in V(T)\})\) of \(G\) is defined recursively as follows. If \(G = K_3\) is reduced to a clique with vertices \(u, v\) and \(w\), its corresponding tree-decomposition consists of a tree \(T\) reduced to a single node \(t_0\) and \(\mathcal{X} = \{X_{t_0} = \{u, v, w\} \subseteq V\}. If \(G\) is obtained from a 2-tree \(H\), with \((u, v) \in E(H)\), by adding a vertex \(x\) adjacent to \(u\) and \(v\), a tree-decomposition \((T_G, X_G = \{X_t^H \mid t \in V(T_G)\})\) of \(G\) is obtained from any tree-decomposition \((T_H, X_H = \{X_t^H \mid t \in V(T_H)\})\) of \(H\) by considering any node \(s \in V(T_H)\) such that \(u, v \in X_s^H\) (show that such a node exists by induction on \(|V|\)) and build \(T_G\) from \(T_H\) by adding a new node \(n_s\) adjacent to \(s\), and \(X_G = X_H \cup \{u, v, x\} \subseteq V\}. Note that a 2-tree may admit several decompositions.

Intuitively, each node of \(T_G\) corresponds to a subset of vertices of \(G\) inducing a maximal clique (triangle) of \(G\). Hence, \((T_G, X_G)\) “organizes” the triangles of \(G\) in a tree-like fashion while satisfying some “connectivity properties” as described by the first 2 items of Lemma 16.

Lemma 16 Let \(G = (V, E)\) be a 2-tree, \((T, \mathcal{X})\) be a tree-decomposition of \(G\) and \(e = \{u, v\} \in E(T)\). Let \(T_u\) (resp. \(T_v\)) be the subtree of \(T \setminus e = (V(T), E(T) \setminus \{e\})\) containing \(u\) (resp., \(v\)) and \(G_u = G[\bigcup_{t \in V(T_u)} X_t]\) and \(G_v = G[\bigcup_{t \in V(T_v)} X_t]\). Then,

\[
\bullet \quad S = X_u \cap X_v = \{x, y\} \text{ where } \{x, y\} \in E(G);
\]
• \( S \) separates \( V(G_u) \setminus S \) from \( V(G_v) \setminus S \) (every path from a vertex in \( V(G_u) \setminus S \) to a vertex in \( V(G_v) \setminus S \) goes through \( S \));

  // in particular, there are no edges between \( V(G_u) \setminus S \) and \( V(G_v) \setminus S \).

Moreover, let \( Q \subseteq S \setminus \{\emptyset\} \). Prove that, because \( S \) is a \((V(G_u) \setminus S, V(G_v) \setminus S)\)-separator:

- If \( K \) is a vertex cover of \( G \) with \( K \cap S = Q \), then \( K' = K \cap V(G_u) \) is a vertex cover of \( G_u \) with \( K' \cap S = Q \).
- If \( K \) is a vertex cover of \( G_u \) with \( K \cap S = Q \), then there exists a vertex cover \( K' \) of \( G \)
  such that \( K = K' \cap V(G_u) \) (and, in particular, \( K' \cap S = Q \)).

The key points are that Vertex Cover is a “local” problem and that 2-trees have small-size separators. Intuitively, extending a vertex cover \( K \) of \( G_u \) to some vertex cover of \( G \) does not depend on the whole \( K \) but only on \( K \cap S \) where \( S \) is a separator between \( G_u \) and the reminding of \( G \). When \(|S|\) is “small”, this can be done efficiently.

**Algorithm 24** Dynamic Programming Algorithm for Minimum size Vertex Cover in 2-trees

**Require:** A 2-tree \( G = (V, E) \) and a tree-decomposition \((T_r, \mathcal{X})\) of \( G \) rooted in some vertex \( r \in V(T_r) \).

**Ensure:** For every \( Q \subseteq X_r \), a minimum-size Vertex Cover \( K_Q \) of \( G \) such that \( K_Q \cap X_r = Q \) and \( K_Q = \infty \) if no vertex cover \( K \) of \( G \) is such that \( K \cap X_r = Q \).

1. if \( V(T_r) = \{r\} \) and \( X_r = \{u, v, w\} \) then
   2. return \((K_Q)_{Q \subseteq X_r} \), with \( K_Q = Q \) if \(|Q| > 1\) and \( K_Q = \infty \) otherwise.
3. else
4. Let \( r_1, \ldots, r_d \) be the children of \( r \) and, for every \( 1 \leq i \leq d \), let \( T_i \) be the subtree of \( T_r \)
   rooted in \( r_i \). Let \( X_i = \{X_t \in \mathcal{X} \mid t \in V(T_i)\} \) and let \( G_i = G[\bigcup_{X \in X_i} X] \) be the subgraph
   induced by the vertices in the sets in \( X_i \).
5. for \( i = 1 \) to \( d \) do
6. Let \((K_Q^i)_{Q \subseteq X_{r_i}} = \text{Algorithm 24}(G_i, (T_i, X_i))\)
7. end for
8. for \( Q \subseteq X_r \) do
9. if \(|Q| \leq 1 \) then
10. Let \( K_Q = \infty \)
11. else
12. for \( i = 1 \) to \( d \) do
13. Let \( Q_i \subseteq X_{r_i} \) be such that \( Q_i \cap X_r = Q \cap X_{r_i} \) and, among such sets, \( |K_Q^i| \) is
   minimum.  //abusing notations, \( |K| = \infty \) if \( K = \infty \)
14. end for
15. Let \( K_Q = Q \cup \bigcup_{i=1}^d K_Q^i \).
16. end if
17. end for
18. return \((K_Q)_{Q \subseteq X_r}\).
19. end if

**Theorem 21** Algorithm 24 is correct and has time-complexity \( O(n) \) where \( n \) is the number of
vertices of \( G \).
Proof. The proof of correctness is by induction on the number of nodes of \( T \). It is clearly true if \( |V(T)| = 1 \) by lines 1-3 of the algorithm. If \( |V(T)| > 1 \) then \( r \) has \( d \geq 1 \) children and, by the induction hypothesis, for every \( 1 \leq i \leq d \) and \( Q_i \subseteq X_r \), \( K_{Q_i}^r \) is a minimum vertex cover of \( G_i \) containing \( Q' \) (or \( K_{Q'}^r = \infty \) if \( Q' \) is not a vertex cover of \( G[X_r] \)).

If \( Q \subseteq X_r \) is such that \( |Q| \leq 1 \), then \( Q \) cannot cover all edges of \( X_r \) and so, there are no vertex cover \( K \) of \( G \) with \( K \cap X_r = Q \), and so \( K_Q = \infty \) (lines 9-10).

Otherwise, \( Q \) is a vertex cover of \( X_r \) and so there exist vertex cover \( K \) of \( G \) such that \( K \cap X_r = Q \) (e.g., \( (V \setminus X_r) \cup Q \)). Let \( K_Q^r \) be any minimum vertex cover of \( G \) such that \( K_Q^r \cap X_r = Q \). For every \( 1 \leq i \leq d \), by Lemma 16, \( K^* \cap V(G_i) \) is a minimum vertex cover (containing \( Q \cap X_r \)) of \( G_i \). Lines 12-15 precisely consider such sets and so, the set \( K_Q \) is a minimum vertex cover of \( G \) such that \( K_Q^* \cap X_r = Q \).

For the complexity, Lines 5-7 needs (by induction) \( \sum_{i=1}^{d} O(|E(T_i)|) \) operations. Then, because \( |X_i| = 3 \) for all \( t \in V(T) \), then the number of sets \( Q \subseteq X_r \) is \( 2^d = O(1) \), and then the loop in Line 8 has \( O(1) \) iterations and the computation of the minima in Line 13 takes constant time. Overall, the complexity is then \( O(|E(T)|) \).

Since any tree-decomposition \((T, \mathcal{X})\) of a 2-tree \( G \) with \( n \) vertices has \( O(n) \) nodes/edges (prove it), this leads to an overall complexity of \( O(n) \).

From previous Theorem and Algorithm, we easily get the linear-time Algorithm 25 that computes a minimum vertex cover in any 2-tree.

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**Algorithm 25** Minimum size Vertex Cover in 2-trees

**Require:** A 2-tree \( G = (V,E) \) and a tree-decomposition \((T_r, \mathcal{X})\) of \( G \) rooted in some vertex \( r \in V(T_r) \).

**Ensure:** A minimum-size vertex cover \( K \) of \( G \\
1: \quad (K_Q) \subseteq X_r = \text{Algorithm 24}(G, (T_r, \mathcal{X})).\)
2: \quad \( K = V \)
3: \quad for \( Q \subseteq X_r \) do
4: \quad if \( |K_Q| \leq |K| \) then
5: \quad \quad \( K \leftarrow K_Q \) //abusing notations, \( |K| = \infty \) if \( K = \infty \)
6: \quad end if
7: \quad end for
8: \quad return \( K \)

---

### 8.3 \( k \)-trees

Let us go a step further. Let \( k \) be any integer \( \geq 1 \).

The class of \( k \)-trees is defined recursively as follows. A complete graph (clique) \( K_{k+1} \) with \( k + 1 \) vertices is a \( k \)-tree. Given any \( k \)-tree \( H \) with some clique \( Q \) of size \( k \) in \( H \), the graph obtained from \( H \) by adding a new vertex \( x \) adjacent to every vertex in \( Q \) is a new \( k \)-tree.

Given a \( k \)-tree \( G = (V,E) \), a tree-decomposition \((T, \mathcal{X} = \{X_t \mid t \in V(T)\})\) of \( G \) is defined recursively as follows. If \( G = K_{k+1} \) is reduced to one clique \( Q \), its corresponding tree-decomposition consists of a tree \( T \) reduced to a single node \( t_0 \) and \( \mathcal{X} = \{X_{t_0} = Q \subseteq V \} \). If \( G \) is obtained from a \( k \)-tree \( H \), with a clique \( Q \) of size \( k \) in \( H \), by adding a vertex \( x \) adjacent to all vertices in \( Q \), a tree-decomposition \((T_G, \mathcal{X}_G = \{X^G_t \mid t \in V(T_G)\})\) of \( G \) is obtained from any tree-decomposition \((T_H, \mathcal{X}_H = \{X^H_t \mid t \in V(T_H)\})\) of \( H \) by considering any node \( s \in V(T_H) \) such that \( V(Q) \subseteq X^H_s \) (show that such a node exists by induction on \( |V| \)) and build \( T_G \) from
Moreover, let \( Q \) and \( G \) be \( T_H \) by adding a new node \( n_x \) adjacent to \( s \), and \( \mathcal{X}_G = \mathcal{X}_H \cup \{X_{n_x} = Q \cup \{x\} \subseteq V\} \). Note that a \( k \)-tree may admit several decompositions.

Intuitively, each node of \( T_G \) corresponds to a subset of vertices of \( G \) inducing a maximal clique of \( G \). Hence, \( (T_G, \mathcal{X}_G) \) “organizes” the maximal cliques of \( G \) in a tree-like fashion while satisfying some “connectivity properties” as described by the first 2 items of Lemma 17.

**Lemma 17** Let \( G = (V,E) \) be a \( k \)-tree, \( (T,\mathcal{X}) \) be a tree-decomposition of \( G \) and \( e = \{u,v\} \in E(T) \). Let \( T_u \) (resp. \( T_v \)) be the subtree of \( T \backslash e = (V(T),E(T) \backslash \{e\}) \) containing \( u \) (resp., \( v \)) and \( G_u = G[\bigcup_{t \in V(T_u)} X_t] \) and \( G_v = G[\bigcup_{t \in V(T_v)} X_t] \). Then,

- \( S = X_u \cap X_v \) is a clique of size \( k \) in \( G \);
- \( S \) separates \( V(G_u) \backslash S \) from \( V(G_v) \backslash S \) (every path from a vertex in \( V(G_u) \backslash S \) to a vertex in \( V(G_v) \backslash S \) goes through \( S \));
- // in particular, there are no edges between \( V(G_u) \backslash S \) and \( V(G_v) \backslash S \).

Moreover, let \( Q \subseteq S \setminus \{\emptyset\} \). Prove that, because \( S \) is a \( (V(G_u) \setminus S,V(G_v) \setminus S) \)-separator:

- If \( K \) is a vertex cover of \( G \) with \( K \cap S = Q \), then \( K' = K \cap V(G_u) \) is a vertex cover of \( G_u \) with \( K' \cap S = Q \).
- If \( K \) is a vertex cover of \( G_u \) with \( K \cap S = Q \), then there exists a vertex cover \( K' \) of \( G \) such that \( K = K' \cap V(G_u) \) (and, in particular, \( K' \cap S = Q \)).

The key points are that Vertex Cover is a “local” problem and that \( k \)-trees have small-size separators (of size \( k \)). Intuitively, extending a vertex cover \( K \) of \( G_u \) to some vertex cover of \( G \) does not depend on the whole \( K \) but only on \( K \cap S \) where \( S \) is a separator between \( G_u \) and the remaining of \( G \). When \(|S|\) is “small”, this can be done efficiently.

**Theorem 22** Algorithm 26 is correct and has time-complexity \( O(2^kn) \) where \( n \) is the number of vertices of any \( k \)-tree \( G \).

**Proof.** The proof of correctness is similar to the one of Algorithm 24.

For the complexity, Lines 5-7 needs (by induction) \( \sum_{i=1}^{d} O(|E(T_i)|) \) operations. Then, because \( |X_t| = k + 1 \) for all \( t \in V(T) \), then the number of sets \( Q \subseteq X_r \) is \( 2^{k+1} = O(2^k) \), and then the loop in Line 8 has \( O(2^k) \) iterations and the computation of the minima in Line 13 takes time \( O(2^k|E(T)|) \). Overall, the complexity is then \( O(2^k|E(T)|) \).

Since any tree-decomposition \( (T,\mathcal{X}) \) of a \( k \)-tree \( G \) with \( n \) vertices has \( O(n) \) nodes/edges (prove it), this leads to an overall complexity of \( O(2^kn) \).

From previous Theorem and Algorithm, we easily get the Algorithm 27 that computes, in time \( O(2^kn) \) a minimum vertex cover in any \( n \)-node \( k \)-tree.

### 8.4 Brief introduction to treewidth and tree-decompositions

Hopping to lead to a better intuition, we first give a definition of the treewidth (and tree-decomposition) following the previous sub-sections. Then, we will give an equivalent but more technical (?) definition that is (maybe) easier to work with.

Let \( k \in \mathbb{N} \). A graph is a partial \( k \)-tree if it is a subgraph of a \( k \)-tree. The **treewidth** of a graph \( G = (V,E) \), denoted by \( tw(G) \), equals the minimum integer \( k \) such that \( G \) is a partial
Algorithm 26 Dynamic Programming Algorithm for Minimum size Vertex Cover in k-trees

**Require:** A k-tree $G = (V,E)$ and a tree-decomposition $(T_r,X)$ of $G$ rooted in some vertex $r \in V(T_r)$.

**Ensure:** For every $Q \subseteq X_r$, a minimum-size Vertex Cover $K_Q$ of $G$ such that $K_Q \cap X_r = Q$ and $K_Q = \infty$ if no vertex cover $K$ of $G$ is such that $K \cap X_r = Q$.

1: if $V(T_r) = \{r\}$ and $X_r = \{u,v,w\}$ then
2: return $(K_Q)_{Q \subseteq X_r}$ with $K_Q = Q$ if $|Q| > k - 1$ and $K_Q = \infty$ otherwise.
3: else
4: Let $r_1, \ldots, r_d$ be the children of $r$ and, for every $1 \leq i \leq d$, let $T_i$ be the subtree of $T_r$ rooted in $r_i$. Let $X_i = \{X_t \in X | t \in V(T_i)\}$ and let $G_i = G[ \bigcup_{X \in X_i} X]$ be the subgraph induced by the vertices in the sets in $X_i$.
5: for $i = 1$ to $d$ do
6: Let $(K^i_Q)_{Q \subseteq X_{r_i}} = Algorithm 24(G_i, (T_i,X_i))$
7: end for
8: for $Q \subseteq X_r$ do
9: if $|Q| \leq k - 1$ then
10: Let $K = \infty$
11: else
12: for $i = 1$ to $d$ do
13: Let $Q_i \subseteq X_{r_i}$ be such that $Q_i \cap X_r = Q \cap X_r$ and, among such sets, $|K^i_{Q_i}|$ is minimum. //abusing notations, $|K| = \infty$ if $K = \infty$
14: end for
15: Let $K_Q = Q \cup \bigcup_{i=1}^d K^i_{Q_i}$.
16: end if
17: end for
18: return $(K_Q)_{Q \subseteq X_r}$.
19: end if

Algorithm 27 Minimum size Vertex Cover in k-trees

**Require:** A k-tree $G = (V,E)$ and a tree-decomposition $(T_r,X)$ of $G$ rooted in some vertex $r \in V(T_r)$.

**Ensure:** A minimum-size vertex cover $K$ of $G$

1: $(K_Q)_{Q \subseteq X_r} = Algorithm 26(G, (T_r,X))$.
2: $K = V$
3: for $Q \subseteq X_r$ do
4: if $|K_Q| \leq |K|$ then
5: $K \leftarrow K_Q$ //abusing notations, $|K| = \infty$ if $K = \infty$
6: end if
7: end for
8: return $K$
k-tree (note that any n-node graph is a partial (n − 1)-tree as subgraph of $K_n$ and so this parameter is well defined).

Following previous sub-sections, a first way to define a tree-decomposition of a graph is as follows. Let $G = (V, E)$ be a partial k-tree, i.e., a subgraph of a k-tree $H = (V_H, E_H)$. Let $(T, \mathcal{X} = (X_t)_{t \in V(T)})$ be a tree-decomposition of $H$ (as defined in previous sub-section). Then, $(T, \mathcal{X} \cap V = (X_t \cap V)_{t \in V(T)})$ is a tree-decomposition of $G$ of width at most $k$. Roughly, the difference with tree-decompositions of k-trees is that, in a tree-decomposition of a k-tree, the sets $X_t$ (called bags) consist of cliques of size $k + 1$, while, in the case of partial k-trees, they are subgraphs of size at most $k+1$. However, as we will see below they share the same connectedness properties. First, let us mention the algorithmic applications of tree-decompositions.

**Theorem 23** There exists an algorithm that, given any n-node graph $G$ of treewidth $tw(G)$ and a tree-decomposition of $G$ of width at most $tw(G)$, computes a minimum vertex cover of $G$ in time $O(2^{tw(G)} \cdot n)$.

**Proof.** Such an algorithm (almost) directly follows Algorithm 27 by modifying the Algorithm 26 in the following way. In Line 2, $|Q| > k − 1$ is replaced by “$Q$ is a vertex cover of $X_r$”, and in Line 9, $|Q| \leq k − 1$ is replaced by “$Q$ is not a vertex cover of $X_r$”.

The algorithm described in the proof of Theorem 23 is an FPT algorithm to compute a minimum Vertex Cover when the parameter is the treewidth (in contrast with previous FPT algorithms we have seen so far where the parameter was always the size of the solution, namely, the size $k$ of a vertex cover).

To further exemplify the algorithmic applications of tree-decompositions, let us mention (without any explanation) the celebrated Courcelle’s meta theorem.

**Theorem 24 (Courcelle 1990)** Every graph property $P$ definable in the monadic second-order logic$^{14}$ of graphs can be decided in linear time on graphs of bounded treewidth. That is, there is a function $f_P$ such that $P$ can be decided in time $O(f_P(k) \cdot n)$ in the class of $n$-node graphs with treewidth at most $k$.

**Complexity of treewidth.** Theorem 23 (and most of the dynamic programming algorithms using tree-decompositions) explicitly requires a “good” (with small width) tree-decomposition as input (Theorem 24 actually requires it implicitly). Unfortunately, the problem of deciding whether $tw(G) \leq k$ is NP-complete$^{15}$. On the positive side, this problem is FPT (with parameter the width itself)$^{16}$ and there exists a $\sqrt{\log k}$-approximation algorithm for the problem$^{17}$. On a practical point of view, it is an important research topic to design efficient approximation algorithms or heuristics that compute “good” tree-decompositions of graphs. The problem can be solved more “efficiently” in particular graphs classes. For instance, there is a cubic $3/2$-approximation algorithm in planar graphs$^{18}$, however, the complexity of the problem in planar graphs is still open...

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$^{14}$See Chapter 7.4 of [4] for an intuitive definition of MSOL. Examples of such problems include Vertex Cover, Dominating Set, 3-Colouring...


Second definition of treewidth and tree-decomposition. So far, we have given a first definition of tree-decomposition and treewidth in terms of partial k-trees because we hope that it is a bit more intuitive. Let us now give a more technical definition that does not rely on a k-tree supergraph. Let \( G = (V, E) \) be a graph. A tree-decomposition\(^{19} \) of \( G \) is a pair \((T, \mathcal{X})\) where \( T = (V(T), E(T)) \) is a tree and \( \mathcal{X} = \{X_t \mid t \in V(T)\} \) is a family of subsets (called bags) of \( V \) such that:

1. \( \bigcup_{t \in V(T)} X_t = V; \)
2. for every \( e = \{u, v\} \in E, \) there exists \( t \in V(T) \) such that \( u, v \in X_t; \)
3. for every \( v \in V, \) the set \( \{t \in V(T) \mid v \in X_t\} \) induces a subtree of \( T. \)

The width of \((T, \mathcal{X})\) equals \( \max_{t \in V(T)} |X_t| - 1 \) and the treewidth, \( tw(G), \) of \( G \) is the minimum width of a tree-decomposition of \( G \) (Note that, for any graph \( G, \) there is a trivial tree-decomposition consisting of a tree with a single note \( t \) such that \( X_t = V \). The \(-1\) in the definition of the width is only there to ensure that \( tw(G) = 1 \) if and only if \( G \) is a forest (i.e., all connected components of \( G \) are trees).

**Exercise 22** Prove that the above definitions of tree-decomposition and treewidth are equivalent to the ones given in terms of partial k-tree.

Let us note that, if a graph \( G = (V, E) \) admits a tree-decomposition \((T, \mathcal{X})\) of width \( k, \) then \( G \) has an infinity of such decompositions. Indeed, for any \( t \in V(T), \) let \( T' \) be the tree obtained from \( T \) by adding a (leaf) vertex \( t' \) adjacent to \( t \) and \( \mathcal{X}' = \mathcal{X} \cup \{X_{t'} = X_t\}, \) then prove that \((T', \mathcal{X}')\) is a tree-decomposition of \( G \) with width \( k. \) To avoid this pathological cases (and simplify next proofs), let us first show that we can always restrict ourself to tree-decomposition \((T, \mathcal{X})\) such that, for every \( t, t' \in V(T), \) \( X_t \setminus X_{t'} \neq \emptyset. \)

Given a graph \( G = (V, E) \) and an edge \( uv \in E, \) let \( G/uv \) be the graph obtained by contracting the edge \( uv \) defined as \( V(G/uv) = (V \setminus \{u, v\}) \cup \{x\} \) and \( E(G/uv) = (E \setminus \{e \in E \mid e \cap u \neq \emptyset \text{ or } e \cap v \neq \emptyset\}) \cup \{xw \mid w \in N(u) \cup N(v)\} \) (roughly, \( u \) and \( v \) are identified).

**Exercise 23** Let \( G = (V, E) \) be a graph and \((T, \mathcal{X})\) be tree-decomposition of \( G \) with width \( k. \) Let \( t' \in E(T) \) such that \( X_{t'} \subseteq X_t. \) Let \( T' = T/tt' \) (with \( x \) being the new vertex resulting from the identification of \( t \) and \( t' \)) and \( \mathcal{X}' = (\mathcal{X} \setminus \{X_t, X_{t'}\}) \cup \{X_x = X_t\}. \) Show that \((T', \mathcal{X}')\) is a tree-decomposition of \( G \) with width \( k. \)

From now on, every considered tree-decomposition \((T, \mathcal{X})\) will be assumed to satisfy that for every \( t, t' \in V(T), X_t \setminus X_{t'} \neq \emptyset. \) Note that, for such a tree-decomposition \((T, \mathcal{X})\) of a graph \( G = (V, E), \) for every \( t \in V(T) \) leaf of \( T, \) there exists \( v \in V \) such that \( v \in X_t \) and \( v \notin X_{t'} \) for every \( t' \in V(T) \setminus \{t\}. \)

The next exercise probably describes the main property of tree-decompositions.

**Exercise 24** Let \( G = (V, E) \) be a graph and \((T, \mathcal{X})\) be tree-decomposition of \( G. \)

- Let \( t \in V(T) \) and let \( T_1, \ldots, T_d \) be the components of \( T \setminus \{t\}. \) For every \( 1 \leq i < j \leq d, \) \( X_t \) separates \( \bigcup_{t' \in T_i} X_{t'} \setminus X_t \) and \( \bigcup_{t' \in T_j} X_{t'} \setminus X_t \) in \( G. \)

---

Exercise 25 Prove that,

- if $H \preceq G$, then $tw(H) \leq tw(G)$; // treewidth is minor-closed
- $tw(C) = 2$ for any cycle $C$;
- $tw(G) = 1$ if and only if $G$ is a forest;
- $tw(K_n) = n - 1$ for any $n \geq 1$;
- Let $G$ be a graph containing a clique $K$ as subgraph. Then, for every tree-decomposition $(T, \mathcal{X})$ of $G$, there exists $t \in V(T)$ with $K \subseteq X_t$, and so $tw(G) \geq |K| - 1$;
- Let $G_{n \times m}$ be the $n \times m$ grid. Then, $tw(G_{n \times m}) \leq \min\{n, m\}$.

Above, we tried to make it clear that graphs with bounded treewidth have “simple” structure that can be efficiently used for algorithmic purposes. Several “real-life” graphs have bounded treewidth\(^{20}\), but, unfortunately, it is not true in many important fields of applications (Internet, road networks...). Therefore, it is natural to ask what is the structure of graphs with large treewidth. Such a “dual” structure for graphs with large treewidth would also be useful for proving lower bounds for the treewidth of graphs (e.g., we will use it to give the exact value of treewidth for grids). One important result of Robertson and Seymour in their Graph Minor theory (see below for more details) is the characterization of such an obstruction for small treewidth.

Given a graph $G = (V, E)$ and $X, Y \subseteq V$, $X$ and $Y$ are touching if $X \cap Y \neq \emptyset$ or if there are $x \in X$ and $y \in Y$ such that $xy \in E$. A bramble $B$ in $G$ is a family of subsets of $V$ pairwise touching (i.e., for every $B, B' \in B$, $B$ and $B'$ are touching). The order of $B$ is the minimum size of a transversal of $B$, i.e., the minimum size of a set $T \subseteq V$ such that $T \cap B \neq \emptyset$ for all $B \in B$. The bramble number, $BN(G)$, of a graph $G$ is the maximum order of a bramble in $G$.

Theorem 25 (Seymour and Thomas 1993)\(^ {21}\) For any graph $G$, $tw(G) = BN(G) - 1$.

An intuitive way to understand (and prove) the above theorem is by considering the equivalence between tree-decompositions and graph searching games\(^ {22}\).

As a consequence of previous theorem, let us show the following lemma.

Lemma 18 Let $G_{n \times m}$ be the $n \times m$ grid. Then, $tw(G_{n \times m}) = \min\{n, m\}$.

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\(^{20}\)e.g., Mikkel Thorup: All Structured Programs have Small Tree-Width and Good Register Allocation. Inf. Comput. 142(2): 159-181 (1998)


\(^{22}\)See Section 4.1 in Nicolas Nisse: Network Decontamination. Distributed Computing by Mobile Entities 2019: 516-548
Proof. Let us assume that $n \leq m$. The upper bound follows from Exercise 25. For the lower bound, by Theorem 25, let us exhibit a bramble of order $n + 1$. Given a grid, a cross consists of the union of any row plus any column. Let $G'$ be the subgrid obtained from $G_{n \times m}$ by removing its first row and its first column. The desired bramble consists of the first row, the first column minus its vertex in the first row, and all crosses of $G'$.

Intuitively, a bramble with large order in a graph $G$ may be seen as a large grid or as a large clique minor in $G$. The following result shows that any planar graph $G$ has a large treewidth if and only if it admits a large grid as minor.

**Theorem 26 (Grid Theorems)** [Robertson and Seymour 1986, Kawarabayashi and Kobayashi 2012, Chuzhoy and Tan 2019]

Any planar graph $G$ with treewidth $\Omega(k)$ has an $k \times k$ grid as minor.

Any graph $G$ with treewidth $\Omega(k^{3\text{poly}\log(k)})$ has an $k \times k$ grid as minor.

There are graphs with treewidth $\Omega(k^2 \log(k))$ without any $k \times k$ grid as minor.

One first interesting application of previous theorem is the framework of bidimensionality theory that we present with an example below.

**Bidimensionality.** Let us consider a function $f_P : \{\text{graphs}\} \to \mathbb{N}$ and consider the problem $P$ that, given a graph $G$ and an integer $k$, aims at deciding whether $f_P(G) \leq k \leq |V(G)|$. Let us assume that $P$ is closed under taking minor, i.e., $f_P(H) \leq f_P(G)$ for every $H \preceq G$, that the problem can be decided in time $O(2^{tw(G)} n)$ and that $f_P(G_{n \times n}) = \Omega(n^2)$ where $G_{n \times n}$ is the grid of side $n$. The Vertex Cover problem is an example of such a problem.

**Theorem 27 (Demaine and Hajiaghayi 2008)** Such a problem $P$ can be solved in sub-exponential time $O(2^{\sqrt{n} \text{poly}(n)})$ in the class of $n$-node planar graphs.

Proof. (Sketch) Consider the following algorithm to decide whether $f_P(G) \leq k$. First, if $tw(G) = O(\sqrt{k})$, which can be decided (and a corresponding tree-decomposition can be computed) in time $O(2^{\sqrt{k}} n)$, then by the second property of $P$, then the solution can be computed in time $O(2^{\sqrt{n}} n)$. Otherwise, by the Grid theorem, $G$ has a $\sqrt{k} \times \sqrt{k}$-grid $H$ as minor. Since $f_P(H) = \Omega(k)$ and $P$ is closed under taking minor, then $f_P(G) = \Omega(k)$.

Finally, since $k \leq n$, the result follows.

The above theorem has been generalized for larger classes of sparse graphs such as bounded genus graphs and even graphs excluding some fixed graph as minor.

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23A graph is planar if it can be drawn on the sphere without crossing edges.


25Ken-ichi Kawarabayashi, Yusuke Kobayashi: Linear min-max relation between the treewidth of H-minor-free graphs and its largest grid. STACS 2012: 278-289

26Julia Chuzhoy, Zihan Tan: Towards Tight(er) Bounds for the Excluded Grid Theorem. SODA 2019: 1445-1464


A third definition of treewidth. For completeness (and to conclude this brief introduction to treewidth), let us give another definition of treewidth. A graph is chordal if it has no induced cycle of length at least 4 as subgraph. Equivalently, a graph is chordal if it is the intersection graph of a family of subtrees of a tree. Given a graph $G$, let $\omega(G)$ be the maximum size of a clique in $G$. The treewidth of a graph $G$ can be defined as the minimum $\omega(H) - 1$ among all chordal supergraphs $H$ of $G$. Note that there is a close relationship between tree-decompositions of a graph $G$ and the clique trees of its chordal supergraphs.

8.5 Graph Minor theory

To conclude this section, let us try to sketch the main reason why Robertson and Seymour introduced tree-decompositions and treewidth. Note that there are very nice surveys on this topic. Recall that a partial order is called Well Quasi Ordered (WQO) if it admits no infinite antichain (i.e., no infinite sequence of elements that are pairwise incomparable). The Wagner’s conjecture (1970) asked whether the minor ordering is WQO over the set of graphs. Along a series of 20 papers (with overall about 500 pages) from 1983 to 2004, Robertson and Seymour answered this question (and many fundamental others) through what is now called the Graph Minor theory (interestingly, the order of publication of these papers does not necessarily correspond to the order of the results).

Theorem 28 (Robertson and Seymour 2004) The minor relationship is WQO.

Before giving a very rough idea of its proof, let us show the algorithmic consequences of the above theorem. A class of graph $\mathcal{G}$ is minor-closed if, for every $H \preceq G$, $G \in \mathcal{G}$ implies that $H \in \mathcal{G}$. Given a graph class $\mathcal{G}$, let the set of obstructions $\text{Obs}(\mathcal{G})$ be the set of minor-minimal graphs not in $\mathcal{G}$, i.e., the set of graphs $H$ such that $H \notin \mathcal{G}$ and $H' \in \mathcal{G}$ for all $H' \prec H$.

Corollary 4 Let $\mathcal{G}$ be a minor-closed class of graphs. Then $\text{Obs}(\mathcal{G})$ is finite.

Proof. Otherwise, by Theorem 28, there would be two graphs $G, G'$ in $\text{Obs}(\mathcal{G})$ such that $G \prec G'$, a contradiction.

As an example, note first that any minor of a planar is also planar. Hence, the class $\mathcal{P}$ of planar graphs is minor-closed.

Theorem 29 [Wagner 1937] A graph is planar if and only if it has no $K_5$ nor $K_{3,3}$ (the complete bipartite graph with 3 vertices in each part) as minor, i.e., $\text{Obs}(\mathcal{P}) = \{K_5, K_{3,3}\}$.

To understand the importance of Corollary 4, let us do a short detour to vertex-disjoint paths in graphs. Given a graph $G = (V, E)$ and two disjoint subsets $X, Y \subset V$ with $|X| = |Y| = k$, the problem of deciding whether there are $k$ vertex-disjoint paths between $X$ and $Y$ (and compute such paths) can be solved in polynomial-time (e.g., using flow algorithm or the proof of Menger’s theorem). In contrast, given a graph $G = (V, E)$ and two disjoint subsets $X = \{s_1, \cdots, s_k\}, Y = \{t_1, \cdots, t_k\} \subset V$ with $|X| = |Y| = k$, the problem of deciding whether there are $k$ vertex-disjoint paths $P_1, \cdots, P_k$, where $P_i$ is a path between $s_i$ and $t_i$ for all $i \leq k$, (and compute such paths) is NP-complete [7]. To see the difference between the two problems,

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30 See the survey of Lovász here and the survey of Robertson and Seymour themselves (1985) here.
consider a cycle with vertices \((s_1, s_2, t_1, t_2)\) (in this order): clearly, there are 2 vertex-disjoint paths from \(X = \{s_1, s_2\}\) to \(Y = \{t_1, t_2\}\), but 2 vertex-disjoint paths \(P_1\) from \(s_1\) to \(t_1\) and \(P_2\) from \(s_2\) to \(t_2\) do not exist.

One of the numerous fundamental contributions of Robertson and Seymour along their Graph Minor serie is the proof that, when \(k\) is fixed, the latter problem \((k\text{-linkage})\), is FPT in \(k^{32}\). This allowed them to show that, given a fixed graph \(H\), the problem that takes an \(n\)-node graph \(G\) as input and asks whether \(H \preceq G\) (\(G\) admits \(H\) as minor) can be solved in time \(O(n^3)\) where the “big O” hides a constant depending on \(H\) (this result has been improved to an \(O(n^2)\)-time algorithm since then).

\textbf{Theorem 30 (Kawarabayashi, Kobayashi and Reed 2012)} Let \(H\) be a fixed graph. The problem that takes an \(n\)-node graph \(G\) as input and decides if \(H \preceq G\) can be solved in time \(O(n^2)\).

To give an intuition of the relationship between the minor containment problem and the \(k\)-linkage problem, let us give the very sketchy following process (whose time-complexity is much worst than the one announced in previous theorem but still polynomial for fixed \(H\)). First, we can “guess” the vertices of \(G\) that correspond to vertices of \(H\) (by trying the \(O(|V(H)|)\) possibilities). For each choice of \(|V(H)|\) vertices in \(G\), then, we have to recover the \(|E(H)|\) edges of \(H\) as \(|E(H)|\) vertex-disjoint paths in \(G\) (with sources and terminal the vertices we have guessed).

Now, we are ready to give the main algorithmic consequence of Robertson and Seymour’s theorem.

\textbf{Theorem 31} Let \(\mathcal{G}\) be any minor-closed graph class. The problem that takes a graph \(G\) as input and asks whether \(G \in \mathcal{G}\) is in \(P\).

\textbf{Proof.} The algorithm is as follows. For each \(H \in \text{Obs}(\mathcal{G})\) (there are a finite number of such graph by Corollary 4), decide if \(H \preceq G\) (can be done in polynomial-time by Theorem 30). If \(H \preceq G\) for some \(H \in \text{Obs}(\mathcal{G})\) then \(G \notin \mathcal{G}\), else \(G \in \mathcal{G}\).

Note that previous theorem is only an existential result since it requires the knowledge of \(\text{Obs}(\mathcal{G})\) for the considered graph class \(\mathcal{G}\). Unfortunately, as far as I know, the set of obstructions is known for very few graph classes. For instance, the full set of obstructions of the class of graphs with \textit{genus} 1 (that can be embedded without crossing edges on a “doughnut”) is still unknown.

\textbf{“Proof” of Robertson and Seymour’s theorem.} To conclude this section, let us give a very very very sketchy (and probably a bit wrong, sorry) idea of the proof of Theorem 28. Roughly, the guideline is to prove that the minor relationship is WQO in graph classes that are more and more large.

\textbf{Theorem 32 (Kruskal 1960)} The minor relationship is WQO in the class of trees.

The next step is naturally the class of graphs with bounded treewidth.


Intuitively, let \((G_1, \cdots)\) be an infinite sequence of graphs with treewidth at most \(k\), and let \((T_1, X_1)\) be a tree-decomposition of width \(k\) of \(G_1\). The sequence \((T_1, \cdots)\) is an infinite sequence of trees and, by Theorem 32, we can extract an infinite sequence \((T_1 \preceq T_2 \preceq \cdots)\). Because the graphs \((G_1, G_2, \cdots)\) have bounded treewidth, the trees \((T_1, T_2, \cdots)\) can be seen as trees with labels of bounded length on their vertices. The result follows (after some work).

Next, the case of planar graphs arises.

**Theorem 34 (Robertson and Seymour 1986)**  

Indeed, very intuitively, let us consider an infinite sequence \(S\) of planar graphs. If infinitely of them have bounded treewidth, then the result follows previous theorem. Otherwise, by the grid Theorem 26, they have arbitrary large grids as minors. Note that, for any planar graph \(G\), there exists a grid \(Gr\) such that \(G \preceq Gr\). Overall, it is possible to find \(G, G' \in S\) such that \(G'\) has a sufficiently large grid \(Gr\) as minor such that \(G \preceq Gr \preceq G'\).

Previous result can then be extended to bounded genus graphs. Roughly, a surface has (orientable) genus at most \(g\) if it can be obtained from a sphere by adding to it \(g\) handles. A graph has genus \(g\) if it can be embedded without crossing edges on a surface with genus \(g\) (planar graphs are graphs with genus 0, graphs with genus \(\leq 1\) are the ones that can be embedded on a doughnut...). See [1] for more formal definitions.

**Theorem 35 (Robertson and Seymour 1990)**  

We now can “conclude”. Let \((G_1, \cdots)\) be an infinite sequence of graphs. For every \(k \geq 2, G_1 \not\preceq G_k\) (since otherwise we are done). Hence, the graphs \(G_2, \cdots\) are all excluding \(G_1\) as minor. A key contribution of Robertson and Seymour is the structural characterization of the graphs excluding a fixed graph \(H\) as minor. Namely, given a fixed graph \(H\), they show that any \(H\)-minor free graph (i.e., excluding \(H\) as minor) admits a particular decomposition\footnote{Neil Robertson, Paul D. Seymour: Graph Minors. XVI. Excluding a non-planar graph. J. Comb. Theory, Ser. B 89(1): 43-76 (2003)} that we try to sketch below.

Very very very roughly (sorry again), a \(H\)-minor free graph \(G\) admits a tree-decomposition \((T, X)\) such that

- for every \(uv \in E(T), |X_u \cap X_v| \leq 3\) (this bound is actually due to Demaine et al.);
- for every \(v \in V(T)\), the bag \(X_v\) induces a graph \(G_v\) that is obtained from: a graph \(G'_v\) that has bounded (in terms of \(|H|\)) genus, to which it can be added a bounded (in terms of \(|H|\)) number of vertices (subgraphs of bounded (in terms of \(|H|\)) “pathwidth” that may be “glued” along non-contractible cycles of \(G'_v\) and then a bounded (in terms of \(|H|\)) number of apices can be added (vertices that can be adjacent to any vertex).

The proof of Theorem 28 then follows from Robertson and Seymour’s decomposition and previous theorems (bounded treewidth, bounded genus...).
Part IV
Linear Programming for graphs

This part is devoted to introduced an important tool for handling many graph problems (NP-hard or not), namely Linear Programming (LP). It is important to note that this tool is widely used in practice. From the theoretical point of view related to previous part, the last section of this part gives an example where LP may be used for the design of FPT algorithms.

9 Linear Programming in a nutshell [8]

This section is NOT a lecture on linear programming, we only try to give you the necessary background to use this very powerful tool for modeling and solving graph problems. See, e.g., [8] for a real course on Linear Programming.

9.1 Definition of a Linear Programme

Consider a set of \( n \) non negative real variables \( x_1, \ldots, x_n \). Moreover, these variables must satisfy a set of \( m \) constraints which all are linear combinations of the variables. That is, for every \( 1 \leq j \leq m \), the constraint \( C_j \) is of the form \( \sum_{1 \leq i \leq n} a_{i,j} x_i \leq b_j \) or \( \sum_{1 \leq i \leq n} a_{i,j} x_i \geq b_j \) where \( a_{i,j} \in \mathbb{R} \) and \( b_j \in \mathbb{R} \) are (given) real constants, for every \( 1 \leq i \leq n \) and \( 1 \leq j \leq m \). Finally, the goal of the problem is to assign values (from the domain) to each variable, satisfying all (subject to) the constraints \( C_1, \ldots, C_m \), and optimizing some objective function which consists of maximizing or minimizing some linear combination \( \sum_{1 \leq i \leq n} c_i x_i \) of the variables \( c_i \in \mathbb{R} \) for every \( 1 \leq i \leq n \).

Note that a constraint \( \sum_{1 \leq i \leq n} a_{i,j} x_i \leq b_j \) can be equivalently replaced by the constraint \( \sum_{1 \leq i \leq n} (-a_{i,j}) x_i \geq -b_j \). Similarly, the objective function “maximize \( \sum_{1 \leq i \leq n} c_i x_i \)” is equivalent to the one of minimizing \( \sum_{1 \leq i \leq n} (-c_i) x_i \). Hence, we may only consider maximization problem with constraints of the form \( \sum_{1 \leq i \leq n} a_{i,j} x_i \leq b_j \).

To sum up, a linear programme\(^{37} \) has the following canonical form:

\[
\begin{align*}
\text{maximize} & \quad \sum_{1 \leq i \leq n} c_i x_i \\
\text{subject to} & \quad \sum_{1 \leq i \leq n} a_{j,i} x_i \leq b_j \quad \forall 1 \leq j \leq m \\
& \quad x_i \geq 0 \quad \forall 1 \leq i \leq n
\end{align*}
\]

Then, the goal is to assign, for each variable \( x_i, 1 \leq i \leq n \), a non negative real value, such that all constraints \( C_j \) are satisfied, and optimizing the objective function. Note that, \( a_{i,j}, b_j \) and \( c_j \) are given real constants (part of the input of the problem) for every \( 1 \leq i \leq n \) and \( 1 \leq j \leq m \).

\(^{37}\)The terminology is due to Dantzig (1947) who formalized it and used it for planning problems in the US Air Force. In this context, “programme” must be understood as “planification” and not as having any relationship with programming languages.
Let us emphasis that, since constraints and the objective function are restricted to be linear combinations of the variables, it is forbidden to multiply two (or more) variables\(^38\).

For completeness, let us mention a matricial way to present a Linear Programme:

\[
\begin{align*}
\text{max.} & \quad C^T \cdot X \\
\text{subject to} & \quad AX \leq B \\
& \quad X \geq 0
\end{align*}
\]

where \(X = [x_1, \ldots, x_n], C = [c_1, \ldots, c_n]\) and \(B = [b_1, \ldots, b_m]\) are column vectors and \(A = [a_{j,i}]_{1 \leq i \leq n, 1 \leq j \leq m}\) is a matrix with \(m\) rows and \(n\) columns (and \(W \cdot U\) is the scalar product between \(W\) and \(U\); and \(W = [w_i]_{1 \leq i \leq q} \leq U = [u_i]_{1 \leq i \leq q}\) iff \(w_i \leq u_i\) for all \(1 \leq i \leq q\)).

A \textit{feasible solution} for a Linear Programme (LP) is an assignment of some values to the variables that satisfies all constraints (including the one that variables must be assigned non negative real\(^39\)). An \textit{optimal solution} is any feasible solution that maximizes the objective function.

### 9.2 A few words on how to solve a Linear Programme

First, let us notice that a Linear Programme (LP) may be of three kinds. First, a LP may admit no feasible solution, as it can easily be checked for the following example with two variables (note that the two constraints are not compatible):

\[
\begin{align*}
\text{max.} & \quad x_1 + 3x_2 \\
\text{subject to} & \quad -x_1 \leq -3 \\
& \quad x_1 \leq 2 \\
& \quad x_1, x_2 \geq 0
\end{align*}
\]

Second, a LP may admit feasible solutions but no optimal solutions (i.e., the value the objective function may be arbitrary large) as in the following example:

\[
\begin{align*}
\text{max.} & \quad x_1 + 3x_2 \\
\text{subject to} & \quad x_2 \leq 3 \\
& \quad x_1, x_2 \geq 0
\end{align*}
\]

Finally, a LP may admit optimal solutions. In this latter case, there may be an infinite number of optimal solutions (see next example) or a single optimal solution (as shown in the last example).

\[
\begin{align*}
\text{max.} & \quad x_1 + 3x_2 \\
\text{subject to} & \quad x_1 + 3x_2 \leq 3 \\
& \quad x_1, x_2 \geq 0
\end{align*}
\]

Indeed, the above LP admits the set \(\{(x_1 = x, x_2 = (3 - x)/3) \mid 0 \leq x \leq 3\}\), as optimal solutions (with maximum value 3 for the objective function).

\[
\begin{align*}
\text{max.} & \quad x_1 + 3x_2 \\
\text{subject to} & \quad x_1 \leq 3 \\
& \quad x_2 \leq 7 \\
& \quad x_1, x_2 \geq 0
\end{align*}
\]

\(^38\)For more general programmes, let us refer to the areas of Constraints Satisfiability Programmes (CSP), quadratic programmes (where it is allowed to multiply two variables but no more) and semi-definite programming (SDP)....

\(^39\)Note that the fact that a variable must be non negative is not a strong constraint. Indeed, assume that a variable \(x\) may be any real, then it can be “simulated” by two non negative real variables \(y\) and \(z\) adding the constraint that \(x = y - z\).
Indeed, it is easy to see that the above LP admits one unique optimal solution \((x_1 = 3, x_2 = 7)\) (with maximum value 24 for the objective function).

Again, this section does not pretend to be a course on Linear Programming. We only aim at giving some intuition of what “happens”. For purpose of illustration, let us consider the following general LP:

\[
\begin{align*}
\text{maximize} & \quad \sum_{1 \leq i \leq n} c_i x_i \\
\text{subject to} & \quad \sum_{1 \leq i \leq n} a_{j,i} x_i \leq b_j \quad \forall 1 \leq j \leq m \\
& \quad x_i \geq 0 \quad \forall 1 \leq i \leq n
\end{align*}
\]

Each constraint \(C_j\) corresponds to an hyperplane (in \(\mathbb{R}^n\)) with equation \(\sum_{1 \leq i \leq n} a_{j,i} x_i = b_j\) (i.e., a line if \(n = 2\)) and so implies that any feasible solution is constrained to belong to the half-space with \(\sum_{1 \leq i \leq n} a_{j,i} x_i \leq b_j\) (a half plane in the case \(n = 2\)). Similarly, the non negativity constraint defined a half-space for each variable. Altogether, taking the intersection of the half-spaces defined by each constraint, the feasible domain (i.e., the set of feasible solutions) is the intersection of a set of half-spaces (each defined by some hyperplane) which is, by definition, a \textit{polytope} (a polygone in the case \(n = 2\)). On the other hand, the objective function corresponds to a family of hyperplanes, the ones with equations \(\sum_{1 \leq i \leq n} c_i x_i = s\), for \(s \in \mathbb{R}\) (for instance, a set of parallel lines if \(n = 2\)). A key point is that a polytope is \textit{convex}. Therefore, it can be proved that, if the polytope \(P\) defining the feasible solutions is not empty (otherwise there are no feasible solutions) and bounded (otherwise there is no bounded optimal solution), then the optimal solutions either correspond to a corner of \(P\) (in which case the optimal solution is unique) or corresponds to a face of \(P\) (infinite number of optimal solutions).

To have a better (more concrete) understanding of previous paragraph, the reader is encouraged to consider the two-dimensional case (i.e., with only two variables) and to learn how to solve it using the \textit{graphical method} (see, e.g., here). More generally, the above properties allow the \textit{simplex method} [Dantzig 1949] to compute an optimal solution by, roughly, going from corner to corner, each time by improving the value of the objective function (the simplex method is actually similar to Gaussian elimination). The simplex method has exponential-time complexity in worst case and it has been a breakthrough when it was proved that solving a LP can be done in polynomial time (in the number of variables and constraints):

\textbf{Theorem 36} (\textit{Ellipsoid method} [Khachiyan 1979], \textit{Interior-point method} [Karmarkar 1984])

\textit{Given a LP, an optimal solution can be computed in time polynomial in the number of variables and in the number of constraints.}

Note that, in practice, the simplex method (while exponential in worst case) is generally very efficient.

\subsection{9.3 Integer Linear Programming}

While being very powerful and being solvable in polynomial time, LP cannot express problems whose solutions must have discrete values. An Integer Linear Programme (ILP) is defined as

\footnote{Recall that a set \(X \subseteq \mathbb{R}^n\) is convex iff, for every \(u, v \in X\), and for every \(0 \leq \lambda \leq 1\) (\(\lambda \in \mathbb{R}\)), \(\lambda u + (1 - \lambda) v \in X\), i.e., every “point” of the “segment” between \(u \in X\) and \(v \in X\) also belongs to \(X\).}
a LP with the difference that its variables must have integral values (or sometimes boolean values). For instance, ILPs have the following possible forms:

\[
\text{maximize } \sum_{1 \leq i \leq n} c_i x_i \\
\text{subject to } (\text{constraint } C_j : ) \sum_{1 \leq i \leq n} a_{j,i} x_i \leq b_j \ \forall 1 \leq j \leq m \\
x_i \in \mathbb{N} \quad \forall 1 \leq i \leq n
\]

or

\[
\text{maximize } \sum_{1 \leq i \leq n} c_i x_i \\
\text{subject to } (\text{constraint } C_j : ) \sum_{1 \leq i \leq n} a_{j,i} x_i \leq b_j \ \forall 1 \leq j \leq m \\
x_i \in \{0, 1\} \quad \forall 1 \leq i \leq n
\]

Contrary to the LP case, solving an ILP is an NP-hard problem [7] and so, no polynomial-time algorithm is known to solve them. One reason for that is that the set of feasible solutions is not convex anymore.

Given an ILP, a fractional relaxation of it is a LP obtained from the ILP by allowing its variables to have real values. For instance, fractional relaxations of both the above ILPs are:

\[
\text{maximize } \sum_{1 \leq i \leq n} c_i x_i \\
\text{subject to } (\text{constraint } C_j : ) \sum_{1 \leq i \leq n} a_{j,i} x_i \leq b_j \ \forall 1 \leq j \leq m \\
x_i \geq 0 \quad \forall 1 \leq i \leq n
\]

and

\[
\text{maximize } \sum_{1 \leq i \leq n} c_i x_i \\
\text{subject to } (\text{constraint } C_j : ) \sum_{1 \leq i \leq n} a_{j,i} x_i \leq b_j \ \forall 1 \leq j \leq m \\
0 \leq x_i \leq 1 \quad \forall 1 \leq i \leq n
\]

Since a feasible solution of an ILP is also a feasible solution for its fractional relaxation, we get

**Lemma 19** The optimal value of the objective function of a maximization (resp., minimization) ILP is upper (resp., lower) bounded by the optimal value of the objective function of its fractional relaxation.

Consider any problem that can be modeled by an ILP and let us denote by \( OPT \) the optimal value of the objective function of this ILP. Moreover, let \( OPT_f \) be the optimal value of the objective function of the fractional relaxation of the ILP. For a maximization (resp., minimization) problem, the ratio \( OPT/OPT_f \) (resp., \( OPT_f/OPT \)) is called the integrality gap (always \( \geq 1 \)). If the integrality gap of a problem equals 1, this means that there exists an integral optimal solution for the fractional relaxation of the ILP. In that case, by previous subsection, the problem can be solved in polynomial time (we will see examples below). More generally,
Lemma 20 If the integrality gap of some problem can be bounded, say by $c$ (a constant or a function of the size of the input), then solving the fractional relaxation of the problem gives a $c$-approximation algorithm for the initial problem.

10 Model graph problems using ILP

This is the main section of this part where we learn how to express various graph problems as Integer Linear Programmes. Note that the main difficulty is to model (graph) problems as ILP. By experience, an ILP looks rather obvious once it has been defined. Hence, I should advice you to think about how to model the following problems before to see the proposed solutions. Also (especially for the first problem below), we try to detail “good” ways to proceed/reflexes that you must think about/have in order to model graph problems as ILP (unfortunately, there is no systematical/magical recipe for this purpose).

Roughly, the main step consists of defining (the meaning of) the variables. Then, the objective function is (generally) rather obvious. Finally, the definition of the constraints follows from a good understanding of the given problem.

10.1 Minimum Vertex Cover

Recall that this problem consists in, given a graph $G = (V,E)$, computing a smallest subset $Q \subseteq V$ of vertices that “touch” all edges of $E$.

Since we aim at computing a subset of vertices, it is “natural” to define one variable $x_v$ per vertex $v \in V$ such that $x_v = 1$ will mean that $v$ belongs to the computed solution (subset of vertices) and $x_v = 0$ otherwise. Note that, each variable will have value in $\{0, 1\}$.

The size of the computed vertex-set is then $\sum_{v \in V} x_v$ which is then the objective function to be minimize.

Now, the problem asks that, for every edge $uv \in E$, at least one of $u$ or $v$ is taken in our solution (our subset of vertices touching all edges). That is, we would like that, for every $uv \in E$, either $x_u = 1$ or $x_v = 1$ (or both). Since the variables have values in $\{0, 1\}$, it is equivalent to say that $x_u + x_v \geq 1$ for every $uv \in E$ (prove it).

Overall, the minimum Vertex Cover problem on a graph $G = (V,E)$ can be modeled by the following ILP:

$$\begin{align*}
\text{minimize} & \quad \sum_{v \in V} x_v \\
\text{subject to} & \quad x_u + x_v \geq 1 \quad \forall uv \in E \\
& \quad x_v \in \{0, 1\} \quad \forall v \in V
\end{align*}$$

Exercise 26 Give the canonical form of the above ILP.

Exercise 27 Prove that there is a one-to-one mapping between any (optimal) solution of the above ILP and (minimum) vertex covers of $G$.

Proof. Let $(x_{v_1}, \ldots, x_{v_n})$ be a feasible solution of the ILP, and let $Q = \{ v \in V \mid x_v = 1 \}$, then $Q$ is a vertex cover (prove it). On the other hand, let $Q$ be a vertex cover and let $(x_{v_1}, \ldots, x_{v_n})$ be defined such that $x_v = 1$ if $v \in Q$ and $x_v = 0$ otherwise, then prove that $(x_{v_1}, \ldots, x_{v_n})$ is a feasible solution for the ILP.

You should now know (I hope) that the minimum Vertex Cover problem is NP-hard in general graphs [7]. This problem is NP-hard in general graphs. Therefore (it also comes from
previous section), solving the corresponding ILP is an NP-hard problem. However, the following fractional relaxation of the above ILP can be solved in polynomial time (by Theorem 36).

\[
\begin{align*}
\text{minimize} & \quad \sum_{v \in V} x_v \\
\text{subject to} & \quad x_v + x_u \geq 1 \quad \forall uv \in E \\
& \quad x_v \geq 0 \quad \forall v \in V
\end{align*}
\]

The following exercise is dedicated to see the difference between an optimal solution of an ILP and an optimal solution of its fractional relaxation.

**Exercise 28** Let $G$ be the graph consisting of a triangle $uvw$. Solve the ILP for the minimum Vertex Cover in $G$ and then solve its fractional relaxation.

**Proof.** For the ILP, there are three optimal solutions: $x_u = x_v = 1$ and $x_w = 0$, or $x_u = x_w = 1$ and $x_v = 0$, or $x_w = x_v = 1$ and $x_u = 0$, all with objective function’s value 2. On the other hand, the optimal solution of the fractional relaxation of the ILP is $x_u = x_v = x_w = 1/2$ with objective function’s value $3/2$.

10.2 Maximum Independent Set

This problem consists in, given a graph $G = (V,E)$, computing a largest subset $Q \subseteq V$ of vertices that are pairwise not adjacent (i.e., for all $x, y \in Q$, $xy \notin E$). This problem is NP-hard in general graphs [7].

Since we aim at computing a subset of vertices, it is “natural” to define one variable $x_v$ per vertex $v \in V$ such that $x_v = 1$ will mean that $v$ belongs to the computed solution (subset of vertices) and $x_v = 0$ otherwise. Note that, each variable will have value in \{0, 1\}.

The size of the computed vertex-set is then $\sum_{v \in V} x_v$ which is then the objective function to be maximize.

Now, the problem asks that, for every edge $uv \in E$, at most one of $u$ or $v$ is taken in our solution (our subset of vertices does not contain two adjacent vertices). That is, we would like that, for every $uv \in E$, at most one of $x_u$ or $x_v$ equals one. Since the variables have values in \{0, 1\}, it is equivalent to say that $x_u + x_v \leq 1$ for every $uv \in E$ (prove it).

Overall, the maximum Independent Set problem on a graph $G = (V,E)$ can be modeled by the following ILP:

\[
\begin{align*}
\text{maximize} & \quad \sum_{v \in V} x_v \\
\text{subject to} & \quad x_v + x_u \leq 1 \quad \forall uv \in E \\
& \quad x_v \in \{0,1\} \quad \forall v \in V
\end{align*}
\]

**Exercise 29** Prove that there is a one-to-one mapping between any (optimal) solution of the above ILP and (maximum) independent sets of $G$.

10.3 Maximum Clique

This problem consists in, given a graph $G = (V,E)$, computing a largest subset $Q \subseteq V$ of vertices that are pairwise adjacent (i.e., for all $x, y \in Q$, $xy \in E$). This problem is NP-hard in general graphs [7].
Since we aim at computing a subset of vertices, it is “natural” to define one variable $x_v$ per vertex $v \in V$ such that $x_v = 1$ will mean that $v$ belongs to the computed solution (subset of vertices) and $x_v = 0$ otherwise. Note that, each variable will have value in $\{0, 1\}$.

The size of the computed vertex-set is then $\sum_{v \in V} x_v$ which is then the objective function to be maximize.

Now, the problem asks that, for every non edge $uv \notin E$, at most one of $u$ or $v$ is taken in our solution. It may be instructive to see that a maximum clique in a graph $G$ is equivalent to a maximum independent set in the graph $\bar{G}$, i.e., the complementary of $G$, obtained from the same vertex-set of $G$ by having an edge $uv$ in $\bar{G}$ when $uv$ is not an edge of $G$ and vice-versa.

Hence, the maximum Clique problem on a graph $G = (V, E)$ can be modeled by the following ILP:

$$\text{maximize} \quad \sum_{v \in V} x_v$$

subject to \hspace{1cm} $x_u + x_v \leq 1 \quad \forall uv \notin E$

$x_v \in \{0, 1\} \quad \forall v \in V$

**Exercise 30** Prove that there is a one-to-one mapping between any (optimal) solution of the above ILP and (maximum) cliques in $G$.

### 10.4 Proper $k$-coloring

Given a graph $G = (V, E)$ and $k \in \mathbb{N}$, a $k$-coloring $c : V \to \{1, \ldots, k\}$ is *proper* if $c(u) \neq c(v)$ for every $uv \in E$ (i.e., two adjacent vertices cannot receive the same color). The *chromatic number* $\chi(G)$ of a graph $G$ is the minimum $k$ such that $G$ admits a proper $k$-coloring.

**Exercise 31** Prove that $\chi(G) \leq 2$ if and only if $G$ is bipartite.

Clearly, $\chi(G) \leq n$ for any $n$-node graph $G$ (simply give a different color to each vertex). Moreover, a greedy algorithm allows to prove that $\chi(G) \leq \Delta + 1$ for any graph $G$ with maximum degree $\Delta$ (simple proof by induction on $|V(G)|$). The *Brooks’ theorem* (1941) states that $\chi(G) = \Delta + 1$ if and only if $G$ is a complete graph or an odd cycle. The celebrated *four-color theorem* states that $\chi(G) \leq 4$ for any planar graph $G$ [Appel and Haken 1976, Robertson, Sanders, Seymour, and Thomas 1997]\(^{41}\). In general, computing $\chi(G)$ is an NP-hard problem [7] and deciding if $\chi(G) \leq 3$ is even NP-hard in the class of cubic planar graphs [7]. The proper coloring problem is a widely studied graph problem that has many applications such as the assignment of frequencies to antennas in order to avoid interferences.

In this section, let us present an ILP aiming at deciding if a graph $G$ admits a 3-coloring, i.e., if $\chi(G) \leq 3$.

For every vertex $v \in V$ and $y \in \{1, 2, 3\}$, let $x_v^y$ be the variable whose meaning is that $x_v^y = 1$ if vertex $v$ has color $y$ and $x_v^y = 0$ otherwise. The first set of constraints expresses the fact that each vertex receives exactly one color in $\{1, 2, 3\}$, and the second set of constraints reflects the fact that the coloring is proper. Note that, here, the objective function has no real meaning since we are considering a decision problem (the question is to know whether a solution exists or not, not to optimize some function).

\(^{41}\)Note that, while the proof of the 4-color theorem is quite complicated, it is easy to prove that $\chi(G) \leq 6$ for any planar graph $G$, by noticing that any planar graph $G$ has degeneracy at most 6 (by Euler’s formula) and using a greedy algorithm. Moreover, the proof of Heawood (1890) that $\chi(G) \leq 5$ for any planar graph $G$ is much easier than the one of the 4-color theorem.
Exercise 32 Let \( k \in \mathbb{N} \). Give an ILP that models the decision problem \( \chi(G) \leq k \)? What is the number of variables and constraints?

10.5 Minimum Spanning Tree

This problem consists in, given a connected edge-weighted graph \( G = (V,E), w : E \to \mathbb{R}^+ \), computing a minimum weight spanning connected subgraph of \( G \). This problem can be solved in polynomial-time as shown in Algorithm 3.

Since we aim at computing a subset of edges (the ones of the subgraph to be computed), it is “natural” to define one variable \( x_e \) per edge \( e \in E \) such that \( x_e = 1 \) will mean that the edge \( e \) belongs to the computed solution and \( x_e = 0 \) otherwise. Note that, each variable will have value in \( \{0,1\} \).

The weight of the computed vertex-set is then \( \sum_{e \in E} w(e)x_e \) which is then the objective function to be minimize.

Moreover, the desired solution must be a spanning tree of \( G \), i.e., a tree on \( |V| \) vertices. By Exercise 2, a tree on \( x \) vertices must have \( x - 1 \) edges. Therefore, let us add the constraint \( \sum_{e \in E} x_e = |V| - 1 \).

Now, let us give two different ways to describe our solution as a tree (and so, two corresponding ILPs).

First, a graph \( H \) on \( n \) vertices and with \( n - 1 \) edges is a tree if and only if \( H \) is acyclic (see Exercise 2). Therefore, a possible way to model the current problem is to ensure that any feasible solution is acyclic, which can be ensured by imposing that any subgraph of the computed solution is acyclic, i.e., for any subset of vertices \( X \), the number of taken edges induced by \( X \) is at most \( |X| - 1 \).

\[
\begin{align*}
\text{minimize} & \quad \sum_{e \in E} w(e)x_e \\
\text{subject to} & \quad \sum_{e \in E} x_e = |V| - 1 \\
& \quad \sum_{u \in X, v \in X, uv \in E} x_e \leq |X| - 1 \quad \forall X \subseteq V \\
& \quad x_e \in \{0,1\} \quad \forall e \in E
\end{align*}
\]

Second, a graph \( H \) on \( n \) vertices and with \( n - 1 \) edges is a tree if and only if \( H \) is connected (see Exercise 2). Therefore, another possible way to model the current problem is to ensure that any feasible solution is connected, which can be ensured by imposing that, for any cut \( (X,V \setminus X), X \subseteq V \), there is an edge of the solution between a vertex of \( X \) and a vertex of \( V \setminus X \).

\[
\begin{align*}
\text{minimize} & \quad \sum_{e \in E} w(e)x_e \\
\text{subject to} & \quad \sum_{e \in E} x_e = |V| - 1 \\
& \quad \sum_{u \in X, v \in X, uv \in E} x_e \geq 1 \quad \forall X \subseteq V \\
& \quad x_e \in \{0,1\} \quad \forall e \in E
\end{align*}
\]
The above two ILPs present at least two important drawbacks. First, there are ILP and so, \emph{a priori}, no efficient (polynomial in the number of variables and constraints) algorithms are known to solve them. Even worse, the number of constraints equals the number of subsets of \( V \), i.e., exponential in the size of the input graph. Therefore, these programmes are generally not appropriate to solve the minimum spanning tree problem (recall it can be solved in polynomial time). We mostly present them for giving examples of how to model problems as (I)LP and we will see later a “better” (polynomial-time solvable) ILP that models the minimum spanning tree problem.

Note however that the first of the above ILP has integrality gap 1 \([\ldots]\). Moreover, using methods such as constraint generation \([\ldots]\) may allow to deal with the second drawback in practice.

### 10.6 Shortest path

Consider a connected graph \( G = (V, E) \) with length function \( w : E \to \mathbb{R}^+ \) and \( s, t \in V \) (a source \( s \) and a target or destination \( t \)). The problem consists in computing a \( s-t \)-path \( (s = v_1, v_2, \cdots, v_{\ell} = t) \) (i.e., \( v_i v_{i+1} \in E \) for all \( 1 \leq i < \ell \)) minimizing the length \( \sum_{1 \leq i < \ell} w(v_i v_{i+1}) \) of the path. Note that, this problem can be solved in polynomial time by using, for instance, the Dijkstra’s algorithm [Dijkstra 1959]. Let us consider the following ILP:

\[
\begin{align*}
\text{minimize} & \quad \sum_{e \in E} w(e)x_e \\
\text{subject to} & \quad \sum_{u \in N(v) \setminus X, uv \in E} x_{uv} = 2 \quad \forall v \in V, s \in X, t \notin X \\
& \quad \sum_{u \in X \setminus v \notin X, uv \in E} x_{uv} \geq 2 \quad \forall X \subseteq V \\
& \quad x_e \in \{0, 1\} \quad \forall e \in E
\end{align*}
\]

**Exercise 33** Explain the meaning of the variables, constraints and objective function of this ILP. Show that the optimal value of the objective function of the above ILP is the length of a shortest \( s-t \)-path. Why is this ILP not an efficient model for the shortest path problem?

### 10.7 Minimum Hamiltonian cycle

Consider a connected graph \( G = (V, E) \) with weight function \( w : E \to \mathbb{R}^+ \). Recall that this NP-hard problem [7] consists in computing a cycle passing exactly once per each vertex and with minimum weight. Let us consider the following ILP:

\[
\begin{align*}
\text{minimize} & \quad \sum_{e \in E} w(e)x_e \\
\text{subject to} & \quad \sum_{u \in N(v)} x_{uv} = 2 \quad \forall v \in V \\
& \quad \sum_{u \in X \setminus v \notin X, uv \in E} x_{uv} \geq 2 \quad \forall X \subseteq V \\
& \quad x_e \in \{0, 1\} \quad \forall e \in E
\end{align*}
\]

**Exercise 34** Explain the meaning of the variables, constraints and objective function of this ILP. Show that there is a one-to-one mapping between any (optimal) solution of the above ILP and minimum Hamiltonian cycles of \( G \).

### 10.8 Maximum flow

The maximum flow problem is a classical graph problem with many practical applications such as Vehicle Routing Problem, TSP, shortest paths, matchings... In this section, we only present basics on the flow problem. For more details, the reader is referred to, e.g., here.
For any network flow

Lemma 21 reader is referred to, e.g., here.

Let us consider a digraph $D = (V, A)$ with capacity function $c : A \to \mathbb{R}^+$ (note that $c(au)$ may be different from $c(ua)$ for any $u, v \in V$) and two specified vertices $s \in V$ (the source) and $t \in V$ (the target). A flow $f$ in $(D, c, s, t)$ is a function $f : A \to \mathbb{R}^+$ such that $f(a) \leq c(a)$ for all $a \in A$ (capacity constraint) and, for every $v \in V \setminus \{s, t\}$, $\sum_{u \in N^-(v)} f(au) = \sum_{u \in N^+(v)} f(ua)$ (flow conservation constraint). That is, a flow defines, for each arc $a$, an amount of units of flow circulating along the arc $a$, such that the flow along the arc $a$ does not exceed the capacity $c(a)$ of the arc $a$, and for every vertex $v$ except the source and the target, the amount of in-coming flow in the vertex $v$ equals the amount of out-coming flow out of $v$ (nothing is created nor disappear from any vertex except the source or the target). The value $v(f)$ of a flow $f$ is the amount $v(f) = \sum_{u \in N^-(s)} f(su)$ of flow created by the source.

The maximum flow problem consists in, given a network flow $(D = (V, A), c : A \to \mathbb{R}^+, s, t \in V)$, computing a flow $f : A \to \mathbb{R}^+$ with maximum value $v(f)$.

Let us give (without proof) some basic properties of flows in graphs. For more details, the reader is referred to, e.g., here.

Using the flow conservation constraint, it can be proved that:

**Lemma 21** For any network flow $(D = (V, A), c : A \to \mathbb{R}^+, s, t \in V)$, and any flow $f : A \to \mathbb{R}^+$, $v(f) = \sum_{u \in N^-(t)} f(ut)$. That is, what leaves the source equals what arrives in the target.

Given a network flow $(D = (V, A), c : A \to \mathbb{R}^+, s, t \in V)$, a $s$-$t$-cut is any bipartition $(S, T)$ of $V$ (i.e., $V \cap T = \emptyset$ and $S \cup T = V$) such that $s \in S$ and $t \in T$. The capacity $\delta(S, T)$ of the cut $(S, T)$ is the sum of the capacity of the arcs from $S$ to $T$, i.e., $\delta(S, T) = \sum_{x \in S, y \in T} c(xy)$.

Using (again) the flow conservation constraint, it can be proved that:

**Lemma 22** For any network flow $(D = (V, A), c : A \to \mathbb{R}^+, s, t \in V)$, for any flow $f : A \to \mathbb{R}^+$ and any s-t-cut $(S, T)$, $v(f) \leq \delta(S, T)$. Informally, any s-t-cut is a bottleneck for any flow from $s$ to $t$.

Solving the maximum flow problem can be (under some conditions) done in polynomial time by using, e.g., the Ford-Fulkerson algorithm (1956).

**Theorem 37 (Ford, Fulkerson 1956)** Let $(D = (V, A), c : A \to \mathbb{Q}^+, s, t \in V)$ be a network flow (with rational capacities), then computing a flow $f : A \to \mathbb{R}^+$ with maximum value $v(f)$ can be done in polynomial time.

Note that the Ford-Fulkerson algorithm may actually compute an optimal flow even if $c : A \to \mathbb{R}^+$ but, in the latter case, the algorithm may not converge (i.e., it may not terminate). By analyzing the Ford-Fulkerson algorithm, it may be proved that:

**Theorem 38 (Minimum Cut-Maximum Flow duality theorem)** For any network flow $(D = (V, A), c : A \to \mathbb{R}^+, s, t \in V)$, the maximum value of a s-t-flow $f : A \to \mathbb{R}^+$ equals the minimum capacity of an s-t-cut.
That is, the upper bound of Lemma 22 is actually tight.
Moreover,

**Lemma 23 (Integrality gap of maximum flow)** For any network flow \((D = (V, A), c : A \to \mathbb{N}, s, t \in V)\), there is a \(s-t\)-flow \(f : A \to \mathbb{R}^+\) with maximum value such that \(f(a) \in \mathbb{N}\) for every \(a \in A\).

To conclude this section, we present a LP (which is our main motivation for describing the flow problem) that models the maximum flow problem. Let \((D = (V, A), c : A \to \mathbb{R}^+, s, t \in V)\) be any network flow. Let us consider a variable \(f_a\) that represents the amount of flow along \(a\) for every \(a \in A\). The first set of constraints represents the capacity constraints and the second set of constraints represents the flow conservation constraints.

\[
\text{maximize} \quad \sum_{u \in N^+(s)} f_{su} \\
\text{subject to} \quad f_a \leq c(a) \quad \forall a \in A \\
\quad \sum_{u \in N^+(v)} f_{uv} = \sum_{u \in N^+(v)} f_{vu} \quad \forall v \in V \setminus \{s, t\} \\
\quad f_a \geq 0 \quad \forall a \in A
\]

10.9 Back to Shortest paths and Minimum spanning trees

To conclude this section, let us present (I)LP models for Shortest paths and Minimum spanning trees using our knowledge on flows. For this purpose, let us consider any graph \(G = (V, E)\) (with weight function \(w : E \to \mathbb{R}^+)\) as a weighted directed graph \(D = (V, A)\) such that, for every \(e = uv \in E\) in \(G\), there are arcs \(uv\) and \(vu\) in \(D\), each with same weight \(w(e)\) (that is, let us consider any graph \(G\) as a symmetric directed graph \(D\)).

First, let us see any path from a source \(s\) to a target \(t\) in \(G\) as a flow (of value 1) from \(s\) to \(t\) in \(D\).

\[
\text{minimize} \quad \sum_{a \in A} w(a)f_a \\
\text{subject to} \quad \sum_{u \in N^+(s)} f_{su} \geq 1 \\
\quad \sum_{u \in N^-(t)} f_{ut} \geq 1 \\
\quad \sum_{u \in N^-(v)} f_{uv} = \sum_{u \in N^+(v)} f_{vu} \quad \forall v \in V \setminus \{s, t\} \\
\quad f_a \in \{0, 1\} \quad \forall a \in A
\]

**Exercise 35** Show that there is a one-to-one mapping between any optimal solution of the above ILP and shortest \(s-t\)-paths. Show that the integrality gap of the above ILP is 1. Conclusion?

For the minimum spanning tree problem, let \(v_0 \in V\) and let us see any spanning tree as a flow where \(s\) sends one unit of flow to each vertex.

\[
\text{minimize} \quad \sum_{a \in A} w(a)f_a \\
\text{subject to} \quad \sum_{u \in N^+(v_0)} f_{v_0u} = n - 1 \\
\quad \sum_{u \in N^-(v_0)} f_{uv} = -1 + \sum_{u \in N^+(v)} f_{vu} \quad \forall v \in V \setminus \{v_0\} \\
\quad f_a \in \{0, 1\} \quad \forall a \in A
\]
Exercise 36 Show that there is a one-to-one mapping between any optimal solution of the above ILP and minimum spanning tree. Show that the integrality gap of the above ILP is 1. Conclusion?

The problems of computing a shortest path or a minimum spanning tree in a graph admit efficient combinatorial polynomial-time algorithms and it is natural to ask why the above LP may be interesting. Actually, these problems are often subproblems of more general problems that might be efficiently solved with (IL)LP part of it including the above ILPs as sub-programmes.

11 A second Kernelization Algorithm for Vertex Cover (using LP)

Recall that, given a graph \( G = (V, E) \), a vertex cover is a set \( Q \subseteq V \) such that every edge is “touched” by some vertex in \( Q \), i.e., \( e \cap Q \neq \emptyset \) for all \( e \in E \). The question is then to compute a vertex cover in \( G \) with minimum size. As shown above, this problem can be modeled by the following ILP:

\[
\begin{align*}
\text{minimize} & \quad \sum_{v \in V} x_v \\
\text{subject to} & \quad x_v + x_u \geq 1 \quad \forall uv \in E \\
& \quad x_v \in \{0, 1\} \quad \forall v \in V
\end{align*}
\]

Solving this ILP being NP-hard, it may be helpful to consider the following fractional relaxation:

\[
\begin{align*}
\text{minimize} & \quad \sum_{v \in V} x_v \\
\text{subject to} & \quad x_v + x_u \geq 1 \quad \forall uv \in E \\
& \quad 0 \leq x_v \leq 1 \quad \forall v \in V
\end{align*}
\]

Given a graph \( G = (V, E) \) and an optimal fractional solution (that can be computed in polynomial time) \( \{x_v \mid v \in V\} \) of the above LP, let \( V_{<1/2} = \{v \in V \mid 0 \leq x_v < 1/2\} \), \( V_{=1/2} = \{v \in V \mid x_v = 1/2\} \) and \( V_{>1/2} = \{v \in V \mid 1/2 < x_v \leq 1\} \).

Lemma 24 Let \( \{x_v \mid v \in V\} \) be an optimal fractional solution of the above LP. There exists a minimum vertex cover \( Q \) of \( G \) such that \( V_{>1/2} \subseteq Q \subseteq V_{=1/2} \cup V_{=1/2} \).

Proof. Let \( \{x_v \mid v \in V\} \) be an optimal fractional solution of the above LP and let \( Q^* \subseteq V \) be a minimum vertex cover of \( G \). Let \( Q = (Q^* \cap V_{<1/2}) \cup V_{>1/2} = (Q^* \setminus \{v \in V \mid 0 \leq x_v < 1/2\}) \cup \{v \in V \mid 1/2 < x_v \leq 1\} \).

First, let us first show that \( Q \) is a vertex cover. Indeed, let \( uv \in E \), then \( x_u + x_v \geq 1 \) and either \( u \in Q^* \) or \( v \in Q^* \) (or both). If \( u \notin Q \), then, it implies (by definition of \( Q \)) that \( x_u \in V_{<1/2} \cup V_{=1/2} \). If \( x_u = 1/2 \), then \( x_v = 1/2 \) and \( u \notin Q^* \) and \( v \in Q^* \cap Q \), or \( x_u < 1/2 \) and then \( x_v > 1/2 \) and so \( v \in Q \).

We will now show that \( |Q| = |Q^*| \), i.e., \( Q \) is a minimum vertex cover satisfying the statement of the lemma. For purpose of contradiction, let us assume that \( |Q| > |Q^*| \). Since, \( |Q| = |Q^*| - |Q^* \cap V_{<1/2}| + |V_{>1/2} \setminus Q^*| \), this implies that \( |Q^* \cap V_{<1/2}| < |V_{>1/2} \setminus Q^*| \). Let \( \epsilon = \min_{v \in V_{<1/2}, \{y_v\}} \left|x_v - 1/2\right| \). Consider the following assignment \( \{y_v \mid v \in V\} \) of the variables defined by \( y_v = x_v - \epsilon \) for all \( v \in V_{>1/2} \setminus Q^* \), \( y_v = x_v + \epsilon \) for all \( v \in Q^* \cap V_{<1/2} \) and \( y_v = x_v \) otherwise. Therefore for every \( uv \in E \), since \( x_v + x_u \geq 1 \) and not both \( v \) and \( u \) are in \( V_{<1/2} \) (since \( (x_v)_{v \in V} \) is a solution of the above LP), \( y_v + y_u \geq 1 \) (by checking all possible cases) and so, \( (y_v)_{v \in V} \)
is a solution of the above LP. But \[ \sum_{v \in V} y_v = \sum_{v \in V} x_v - \epsilon(|V_{>1/2} \setminus Q^*| - |Q^* \cap V_{<1/2}|) < \sum_{v \in V} x_v, \]
contradicting the optimality of \((x_v)_{v \in V}\). \hfill \blacksquare

The next lemma is not difficult and its proof is left as an exercise to the reader.

**Lemma 25** Let \( \{ x_v \mid v \in V \} \) be an optimal fractional solution of the above LP. If \( vc(G) \leq k \) and \( |V_{>1/2}| = 0 \), then \( |V| = |V_{=1/2}| \leq 2k \).

We are now ready to present the algorithm whose correctness can be proved using previous lemmas.

**Algorithm 28** 2nd Kernelization Alg. to decide if \( vc(G) \leq k \), where \( k \in \mathbb{N} \) is a fixed parameter.

**Require:** A graph \( G = (V, E) \) and an integer \( \ell \leq k \).

**Ensure:** The minimum size of a Vertex Cover of \( G \) if \( vc(G) \leq \ell \) or \( \infty \) otherwise.

1. Let \( I \subseteq V \) be the set of isolated vertices in \( G \). Remove \( I \) from \( G \).
2. Let \( (x_v)_{v \in V} \) be an optimal fractional solution of the above LP.
3. if \( \sum_{v \in V} x_v > \ell \) or \( |V_{>1/2}| > \ell \) then
   4. return \( \infty \)
5. else
6. if \( |V_{=1/2}| = |V| \) then
7. return Algorithm 18\((G, \ell)\)
8. else
9. return Algorithm 28\((G \setminus V_{>1/2}, \ell - |V_{>1/2}|) + |V_{>1/2}|\)
10. end if
11. end if

**Exercise 37** Prove the correctness of Algorithm 28 and give its time-complexity (in function of \( n, k \) and \( f(n) = n^{O(1)} \), the time-complexity of solving the above LP with \( n \) variables).

**Part V**

**Shortest Path Problem**

So far, we have mainly considered NP-hard problems and presented various algorithmic techniques to design efficient algorithms to solve (or approximate) these problems. We also studied some problems that can be solved in polynomial time (e.g., matching, spanning tree, flows...) mostly because they may be use as basic tools in the design of algorithms for harder problems.

In this chapter, we focus on an “easy” problem, namely computing shortest paths, for itself. Our goal is to show that, even for well studied easy problems, current practical applications still require to improve algorithms to solve them, which lead to new algorithmic challenges and to an important current research trend on such topics.

The main problem considered in this chapter takes a (directed or not) graph \( G = (V, E) \) with non-negative edge-length function \( \ell : E \rightarrow \mathbb{R}^+ \) and two vertices \( s, d \in V \) (the source and the destination respectively) as inputs and must compute the distance \( dist_G(s, d) \) in \( G \), i.e., the minimum length of a shortest \( s \)-d-path in \( G \), and possibly a shortest \( s \)-d-path.
12 Dijkstra’s algorithm

Computing a shortest path is probably one of the first result on graphs that students learn during their studies in computer science. Hence, you probably already know the Dijkstra’s algorithm which is the best known algorithm for this problem in general graphs with non-negative edge-weights. We recall it here in details because it will be important to know it well in the continuation of the chapter and in next chapter.

The output of the Dijkstra’s algorithm is actually (a bit) more general than computing a shortest path. Precisely, it takes as inputs an edge-weighted (di)graph \((G = (V, E), \ell)\) and one single vertex \(s\in V\) (the source) and computes \(\text{dist}(s,v)\) and a shortest-path tree \(T\) rooted in \(s\), i.e., a spanning tree \(T\) of \(G\) such that \(\text{dist}_T(s,v) = \text{dist}_G(s,v)\) for every \(v\in V\) (where \(\text{dist}_T(a,b)\) denotes the distance between \(a\) and \(b\) in \(T\)). In what follows, we restrict our description to undirected graphs. Note that, the presentation of Algorithm 29 is not optimal (some operations may be factorized) but it is done in a way to understand it more easily.

---

**Algorithm 29 Dijkstra’s algorithm** [Edsger W. Dijkstra,1956].

**Require:** A connected graph \(G = (V, E), \ell : E \to \mathbb{R}^+\) and \(s \in V\).

**Ensure:** \(D = (\text{dist}_G(s,v))_{v \in V}\) and a shortest-path tree \(T\) rooted in \(s\).

1. Let \(D = (d(v))_{v \in V}\) with \(d(s) = 0\) and \(d(v) = \infty\) for all \(v \in V \setminus \{s\}\).
2. Let \(Done = \emptyset\), \(Border = \{s\}\) and \(T = (\{s\}, \emptyset)\).
3. **while** \(Border \neq \emptyset\) **do**
   4. Let \(v \in \text{Border}\) that minimizes \(d(v)\) in \(\text{Border}\).
   5. Add \(v\) to \(\text{Done}\) and remove \(v\) from \(\text{Border}\).
   6. **for** \(w \in N(v)\) **do**
      7. **if** \(w \notin Done\) **then**
         8. **if** \(w \notin \text{Border}\) **then**
            9. Add \(w\) to \(\text{Border}\) and to \(V(T)\)
            10. \(d(w) \leftarrow d(v) + \ell(vw)\)
            11. Add \(vw\) to \(E(T)\)
         **end if**
      **else if** \(d(v) + \ell(vw) < d(w)\) **then**
         12. \(d(w) \leftarrow d(v) + \ell(vw)\)
         13. Let \(e\) be the edge of \(T\) incident to \(w\), \(E(T) \leftarrow (E(T) \setminus \{e\}) \cup \{vw\}\).
      **end if**
   **end for**
**end while**

**return** \((D, T)\)

---

**Theorem 39 (Dijkstra’s algorithm)** Given \(G = (V, E), \ell : E \to \mathbb{R}^+\) and \(s \in V\), Algorithm 29 computes \((\text{dist}_G(s,v))_{v \in V}\) and a shortest-path tree \(T\) rooted in \(s\) in time \(O(|E| + |V| \log |V|))\).

**Proof.** The proof of the correctness of Algorithm 29 is by induction on the number of iterations of the While-loop and of its internal For-loop. Precisely, at any moment of the execution of the algorithm, the following invariants can be proved: (1) \(T\) is a spanning tree of \(\text{Done} \cup \text{Border}\) where each vertex in \(\text{Border}\) is a leaf and internal vertices are in \(\text{Done}\) (note that some vertices of \(\text{Done}\) may be leaves); (2) for any \(v \in \text{Done} \cup \text{Border}\), \(\text{dist}_G(s,v) \leq \text{dist}_T(s,v) = d(v)\); and (3) \(d(v) = \text{dist}_G(s,v)\) for all \(v \in \text{Done}\). These properties clearly hold before the first iteration.
of the While-loop. It is also easy to check that they hold just after the first iteration of the
While-loop.

We only prove the third property, the other two can be proved easily. Let us consider an
iteration of the While-loop and let \( v \) be the vertex considered at this iteration. That is, \( v \) is a
vertex of \( \text{Border} \) minimizing \( d(v) \) and, at this iteration, \( v \) is added to \( \text{Done} \). We aim at proving
that \( d(v) = \text{dist}_G(s,v) \).

By (2), \( \text{dist}_G(s,v) \leq d(v) \). For purpose of contradiction, let us assume that \( \text{dist}_G(s,v) <
\text{dist}_\ell(s,v) \). Let \( P \) be a shortest \( s\text{-}v \) path in \( G \) and let \( v' \) be a vertex of \((V(P) \setminus \{v\}) \cap \text{Done} \) that
is closest (in terms of \( \ell \) and in terms of number of hops if there are ties) to \( v \) in \( G \) (\( v' \) exists
since, after the first iteration of the While-loop, \( s \in \text{Done} \). Let \( v'' \) be the neighbor of \( v' \) on the
subpath \( P' \) of \( P \) between \( v' \) and \( v \). In particular, \( \ell(P') = \ell(v'v'') + \text{dist}_G(s,v') = \text{dist}(s,v'') \).

Since all edge-lengths are non negative, \( \text{dist}(s,v'') \leq \text{dist}(s,v) = \ell(P) < d(v) \). Let us show
that \( v'' \in \text{Border} \) and that \( d(v'') < d(v) \), contradicting the choice of \( v \). First, let us note
that \( v'' \in \text{Border} \). Indeed, there is a previous iteration of the While-loop during which \( v' \)
has been considered (since \( v' \in \text{Done} \), and after this iteration, \( N(v') \subseteq \text{Done} \cup \text{Border} \) (so \( v'' \notin N(v') \) must be in \( \text{Border} \) since \( v' \) is the vertex of \( P \cap \text{Done} \) that is closest to \( v \)) and \( d(v'') \leq
\ell(v'v') + \text{dist}_G(s,v') \) (Line 10 or 13 of the Algorithm). Moreover, by (2), \( \text{dist}_G(s,v'') \leq d(v'') \).
So, \( \ell(v'v'') + \text{dist}_G(s,v') = \text{dist}(s,v'') \leq d(v'') \leq \ell(v'v') + \text{dist}_G(s,v') \), i.e., \( d(v'') = \ell(v'v') +
\text{dist}_G(s,v') = \text{dist}(s,v'') \). Finally, since \( d(v'') = \text{dist}(s,v'') < d(v) \), we get our contradiction.

About the time-complexity, there are \( n = |V| \) iterations of the While-loop since all vertices
must be added to \( \text{Border} \) exactly once. In each iteration of the While-loop, we must first extract
the minimum from \( \text{Border} \) (let \( v \) be the considered vertex), then, for every neighbor \( w \) of \( v \)
(there are at most \( \Delta \) such neighbors if \( \Delta \) is the maximum degree of \( G \)), we need to update \( d(w) \)
and add \( w \) to \( \text{Border} \) if it was not there yet. Overall, at first glance, the complexity is upper
bounded by \( O(n \times (\text{TimeToExtractMin} + \Delta \times (\text{TimeToAddInBorder} + \text{Update}))) \).

To achieve a good time-complexity, we first need to use an appropriate data structure for
\( \text{Border} \). For this purpose, \( \text{Border} \) can be implemented using a heap (for which \( \text{TimeToExtractMin} +
\text{TimeToAddInBorder} = O(\log n) \)). Second, we need to count the operations globally rather than
for each iteration of the While-loop. Hence, note that each vertex is added exactly once
into \( \text{Border} \). Then, to count the number of updates, it can be noted that each edge is considered
exactly once. Hence, the complexity is \( O(n \times (\text{TimeToExtractMin} + \text{TimeToAddInBorder}) +
|E| \times \text{Update}) \). Since the time to update is \( O(1) \), we get a time complexity bounded by
\( O(|V| \log |V| + |E|) \).

13 Going faster in practice

In this (rather informal) section, we briefly present some current research trend and explain
the motivations for it. Computing a shortest path in a network is clearly a daily-life question
(e.g., when you look for your itinerary using your smartphone). Consider a network with 20M
vertices (e.g., European road network) and a basic computer (laptop, smartphone), then a
(good) implementation of the Dijkstra’s algorithm would compute (in average) a shortest path
between a source and a destination in few seconds (the numbers given here are not precise but
are correct in terms of order of magnitude). Clearly (“normally”), you would not accept to
wait for 3-4 seconds to have your itinerary. Therefore, some better solutions must be provide
in practice.

13.1 Bidirectional Dijkstra’s algorithm and \( A^* \) algorithm(s)

Note that this subsection is purely informal.
Here, the problem is to find a shortest path from a source $s$ to a destination $d$. A first natural improvement of Dijkstra’s algorithm is as follows: launch Dijkstra’s algorithm from $s$ and stop its execution as soon as the distance to $d$ has been found (technically, as soon as $d \in \text{Done}$). Thinking a bit more, launching two executions of the Dijkstra’s algorithm (bidirectional Dijkstra), one from $s$ and the other from $d$ (alternating the iterations of the While-loop between the two executions) and stoping the executions as soon as they “meet” (i.e., when the two sets $\text{Done}$ intersect) should give a faster answer (to have an intuitive idea of why, see difference between the number of considered vertices, i.e., the number of iterations of the While-loop, in an execution of Dijkstra’s algorithm and in an execution of bidirectional Dijkstra’s algorithm in Figures 1-a,b, where the “number” is represented by the areas of the disks). Indeed, in practice (same network with $20M$ vertices as before), the computation time goes down to (an order of magnitude of) 1 second. Still, this looks too much with respect to the classical expectations of users.

The $A^*$ algorithm aims at introducing some bias in the next vertex to be considered at each iteration of the Dijkstra’s algorithm. We only give an intuitive presentation of the $A^*$ algorithm. Note that the Dijkstra’s algorithm starting from some vertex $s$ considers the vertices in non-decreasing order of their distance to $s$, independently from their position relatively to the destination (i.e., the next vertex $v$ to be considered is always a one that minimizes $d(v)$) (see Figure 1-a). Assume that you have further information on the relative positions of the vertices. For instance, considering a road network, we may know the distance as the crow flies $dcf(x, y)$ between every two vertices $x, y \in V$. In that case, at each iteration of the Dijkstra’s algorithm (on line 4 of Algorithm 29), we may for instance give priority to a vertex $v$ minimizing $\lambda d(v) + (1-\lambda)dcf(v, d)$ ($0 \leq \lambda \leq 1$) rather than minimizing $d(v)$ (see Figure 1-c for an intuitive illustration). While such an algorithm is only a heuristic (theoretically, it only provides an upper bound on the distance between $s$ and $d$), it works very well in practice (for road networks). Moreover, on a network with $20M$ vertices as before, the computation time of the bidirectional $A^*$ Algorithm (see Figure 1-d) goes down to (an order of magnitude of) 100 micro seconds.

![Figure 1: Very (very) intuitive schemes of (bidirectional) Dijkstra’s and $A^*$ algorithms for computing a shortest path between a source $s$ and a destination $d$.](image)

### 13.2 Pre-computing (Contraction Hierarchy and Hub Labeling)

Previous subsection presented the bidirectional $A^*$ algorithm that may look efficient enough for users (roughly, few micro seconds to compute a shortest path in huge graphs). However, from the point of view of a server that must answer a huge number of such requests at any time, that
is still not sufficient and, therefore, many research efforts have been (and still are) devoted to improve the performance of such algorithms.

A hub system is a set \( (H_u)_{u \in V} \) such that, every vertex \( u \in V \) is assigned a hub set \( H_u \subseteq V \) such that, for every \( x, y \in V \times V \), there exists \( w \in H_x \cap H_y \) with \( \text{dist}_G(x, y) = \text{dist}_G(x, w) + \text{dist}_G(w, y) \). In other words, a hub system must ensure that for any pair of vertices \( x, y \), the hub sets \( H_x \) and \( H_y \) must contain a common vertex that belongs to a shortest \( x-y \) path.

To be continued

14 Diameter

For ease of presentation, in this section, all graphs are undirected and unweighted (i.e., the length of a path is its number of edges). However, all results mentioned there can be generalized to weighted (di)graphs.

Given an undirected unweighted connected graph \( G = (V, E) \), its diameter \( \text{diam}(G) = \max_{u,v \in V} \text{dist}(u, v) \) is the maximum distance \( \text{dist}(u, v) \) (in terms of number of edges) between any two vertices \( u \) and \( v \) of \( G \). Also, for every \( v \in V \), the eccentricity \( \text{ecc}(v) \) of the vertex \( v \) is the maximum distance \( \max_{u \in V} \text{dist}(u, v) \) between \( v \) and any vertex of \( G \) (i.e., it is the distance between \( v \) and a vertex furthest from \( v \) in \( G \)).

Exercise 38 Let \( G = (V, E) \) be a connected undirected unweighted graph. Show that, for every \( v \in V \), \( \text{ecc}(v) \leq \text{diam}(G) \leq 2 \cdot \text{ecc}(v) \).

In particular, show that \( \max_{v \in V} \text{ecc}(v) = \text{diam}(G) \leq 2 \cdot \min_{v \in V} \text{ecc}(v) \).

The question of interest in this section is, given a undirected connected \( n \)-node \( m \)-edge graph \( G \), to compute the diameter of \( G \). A naive algorithm for this purpose consists in launching \( n \) executions of the Dijkstra’s algorithm (one execution from every vertex of \( G \)) in order to compute \( (\text{dist}_G(u, v))_{u,v \in V \times V} \) and then to extract the maximum of it. From Theorem 39, such an algorithm has time-complexity \( O(n(n \log n + m)) = O(n^3) \). The best known algorithm for this purpose is currently \( [] \) with time complexity and uses the best known algorithm for matrix multiplication \( [] \). If \( G \) is unweighted, then Dijkstra’s algorithm may be replaced by a simple BFS (with linear-time complexity) from each vertex, leading to a \( O(n^2) \)-time algorithm to compute the diameter. It is a current challenge to prove that no algorithm can solve this problem with time-complexity \( o(n^2) \) \( [] \).

Below, we show that in particular graph classes or in practical instances, only a few (a constant number of) executions of BFS are sufficient to compute the diameter, leading to a \( O(n) \) algorithm to compute the diameter in practical cases or in graphs having particular structural properties.

14.1 Diameter of trees (with only 2 BFSs)

<table>
<thead>
<tr>
<th>Algorithm 30 Diameter of trees.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Require:</strong> An unweighted tree ( T = (V, E) ).</td>
</tr>
<tr>
<td><strong>Ensure:</strong> ( \text{diam}(T) ).</td>
</tr>
<tr>
<td>1: Let ( r \in V ) be any arbitrary root.</td>
</tr>
<tr>
<td>2: Do a BFS from ( r ) in ( T ) and let ( x ) be such that ( \text{dist}(x, r) = \text{ecc}(r) ).</td>
</tr>
<tr>
<td>3: Do a BFS from ( x ) in ( T ) and let ( y ) be such that ( \text{dist}(y, x) = \text{ecc}(x) ).</td>
</tr>
<tr>
<td>4: return ( \text{dist}(x, y) ).</td>
</tr>
</tbody>
</table>
Theorem 40  Alg. 30 computes the diameter of any n-node tree in time $O(n)$ (using 2 BFSs).

Proof. The time complexity is obvious. Let us show the correctness of the algorithm.

For purpose of contradiction, let us assume that $\text{dist}(x, y) < \text{diam}(G)$ and let $a, b \in V$ such that $\text{diam}(G) = \text{dist}(a, b)$.

First, note that $x, y, a$ and $b$ are leaves of $T$. Indeed, for purpose of contradiction, assume that $a$ is not a leaf and let $a'$ be its (unique) neighbor on the unique $a$-$b$ path (see Exercise 2, first item). Then, let $a'' \in N(a) \setminus \{a'\}$ be any other neighbor of $a$. Then, $\text{dist}(a'', b) = \text{dist}(a, b) + 1 > \text{diam}(G)$, a contradiction. The result follows similarly for $x, y$ and $b$.

W.l.o.g., let $a$ be such that $\text{dist}(a, r) \geq \text{dist}(b, r)$. We now show that $\text{dist}(a, b) \leq \text{ecc}(x)$. Let $u$ be the least common ancestor of $a$ and $b$ in $T$ rooted in $r$. Note that $\text{dist}(a, b) = \text{dist}(a, u) + \text{dist}(u, b)$. Let $u'$ be the least common ancestor of $a$ and $x$. There are several cases to be considered.

- If $r$ is on the $u$-$x$ path (then $u' = r$), then, $\text{dist}(a, b) = \text{dist}(a, u) + \text{dist}(u, b) \leq \text{dist}(a, u) + \text{dist}(r, b) \leq \text{dist}(a, u) + \text{dist}(u, x) \leq \text{dist}(a, u) + \text{dist}(u, r) + \text{dist}(r, x) = \text{dist}(a, x) \leq \text{ecc}(x)$.

- If $u'$ is on the $u$-$r$ path (possibly $u = u'$), and since $\text{dist}(r, x) = \text{dist}(r, u') + \text{dist}(u', x) \geq \text{dist}(r, b) = \text{dist}(r, u) + \text{dist}(u', b)$ then $\text{dist}(u', x) \geq \text{dist}(u', b) = \text{dist}(u', u) + \text{dist}(u, b)$.

Therefore, $\text{ecc}(x) \geq \text{dist}(a, x) = \text{dist}(a, u) + \text{dist}(u, u') + \text{dist}(u', x) \geq \text{dist}(a, u) + \text{dist}(u, b) = \text{dist}(a, b)$.

- Finally, if $u$ is on the $u'$-$r$ path, since $\text{dist}(r, x) = \text{dist}(r, u') + \text{dist}(u', x) \geq \text{dist}(r, a) = \text{dist}(r, u') + \text{dist}(u', a)$ then $\text{dist}(u', x) \geq \text{dist}(u', a)$. Therefore, $\text{ecc}(x) \geq \text{dist}(x, b) = \text{dist}(x, u') + \text{dist}(u', u) + \text{dist}(u, b) \geq \text{dist}(a, u') + \text{dist}(u', u) + \text{dist}(u, b) = \text{dist}(a, b)$.

Hence, $\text{diam}(G) = \text{dist}(a, b) \leq \text{ecc}(x) = \text{dist}(x, y) \leq \text{diam}(G)$.

The key point to remember is that, while in general it seems necessary to compute $n$ BFSs to compute the diameter of a graph, only 2 BFSs are sufficient in trees.

14.2 Diameter in practice (iFUB)

It is important to understand that, even a “simple” algorithm that consists in doing $n$ BFSs, i.e., with complexity $O(n^2)$, is far to be usable in practice for huge graphs as current social networks. On the other hand, a single application of a BFS from some vertex $r$ gives valuable informations, a lower bound $\text{ecc}(r)$ and an upper bound $2\text{ecc}(r)$, for the diameter. Crescenzi et al. used this remark to design iFUB (iterative Fringe Upper Bound)\textsuperscript{42} 43 44 45, an algorithm that allowed to compute the diameter of huge networks such as Facebook. Here we only present a simplified version of the Fringe algorithm.

While above has worst-case time complexity $O(n^2)$, it is actually very efficient in practice. The iFUB algorithm (which roughly proceeds similarly) used only 18 BFSs to compute

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\textsuperscript{42} Pierluigi Crescenzi, Roberto Grossi, Claudio Imbrenda, Leonardo Lanzi, Andrea Marino: Finding the Diameter in Real-World Graphs - Experimentally Turning a Lower Bound into an Upper Bound. ESA (1) 2010: 302-313

\textsuperscript{43} Pierluigi Crescenzi, Roberto Grossi, Leonardo Lanzi, Andrea Marino: On Computing the Diameter of Real-World Directed (Weighted) Graphs. SEA 2012: 99-110


Algorithm 31 Diameter of graphs.

Require: An unweighted graph \( G = (V, E) \).

Ensure: \(\text{diam}(G)\).

1: Let \( r \in V \) be any arbitrary root.
2: Do a BFS from \( r \) in \( T \) and let \( v_1, v_2, \ldots, v_{n-1} \) be the vertices ordered in such a way that
\( \text{dist}(v_i, r) \geq \text{dist}(v_j, r) \) for all \( i < j \).
3: Let \( LB = \text{ecc}(r) \) and \( UB = 2\text{ecc}(r) \) and \( i = 1 \).
4: while \( LB < UB \) do
5: Do a BFS from \( v_i \).
6: \( LB = \max\{LB, \text{ecc}(v_i)\} \) and \( UB = \min\{UB, 2\text{ecc}(v_i)\} \)
7: \( i \leftarrow i + 1 \)
8: end while
9: return \( LB \).

the diameter of Facebook! Understanding why such algorithms are efficient in practice is an interesting current research direction\(^{46}\).

15 Small World phenomenon and Distributed Computing

Part VI

Planar graphs

This chapter is mainly inspired from http://courses.csail.mit.edu/6.889/fall11/lectures/ (lectures 2 to 4).

Informally, a graph is planar if it can be “drawn” on the plane (i.e., \( \mathbb{R}^2 \)) (equivalently on a sphere) without crossing edges.

More precisely, an embedding of a graph \( G = (V, E) \) in the plane is a mapping \( \xi \) that maps \( V \) to disjoint points in \( \mathbb{R}^2 \) and that maps each edge \( uv \in E \) to a simple curve\(^{47}\) of \( \mathbb{R}^2 \) that joins \( \xi(u) \) and \( \xi(v) \). An embedding is planar if the interior of the curves \( \xi(e) \) for all \( e \in E \) are pairwise disjoint. Finally, a graph is planar if it admits a planar embedding.

The above definition of planar graphs is topological, which implies that further proofs might use complicated topological arguments. In that course, we will not enter into topological “details” and just keep the informal definition that a planar graph can be drawn on the plane without crossing edges. In particular, some arguments in the proofs may be a bit handwavy (sorry). Before going on, note that there is a purely combinatorial way to define planar graphs (using what is sometimes called rotation system [Youngs 1963] and the Euler’s formula, see Lecture 2 of the MIT course mentioned above).

Planar graphs play an important role both theoretically and practically. In practice, many important networks are planar or “almost” planar: for instance, road networks have generally few bridges or tunnels. Theoretically, many problems can be solved more efficiently when restricted to planar graphs. This chapter is dedicated to give some examples of such problems and algorithms.

\(^{46}\)Feodor F. Dragan, Michel Habib, Laurent Viennot: Revisiting Radius, Diameter, and all Eccentricity Computation in Graphs through Certificates. CoRR abs/1803.04660 (2018)

\(^{47}\)A simple curve is the image of a continuous one-to-one mapping \( f : [0, 1] \to \mathbb{R}^2 \). A curve joins two points \( a \) and \( b \) if \( f(0) = a \) and \( f(1) = b \). The interior of the curve is \( f([0,1]) \).
16 Preliminaries on planar graphs

From now on, a graph is planar if it can be drawn on the plane without crossing edges (note that edges are not constrained to be drawn as straight lines). Such a drawing is called a planar **embedding**. Note that any graph have several embeddings, some of them may be planar or not (as an example, draw $K_4$, the complete graph with 4 vertices, in a non-planar way and in a planar way). So, it is not difficult to show that $K_4$ is planar (it admits a planar embedding). Proving that $K_5$ is not planar is, at first glance, much more complicated (can you prove that $K_5$ cannot be drawn on the plane without crossing edges?).

Exercise 39 Is $K_4$ planar? Is $K_5$ planar? Is $K_{3,3}$ (the complete bipartite graph with two parts each of size 3) planar?

16.1 Euler Formula

Given a planar graph $G$ and a planar embedding $\xi(G)$ of $G$, a **face** of $\xi(G)$ is any connected component of $\mathbb{R}^2 \setminus \xi(G)$. Note that each edge of $G$ is in the border of one or two faces of $\xi(G)$ (here is a first handwavy argument mentioned above). Note also that, according to the above definition of an embedding, all faces are finite (bounded by simple closed curve in $\mathbb{R}^2$) but one that is infinite. Let $F(\xi(G))$ be the set of faces of an embedding $\xi(G)$ of $G$. Note that the border of a face of $\xi(G)$ is actually a cycle of $G$, we will often identify the face and the corresponding cycle.

**Theorem 41 (Euler’s formula)** For any planar connected graph $G = (V,E)$ and any planar embedding $\xi(G)$, $|V| - |E| + F(\xi(G)) = 2$.

**Proof.** The proof is by induction on $|V|$. If $G$ is reduced to a single vertex, then $|V| - |E| + F(\xi(G)) = 1 - 0 + 1 = 2$ (in that case, whatever be the embedding, there is unique face, the infinite one). By induction, let us assume that the statement holds for any planar graph with $n \geq 1$ vertices and let $G$ have $n+1$ vertices. Let $v$ be any vertex of $G$ and let $d$ be its degree in $G$. Note that $d \geq 1$ because $G$ is connected. Let us prove the result by induction on $d$. If $d = 1$, let $w$ be the unique neighbor of $v$. Adding the vertex $v$ and the edge $vw$ to $G' = G \setminus \{v\}$ does not create any new face (again an handwavy argument), then $|V(G')| - |E(G')| + F(\xi(G)) = |V(G')| + 1 - |E(G')| - 1 + 1 = 2$ (where $\xi(G')$ is the embedding of $G'$ obtained from $\xi(G)$ restricted to $G'$, i.e., when removing $v$ and the edges incident to it). If $d \geq 2$, let $w$ with a neighbor of $v$ in $G$ and let $G' = (V,E \setminus \{vw\})$. Then, adding the edge $uw$ divides one face $f$ of $\xi(G')$ into two faces (i.e., the edge $vw$ divides the cycle corresponding to $f$, containing both $v$ and $w$, into two cycles). Hence, $|V(G)| - |E(G)| + F(\xi(G)) = |V(G')| - |E(G')| - 1 + 1 = 2$.

Note that Euler’s formula implies that any planar embedding of a graph $G$ has the same number of faces.

**Corollary 5 (Sparsity lemma)** Let $G = (E,V)$ be a simple connected planar graph. Then $|E| \leq 3|V| - 6$. Moreover, if $G$ is bipartite, $|E| \leq 2|V| - 4$.

**Proof.** Let $G$ be a planar graph and $\xi(G)$ be any planar embedding of it. Assume that any face $f$ has length $\ell(f)$ at least $x$ (i.e., the cycle corresponding to $f$ has at least $x$ edges). Note that, if $G$ is simple (no parallel edges nor loops), then $x \geq 3$, and if moreover $G$ is bipartite (iff $G$ has no odd cycle) then $x \geq 4$. Then, $2|E| = \sum_{f \in F(\xi(G))} \ell(f) \geq x \cdot |F(\xi(G))|$. 

67
By Euler’s formula, 2 = |V| − |E| + F(ξ(G)) ≤ |V| − |E| + 2x|x|^{-1}E|. Hence, 2x ≤ x|V|−(x−2)|E|. Therefore, |E| ≤ \frac{x}{2x-2}|V| − \frac{2x}{2x-2}.

Note that Corollary 5 provides a simple proof that $K_5$ and $K_{3,3}$ are not planar (see Exercise 39).

Let $d \in \mathbb{N}$. A graph $G$ is $d$-degenerated if $G$ has a vertex $v$ of degree at most $d$ and $G \setminus \{v\}$ is also $d$-degenerated (for instance, forests (i.e., acyclic graphs) are exactly the 1-degenerated graphs).

**Corollary 6** Any planar simple graph is 5-degenerated

**Proof.** By contradiction, assume that a planar graph $G = (V, E)$ has all its vertices with degree at least 6. Then $2|E| = \sum_{v \in V(G)} \deg(v) \geq 6|V|$, contradicting Corollary 5.

16.2 Wagner-Kuratowski theorem

We already mentioned the following theorem in Section 8.5, we give here a sketch of its proof for completeness. Recall that $H$ is a minor of $G$ is $H$ is any subgraph of any graph obtained from $G$ by edge-contractions.

**Theorem 28** (Wagner 1937) A graph is planar if and only if it has no $K_5$ nor $K_{3,3}$ as minor.

**Proof.**[Sketch] $\Rightarrow$. Since, $K_5$ and $K_{3,3}$ are not planar (see above), and because the class of planar graph is closed under taking minor, any planar graph admits neither $K_5$ nor $K_{3,3}$ as minor.

$\Leftarrow$. For purpose of contradiction, let $G$ be a minimal counter example, i.e., a minimum-order non-planar graph with neither $K_5$ nor $K_{3,3}$ as minor. If $G$ is not 4-connected, let $X$ be a minimal separator, $|X| < 4$ (by Menger’s theorem), let $G'_1, G'_2$ be 2 graphs with at least $|X| + 1$ vertices, such that $G = G'_1 \cup G'_2$ and $X = V(G'_1) \cap V(G'_2)$. Let $G_i$ being obtained from $G'_i$ by completing $X$ into a clique. Then, prove that $G_i$ has no $K_5$ or $K_{3,3}$ as a minor (trivial if $|X| < 3$). Then, by minimality of $G$, $G_i$ is planar. Moreover, we can choose the face bordered by vertices of $X$ as infinite face of an embedding. This allows to glue $G_1$ and $G_2$, proving that $G$ is planar, a contradiction.

Now, assume $G$ is 4-connected. Then, contract an edge $\{x, y\}$ into vertex $z$. By minimality of $G$, the resulting graph is planar. Moreover, since $G$ is 4-connected, the resulting graph is 2-connected. Consider the faces surrounding $z$ in a planar embedding of it. By studying the neighbors of $y$ and $x$ in this embedding, we get that $G$ is planar, otherwise it would admit $K_5$ or $K_{3,3}$ as a minor. A contradiction.

Wagner’s theorem implies that planar graphs may be “simply” defined by two excluded minors ($K_5$ and $K_{3,3}$). The Graph Minor Theorem ?? states that, actually, any class of graphs that is closed under taking minor can be defined by a finite number of excluded minors. Unfortunately, not all such graph classes have a simple obstruction set such as planar graphs. For instance, the class of graphs that have genus 1 (roughly, that can be drawn on a donut without edge crossings) is closed under taking minors, but its obstruction set is not explicitly known [7]. On the positive side, some other graph classes can be defined by their obstruction sets, e.g., the class of graphs of treewidth at most 2 is the class of graphs that have no $K_4$ as minors [7].
16.3 Four Colors theorem

Let \( k \in \mathbb{N} \). Recall that a \( k \)-proper coloring of a graph \( G = (V,E) \) is any function \( c : V \to \{1, \cdots, k\} \) such that \( c(u) \neq c(v) \) for every \( uv \in E \). Recall also that the chromatic number \( \chi(G) \) of a graph \( G \) is the minimum \( k \) such that \( G \) admits a proper \( k \)-coloring (see Section 10.4).

In 1852, the mathematician and botanist Francis Guthrie asked whether a plane map of countries/regions can be colored with four colors (giving one color to each region) in such a way that two regions sharing some common border (not reduced to an single point) received different colors. In graph terminology, it is equivalent to ask whether \( \chi(G) \leq 4 \) for any planar graph \( G \).

After more than one century of research and several wrong proofs, this conjecture has finally been confirmed with the following celebrated theorem. Note, in particular, that it is one of the first (famous) mathematical results that has been proved using computers’ power.

**Theorem 41 (Four Color Theorem)** [Appel,Haken 1976],[Robertson,Sanders,Seymour and Thomas 1997] For any planar graph \( G \), \( \chi(G) \leq 4 \).

The proof of above theorem is quite involved (the problem was open for more than one century). We give here an almost trivial proof of a slightly weaker result.

**Lemma 26** For any planar graph \( G \), \( \chi(G) \leq 6 \).

**Proof.** The proof is by induction on \( |V(G)| \). It is clear if \( |V(G)| \leq 6 \). Assume that the result holds for any planar graph with \( n \geq 1 \) vertices. Let \( G \) be any planar graph with \( n + 1 \) vertices. Let \( v \in V(G) \) with degree at most 5 (\( v \) exists by Corollary 6) and let \( G' = G \setminus v \) and note that \( G' \) is planar. By induction, \( G' \) admits a proper coloring with at most 6 colors. Now, \( v \) having at most 5 neighbors, it can be properly colored with a color not appearing in its neighborhood.

Recall that an independent set (or a stable set) in a graph \( G \) is any set of pairwise non-adjacent vertices in a graph \( G \). Note that a \( k \)-proper coloring of \( G = (V, E) \) is equivalent to a partition of \( V \) into at most \( k \) stable sets (each part of the partition corresponding to the set of vertices with the same color). Therefore, Theorem 41 has the following corollary that will be used in Section 18.1:

**Corollary 7** Any planar \( n \)-node graph admits a stable set of size at least \( n/4 \).

16.4 Dual of a planar graph

Let \( G \) be a connected planar graph given with a planar embedding \( \xi(G) \). The dual \( G^* \) of \( G \) is the graph with vertex-set the faces of \( \xi(G) \) and two faces \( f \) and \( f' \) in \( V(G^*) \) are adjacent, i.e., there is an edge \( e^* = ff' \in E(G^*) \), if an edge \( e \) of \( G \) “divides” \( f \) and \( f' \) (i.e., if \( e \) is in the border of both \( f \) and \( f' \)) in \( \xi(G) \). Note that there is a one-to-one mapping between \( E \) and \( E(G^*) \) that associates every \( e \in E \) to the corresponding edge \( e^* \).

The following lemma (whose proof is straightforward when using the combinatorial definition of planar graphs) justifies the fact that \( G^* \) is called the dual. We do not prove it here.

**Lemma 27 (The dual of the dual is the primal)** For every planar embedding of a graph \( G \), \( (G^*)^* = G \).

Given a connected graph \( G = (V,E) \), a set \( C \subseteq E \) is a simple cut or a bond if \( G' = (V,E \setminus C) \) consists of two connected components. To avoid tedious topological arguments (in particular, it uses the Jordan’s curve theorem [Camille Jordan (1838-1922)] that states that any simple closed curve divides the plane into two connected parts, see [1]), we do not prove the following important lemma.
Lemma 28 (Duality between cycles of primal and bonds of dual) For any connected graph \( G = (V, E) \) with planar embedding \( \xi(G) \), there is a one-to-one mapping between the cycles of \( G \) and the bonds of \( G^* \).

By Lemma 27, previous lemma also implies that there is a one-to-one mapping between the cycles of \( G^* \) and the bonds of \( G \).

Lemma 29 (Interdigitating trees lemma) Let \( G = (V, E) \) be a planar graph with planar embedding \( \xi(G) \). Let \( T \) be any spanning tree of \( G \) and let \( F = \{ e \in E \mid e \notin E(T) \} = E \setminus E(T) \). Then, the subgraph \( T^* \) of \( G^* \) induced by \( V(T^*) \) and \( \{ e^* \in E(G^*) \mid e \in F \} \) is a spanning tree of \( G^* \).

Proof. [handwavy proof] By definition, \( T^* \) is spanning. For purpose of contradiction, let us assume that \( T^* \) contains a cycle \( C^* \). Then, this cycle of \( G^* \) corresponds to a simple closed curve of \( \mathbb{R}^2 \) which, by the Jordan’s curve theorem, separates the plane into two connected parts \( A \) and \( B \). Moreover, there are \( u, v \in V(G) \) such that \( \xi(u) \in A \) and \( \xi(v) \in B \). By Lemma 28, the edges of \( C^* \subseteq E(T^*) \) corresponds to a bond \( C \) of \( G \) separating \( u \) and \( v \). Since \( C \subseteq F \), this contradicts that \( T \) is a spanning tree of \( G \).

Hence, \( T^* \) is acyclic. Note that \( |V(G^*)| \) is the number of faces of \( \xi(G) \). Moreover, \( |E(T^*)| = |F| = |E(G)| - (|V(T)| - 1) = |V(G^*)| - 2 + 1 = |V(G^*)| - 1 \) (by Euler’s formula) and so \( |E(T^*)| = |V(G^*)| - 1 = |V(T^*)| - 1 \) (because \( T^* \) is spanning). By Exercice 2, \( T^* \) being acyclic, it is a tree.

Too well understand the previous lemma (and its name), you are encouraged to draw a picture of it.

17 Small balanced separators

The key point that many problems are “easier” in planar graphs is that planar graphs can be recursively “well” separated which is well appropriate for divide and conquer algorithms. Intuitively, this section is devoted to show that planar graphs admit small balanced separators.

Precisely, given a graph \( G = (V, E) \), a separation of \( G \) is a any partition \((A, B, S)\) of \( V \) such that there are no edges between vertices in \( A \) and vertices in \( B \), i.e., \((A \times B) \cap E = \emptyset\), i.e., every path from a vertex in \( A \) to a vertex in \( B \) intersects \( S \) (Note that neither \( A \) nor \( B \) nor \( S \) is required to be connected). Then, \( S \) is called a separator. Note that all graphs do not admit some separation (e.g., consider any complete graph). If \( G \) is given with vertex-weight function \( w : V \to \mathbb{R}^+ \), for \( 0 < \beta < 1 \), the separation \((A, B, S)\) is \( \beta \)-balanced if \( w(A) = \sum_{v \in A} w(v) \leq \beta \cdot w(V) = \beta \sum_{v \in V} w(v) \) and \( w(B) \leq \beta \cdot w(V) \). The interest of finding recursive \( \beta \)-balanced separations is because the number of levels of recursion is then \( O(\log w(V)) \). When a graph admits a \( \beta \)-balanced separation, the difficult part will be to find a separation that is both \( \beta \)-balanced and such that \( |S| \) (number of vertices in \( S \)) is “small”.

17.1 Case of trees and grids

This section is devoted to the search of small balanced separators in trees and grids in order to give examples, to provide tools that will be used later on (case of trees) and to explain some further hypotheses that will be made (trees and grids).

In trees, we will look for a “well balanced” separation using a separator consisting of one node. First, let us consider a star with three leaves, each leaf being of weight \( w(V)/3 \) (so the center has weight 0). Then, it is easy to check that no one-vertex separator leads to a \( \beta \)-balanced separation with \( \beta < 2/3 \).
Lemma 30 Let $T = (V, E)$ be a vertex-weighted tree with $w : V \to \mathbb{R}^+$. Then $(T, w)$ admits a $2/3$-balanced separation $(A, B, S)$ with $|S| = 1$.

Proof. Let $v \in V(T)$ be any node and let $T_1, \ldots, T_d$ be the connected components of $T \setminus v$ (with $d$ the degree of $v$) ordered by weight, i.e., $w(T_1) \leq \cdots \leq w(T_d)$. 

First, let us assume that $w(T_d) \leq w(T)/2$. Then, let $0 \leq j < d$ be the smallest integer such that $w(T_j) \geq w(T)/2$ (with $T_0 = \emptyset$). Note that $j < d$ since $w(T_d) \leq w(T)/2$. Let $X = \bigcup_{0 \leq i < j} V(T_i)$ and $Y = V \setminus (\{v\} \cup A)$. Then, $w(Y) = w(T) - (w(v) + w(X)) \leq w(T)/2$. If $j = 0$, then $X = \emptyset$ and so, $w(X) \leq w(T)/2$. In this case, let us set $(A, B, S) = (X, Y, \{v\})$.

Else, let $X' = \bigcup_{1 \leq i < j} V(T_i)$. Note that $w(X') < w(T)/2$. If $w(X') \geq w(T)/3$, then $w(Y) < w(T)/3$, and $w(T_j) = w(T)/3$.

Hence, let us set $(A, B, S) = (X, Y, \{v\})$.

Second, if $w(T_d) > w(T)/2$ (note that $w(T_i) < w(T)/2$ for all $1 \leq i < d$), then let $u$ be the neighbor of $v$ in $T_d$ and let $T_1' = \{v\} \cup \bigcup_{1 \leq i < d'} T_i, T_2', \ldots, T_d'$ be the connected components of $T \setminus u$ (with $d'$ the degree of $u$). Note that $w(T_1') = w(T) - w(T_d) \leq w(V)/2$ and that, for all $1 < j \leq d'$, $T_j$ is a component of $T_d$, and therefore $\max_{1 < j \leq d'} w(T_j) \leq w(T_d) - w(u)$. If $\max_{1 \leq j \leq d'} w(T_j) \leq w(T)/2$, we are back to previous case with $u$ instead of $v$. Otherwise, let $1 < j' \leq d'$ be such that $w(T_j') = \max_{1 \leq j \leq d'} w(T_j)$, then we go on toward the neighbor $u'$ of $u$ in the subtree $T_j'$, and so on, until we get the first case (this process eventually terminates by previous remarks).

In what follows, we will need to find balanced separators of trees using trees rather than vertices. We show here that finding edge-separators requires further hypothesis. Given a weighted tree $(T = (V, E), w)$, and edge $e \in E$ is a $\beta$-balanced edge-separator if $w(T_1), w(T_2) \leq \beta w(T)$ for both subtrees $T_1$ and $T_2$ of $T \setminus e$ (obtained from $T$ by removing the edge $e$, keeping its endpoints).

In the edge-separator case, there is no $\beta$-balanced edge-separator with $\beta < \max_{v \in V} w(v)/w(T)$ (for instance, consider the tree reduced to a single edge), then from now on, we will assume that each vertex of $T$ has a bounded fraction of $w(T)$ as weight. On the other hand, consider the star with $n$ leaves, each with weight $w(T)/n$, then this tree has no $\beta$-balanced edge-separator with $\beta < (1 - 1/n)$. To handle this latter problem, it is necessary to bound the degree of $T$. Finally, the following lemma can be proved (do it!) using a proof similar to the one of previous lemma.

Lemma 31 Let $T = (V, E)$ be a vertex-weighted tree with maximum degree 3 and with $w : V \to \mathbb{R}^+$ such that $w(v) \leq w(T)/4$ for all $v \in V$. Then $(T, w)$ admits a $3/4$-balanced edge-separator.

We have seen that trees admit small (one vertex/edge) balanced separators. Unfortunately, we now show that not all planar graphs can expect such small balanced separators. For instance, let us consider any $n \times n$ grid $G$. A natural 1/2-balanced separator is a middle “column”, which has size $n = \sqrt{V(G)}$. Another natural separator could be any “diagonal”. Any diagonal of size $k$ separates the grid $G$ into two parts one of them of size $O(k^2)$. For such a diagonal to be a $\beta$-balanced separator, it follows that $O(k^2) \leq \beta n^2$ and, again, $k = O(n) = O(\sqrt{V(G)})$. Actually, it can be proved that any $n \times n$ grid $G$ has no $O(1)$-balanced separator with size $o(n)$ (cf. Exercise 25).

From previous paragraph, we will now look for balanced separators of size $O(\sqrt{n})$ in $n$-node planar graphs.
17.2 Fundamental cycle separator lemma

Let us first prove a lemma that will be used in the proof of the main theorem of this section.

**Lemma 32 (Fundamental cycle separator lemma)** Let \( G = (V, E) \) be a planar graph, \( w : V \to \mathbb{R}^+ \) such that \( w(v) \leq w(V)/6 \) for all \( v \in V \), and let us assume that \( G \) admits a rooted spanning tree of depth at most \( d \). Then, \( G \) admits a \( 3/4 \)-separation \((A, B, S)\) such that \(|S| \leq 2d + 1\).

**Proof.** Let \( T \) be a spanning tree of \( G \), rooted in \( r \in V \), and of depth at most \( d \).

Let us triangulate \( G \), i.e., add edges in such a way that each face of the obtained graph \( H \) is a triangle. Note that \( T \) is also a spanning tree of \( H \). Let \( H^* \) be the dual of \( H \), note that \( H^* \) is cubic (each vertex has degree 3). Let assign some weight \( w'(f) \) to each vertex \( f \) of \( H^* \) (face of \( H \)) by “distributing” the weights of the vertices of \( V(H) = V(G) \) to the faces they are incident to. More precisely, for every \( v \in V(G) = V(H) \), let \( n_v \geq 2 \) be the number of faces \( v \) is incident to in \( H \), and for every face \( f = (u, v, w) \) of \( H \) (identifying a face with the three vertices incident to it), let \( w'(f) = \sum_{x \in \{u,v,w\}} w(x)/n_x \leq w(V)/4 \). Note also that \( w'(V(H^*)) = w(V) \).

By Lemma 29, there exists a spanning tree \( T^* \) of \( H^* \) interdigitating with \( T \). Moreover, since \( H^* \) is cubic, \( T^* \) has maximum degree at most 3. Hence, by Lemma 31, there exists an edge \( e^* \in E(T^*) \subseteq E(H^*) \) that is a \( 3/4 \)-balanced edge-separator of \( T^* \). Let \( T^*_1 \) and \( T^*_2 \) be the two connected components of \( T^* \setminus e^* \). Let \( e = uv \) be the edge of \( E(H) \setminus E(T) \) corresponding to \( e^* \) and let \( P \) be the path between \( u \) and \( v \) in \( T \). Let \( S \) be the cycle of \( H \) that consists of the path \( P \) and the edge \( e \), this cycle is called the fundamental cycle of \( e \) with respect to \( T \) (note that \( C \) is either a path or a cycle in \( G \)). Since \( T \) has depth at most \( d \), then \(|C| \leq 2d + 1\).

Let \( F^* \) be the set of edges of \( H^* \) corresponding to the edges of \( E(C) \), by Lemma 28, it is a bond in \( H^* \) separating \( V(T^*_1) \) and \( V(T^*_2) \). Let \( A \subseteq V \) (resp., \( B \)) be the set of vertices incident only to faces in \( V(T^*_1) \) (resp., in \( V(T^*_2) \)). Note that \((A, B, S)\) is a partition of \( V \). Moreover, \( w(A) \leq w'(V(T^*_1)) \leq \frac{3}{4} w'(H^*) = \frac{3}{4} w(V) \) and similarly, \( w(B) \leq \frac{3}{4} w(V) \).

17.3 Lipton-Tarjan’s theorem

**Theorem 42 [Lipton-Tarjan 1979]** Let \( G = (V, E) \) be a planar graph with \( w : V \to \mathbb{R}^+ \) such that \( w(v) \leq w(V)/6 \) for all \( v \in V \). Then, \( G \) admits a \( 3/4 \)-separation \((A, B, S)\) such that \(|S| \leq 4\sqrt{|V|}\).

**Proof.** Let \( r \in V \) be any vertex and let \((v_1, \ldots, v_n)\) be a BFS ordering of \( V \) starting in \( r \) (with \( n = |V| \)), that is \( \text{dist}(v_i, r) \leq \text{dist}(v_j, r) \) for all \( i \leq j \) (where \( \text{dist}(u, v) \) denotes the minimum number of edges of a path between \( u \) and \( v \)). For all \( 0 \leq i \leq \text{ecc}(r) \) (where \( \text{ecc}(r) \) is the eccentricity of \( r \)), let \( L_i = \{ v \in V \mid \text{dist}(v, r) = i \} \). For technical reason, let us add a dummy level \( L_{\text{ecc}(r)+1} = \emptyset \). Let \( 1 \leq j_0 \leq n \) be the smallest integer such that \( \sum_{i \leq j_0} w(v_i) \geq w(V)/2 \) and let \( 0 \leq i_0 \leq \text{ecc}(r) \) be such that \( v_{j_0} \in L_{i_0} \). Let \( L^- = \bigcup_{i < i_0} L_i \) and \( L^+ = \bigcup_{i > i_0} L_i \), note that \( w(L^-), w(L^+) < w(V)/2 \). If \(|L_{i_0}| \leq 4\sqrt{|V|} \), then \((L^-, L^+, L_{i_0})\) is the desired separation.

Otherwise, let \( i^- \) be the largest integer \( 0 \leq j < i_0 \) such that \( |L_j| \leq \sqrt{|V|} \) (\( i^- \) exists since \( |L_0| = 1 \)) and let \( i^+ \) be the smallest integer \( i_0 < j \leq \text{ecc}(r) + 1 \) such that \( |L_j| \leq \sqrt{|V|} \) (\( i^+ \) exists since \( |L_{\text{ecc}(r)+1}| = 0 \)). Note that \( i^- + i^+ < \sqrt{|V|} \) since otherwise \( \sum_{i < j < i^+} |L_j| > |V| \).

For all \( 0 \leq i \leq \text{ecc}(r) \), let \( L^{\leq i} = \{ v \in V \mid \text{dist}(v, r) \leq i \} \) and let \( L^{> i} = \{ v \in V \mid \text{dist}(v, r) \geq i \} \). Then, let \( G' \) be obtained from \( G \setminus L^{> i} \), by contracting all vertices of \( L^{\leq i} \) into one single vertex \( r' \) (with weight \( w(L^{\leq i}) \)). Note that \( G' \) has a spanning tree rooted in
r' of depth at most $i^+ - i^- < \sqrt{|V|}$. By Lemma 32, there exists a $\frac{3}{4}$-separation $(A', B', S')$ of $G'$ with $|S'| < 2\sqrt{|V|}$. Finally, let $\{A_1, A_2\} = \{A', B'\}$ and $\{B_1, B_2\} = \{L \leq i^-, L \geq i^+\}$ such that $w(A_1 \cup B_1) \leq 3w(V)/4$ and $w(A_2 \cup B_2) \leq 3w(V)/4$ (prove this exists). Then, $(A_1 \cup B_1, A_2 \cup B_2, (S' \setminus r') \cup L_{i^-} \cup L_{i^+})$ is the desired separation. 

17.4 \textbf{r-division}

Given a n-node graph $G = (V, E)$, a r-division of $G$ is a a partition of $V$ into $O(n/r)$ parts, each with size $O(r)$ and border (the border of a part is the set of vertices of this part with neighbors in other parts) of size $O(\sqrt{r})$. Note that, in a r-division, the total number of boundary vertices is $O(n/\sqrt{r})$.

Applying recursively Theorem 42, it is “easy” to show that, given a planar graph $G$, a partition of $V$ into $O(n/r)$ parts, each with size $O(r)$, and with total number of boundary vertices is $O(n/\sqrt{r})$ can be computed in time $O(n \log n)$ (note that, here, the size of the border of each part is not bounded). With more work:

\textbf{Theorem 43} [\cite{Hastad, 1999}] Let $r \in \mathbb{N}$ and $G = (V, E)$ be a planar graph. A r-division of $G$ can be computed in time $O(|V|)$.

18 \textbf{Examples of algorithmic applications}

18.1 \textbf{Maximum Independent Set’s approximation in planar graphs}

Let $G = (V, E)$ be an n-node graph. Recall that an independent set (or stable set) is a set $I \subseteq V$ of pairwise non-adjacent vertices. Note that a stable set in the complementary $\bar{G} = (V, \bar{E} = (V \times V) \setminus E)$ of $G$ (and vice versa). Hence, the problem of computing a maximum independent set or of computing a maximum clique are slightly related. For all $\epsilon > 0$, there is no $O(n^{1/2-\epsilon})$-approximation algorithm (unless $P = NP$), and there exists no $O(n^{1-\epsilon})$-approximation algorithm (unless $NP = ZPP$)[\cite{Hastad, 1999}]. Roughly, this means that, in general graphs, a best approximation algorithm for computing a maximum stable set (or a maximum clique) simply returns one single vertex! Here, we show that a much better solution can be obtained in planar graphs.

\textbf{Theorem 44} The maximum independent set has a $O(1 - \frac{1}{\sqrt{\log \log n}})$-approximation (in time $O(n \frac{\log n}{\log \log n})$) in n-node planar graphs.

\textbf{Proof.} Let $r = \log \log n$ and let $G = (V, E)$ be a n-node planar graph. Let $(V_1, \cdots, V_t)$ be a r-division of $G$ (computed in linear time) with $t = O(n/r)$. Let $B$ be the set of border vertices of the r-division. For every $1 \leq i \leq t$, let $I_i$ be a maximum stable set of $V_i \setminus B$. Let $I = \bigcup_{1 \leq i \leq t} I_i$.

Each of $I_i$ can be computed using brute force in time $O(2^{|V_i|}) = O(2^r) = O(\log n)$, and so, $I$ can be computed in time $O(t \log n) = O(n \frac{\log n}{\log \log n})$.

Let $I^*$ be a maximum independent set of $G$. By Corollary 7, $|I^*| \geq n/4$. For every $1 \leq i \leq t$, $I^* \cap (V_i \setminus B)$ is a stable set of $V_i \setminus B$, and so, $|I^* \cap (V_i \setminus B)| \leq |I_i|$. Then, $|I^*| = |B \cap I^*| + \sum_{1 \leq i \leq t} |I^* \cap (V_i \setminus B)| \leq |B| + \sum_{1 \leq i \leq t} |I_i| = |B| + |I| \leq \frac{n}{\sqrt{\log \log n}} + |I| \leq \frac{|I^*|}{4\sqrt{\log \log n}} + |I|$. Hence, $|I| \geq O(1 - \frac{1}{\sqrt{\log \log n}})|I^*|$. 

73
18.2 Improving Dijkstra’s algorithm in planar graphs

Recall that, given a graph \( G = (V, E) \) with non-negative length function \( \ell : V \to \mathbb{R}^+ \) and \( s \in V \), the Dijkstra’s algorithm computes a shortest path tree from \( s \) in time \( O(|E| + |V| \log |V|) \). If \( G \) is a simple planar graph, then \( |E| = O(|V|) \) (Lemma 5) and so Dijkstra’s algorithm performs in time \( O(|V| \log |V|) \). Let us show how to improve this time-complexity in planar graphs. In what follows, we present a more efficient algorithm whose correctness is left as an exercise.

**Theorem 45** There exists an algorithm that, given a planar \( n \)-node graph \( G = (V, E) \) with \( \ell : V \to \mathbb{R}^+ \) and \( s \in V \), computes a shortest path tree rooted in \( s \) in time \( O(n \sqrt{\log n \log \log n}) \).

**Proof.** Let \( r = \frac{\log n}{\log \log n} \). Let \( (V_1, \ldots, V_i) \) be a \( r \)-division of \( G \) (computed in linear time) with \( t = O(n/r) \) and, for every \( 1 \leq i \leq t \), let \( B_i \) be the set of vertices of the border of \( V_i \), note that \( |B_i| = O(\sqrt{r}) \). Let \( B = \bigcup_{1 \leq i \leq t} B_i \), and note that \( |B| = O(n \sqrt{r}) \). We may assume that \( s \in B \) (otherwise, let us artificially add \( s \) to \( B \)).

For every \( 1 \leq i \leq t \) and for \( u, v \in B_i \), let \( w_i(uv) \) be the distance between \( u \) and \( v \) in \( G[V_i] \). Note that, for every \( u \in B_i \), \( \{w_i(uv) \mid v \in B_i\} \) can be computed in time \( O(|V_i| \log |V_i|) = O(t \log r) \) by applying the Dijkstra’s algorithm from \( u \) in the planar graph induced by \( V_i \). In total, this step takes time \( O(t \cdot \sqrt{r} \cdot r \log r) = O(n \sqrt{r} \log r) \).

Let \( G' \) be the weighted graph with vertex set \( B \) and such that \( u, v \in B \) are adjacent if there is \( 1 \leq i \leq t \) such that \( u, v \in B_i \) (i.e., if \( u \) and \( v \) are in the border of a same part), and in that case, \( w(uv) = \min_{1 \leq i \leq t} w_i(uv) \). Note that \( G' \) is not necessarily planar and that \( |E(G')| = O(tr) \).

Using Dijkstra’s algorithm, compute a shortest path tree from \( s \in B = V(G') \) in \( G' \). This takes time \( O(|E(G')| + |V(G')| \log |V(G')|) = O(tr + \frac{n}{\sqrt{r}} \log \frac{n}{\sqrt{r}}) \). Note that, this step allows to compute \( \text{dist}(s, v) \) for all \( v \in B \).

Finally, for every \( 1 \leq i \leq t \), it remains to compute \( \text{dist}(s, v) \) for all vertices \( v \in V_i \setminus B \). For this purpose, it is sufficient to execute Dijkstra’s algorithm once, in \( G[V_i] \), starting with labels \( \text{dist}(s, w) \) (computed in previous step) for all \( w \in B \cap V_i \). Since \( G[V_i] \) is planar, this step takes time \( O(t \cdot r \log r) \) in total.

The overall complexity of the above algorithm is dominated by its first step (2nd paragraph of this proof), which gives a time-complexity of \( O(n \sqrt{r} \log r) = O(n \sqrt{\log n \log \log n}) \).

Roughly, the algorithm presented in the above proof follows a natural intuition in road networks: to go from one city \( u \) to another one \( v \) in a road network, we first follow short local routes (in the part containing \( u \)), then we go through highways (in \( G' \)) and then use short local routes (in the part containing \( v \)) to eventually reach \( v \). Note that the above algorithm can be improved since computing shortest path trees in planar graphs can actually be computed in linear time by recursively decomposing planar graphs, and using much more subtle arguments [].

**References**


\[ \text{Here, it is important to note that Dijkstra’s algorithm may be executed wherever be the initial label of every vertex.} \]


