Jcalm 42-AM/2015 Counting : Algorithms and Complexity

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COUNTING, GENERATING, SAMPLING : ALGORITHMIC POINT OF VIEW 1/36

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Counting, Generating why ?

- Mesure probabilities, volumes : Area of a shape.
 - Math solution : Triangulate, divide into simplexes decompose into shapes for which we have a formula.
 - High dimension ? ⇒ Even a polytope do have exponential number of vertices, non practical.
 - Can we get an efficient algorithm ?
- **Example:** Tree Polytope of G = (V, E)

 $\begin{array}{c} w: E \Longrightarrow \mathbf{R}^+ \\ \forall V' \subset V, w([V', V']) \leq |V'| - 1 \\ w([V, V]) = |V| - 1 \end{array}$ Polytope Vertices = The spanning trees

Why do we need algorithms for that

(How \setminus Can) we deal with that ?

Why do we need algorithms for that

Counting to Evaluate probabilities

(Discretes|finites Probabilities) \iff Counting

Question

- Network N = (V, E), edges i.i.d failures $(p = \frac{1}{2})$. Compute B(N) = Prob(N gets disconnected)?

$$B(N) = Prob[\cup_{S \in V, S \notin \{\emptyset, V\}} [S, \overline{S}] \text{ fails }] \sim \cup_{S \in V, S \notin \{\emptyset, V\}} 2^{-|[S, \overline{S}]|}$$

- Random *N* with a fixed support \rightarrow Probability of a property ?
- Erdűs Reynii : (trivial) Case $N = K_n \rightarrow$ Formulas, theorems ...
- Other Random distributions: degree sequences, Euclidian, planar, whatever $\ldots \rightarrow$ Again formulas.

Generating and Sampling

Typical Questions

- Generate a random tree of G/
- Generate a random simple path from *u* to *v*.
- Generate a random failure scenario .
- Generate complex items for simulation or testing, but in a fair way.
- Make experiment on a random graph that looks like a typical case.

What about Enumerative Combinatorics?

- Usually about a fixed object (K_n or the Hypercube ...)
- Fibbonacci, # partitions, "usual stuff" \rightarrow 95 % of the time when we count we build bijections.
- Many (most?) inductive counting argument \rightarrow inductive constructions.
- **Often :** Can count \rightarrow Can Generate.

Why do we need algorithms for that

Naive empiral integration is easy ... deeper than it seems

Maths Sucks method (Naive Monte Carlo)

Monte Carlo Uber Generator

- Throw random points in the square (we know how to sample it)
- point belongs to $A ? \rightarrow$ returns it.
- Great generator, works for any **NP**problem

Super Counting Algorithm

- Throw *n* random points in the square, *a*(*n*) points lie in *A*
- Return $Vol(P) = \frac{a(n)}{n} Vol(Square)$



Works great if $\frac{Vol(A)}{Vol(Square)}$ is not too small (ie polynomial)

Math Reason, empirical mean often works

Chernoff Bound

Z : Sum of *n* i.i.d Bernouilli variables $X_1, X_2, ..., X_n$ (random (*A*, 1 – *A*) biased coins) $\mu = E[Z] = n \cdot A$,

$$\Pr[|Z(\omega) - \mu| \ge \delta \mu] \le 2e^{\delta^2 \mu/3}$$

Almost good and quite sure ?

- We want $\mu = \frac{1}{k}$
- and $2e^{-\delta^2 \mu/3} \le \frac{1}{2}$

So we want $\mu \geq 3 \ln 4 \delta^2$ So

 $n \sim$ Who care 1 barbu c'est un barbu et le deuxième momemnt suffit zzz

We need *n* of order *vol*(*A*)/*Vol*(*Square*), up to polylog things , indeed we simply need to see events of *A* happening.

Approx + Randomized + couting + generating The #P Class A Variant of Cook Theorem Toda Theorem Non proof ??

Some formalism (sorry for that) Counting Algo.

Input :A ground set X and some predicate $I (\in \mathbf{P})$ output :an estimation of $\sharp \{x \in X | I(x) = True\} \stackrel{\text{def}}{=} \sharp x$ e.g. (Ham. cycle) : $X = \mathcal{P}(E)$, and f(x) is true if x is a Hamilton cycle

Random Algorithm

Uses fair independent random bits (don't ask me how we get them)

Qualities

Approximation	$e^{- ho} \sharp x \leq output(x) \leq e^{ ho} \sharp x$	$(\varepsilon - Approx)$
$Success \geq \tau$	<i>Prob</i> [to be ρ – <i>approximated</i>] $\geq \tau$	(1)

Sampling Algo.

Input : A finite Probability measure P(X), over X output : Algorithm returns X with proba : $P_{Algo}(x)e^{\rho} \le P(X) \le P_{Algo}e^{-\rho}$

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Counting \rightarrow Sampling ?

We need a bit more than couting

we Assume that we can still count when we fix a part of the solution

Classical usage of conditional expectations

Example

- $\mu(G, F_1, F_0) =$ Number of matching in *G* containing F_1 discarding F_0
- Nothing more than μ(H = f(G, F₁, F₀)) (here H = remove from G vertices appearing in F and remove F₀ from E)
 Algo:
 - Compute $N = \mu(G, \emptyset)$ and $p(e) = \mu(G, \{e\}, \{\})$ and

 $1 - p(e) = \mu(G, \{\}, \{e\})$

- Pick e with probability p(e), otherwise discard it
- Procede inductively, either with $(G, \{e\}, \{\})$ or $(G, \{\}, \{e\})$
- If μ () is exact \rightarrow Perfect Random Generator of matchings.
- Error e^{ε} on $\mu \to \text{Drift}$ of $e^{t\varepsilon}$ (*t* steps) (gen. $exp(\sum_{i=0,...t} \varepsilon_i)$)

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Sampling \rightarrow Counting ?(Prince Albert Revenge)

Monte Carlo on nested areas (often works)

$$\mu(A_n) = \frac{\mu(A_n)}{\mu(A_{n-1})} \dots \times \frac{\mu(A_1)}{\mu(A_0)} \mu(A_0)$$

$$Pr[A_{i+1}|A_i] = \mu(A_{i+1})/\mu(A_i) = \alpha_i$$

$$(1 + \varepsilon_0) \text{ approx of } \alpha_i \text{ takes likes } \frac{1}{\alpha_i \varepsilon_0}$$

$$n \text{ steps } \varepsilon = \sum \varepsilon_i, \ \varepsilon_i = \frac{\varepsilon}{n}$$
if $\alpha_i \ge \beta \rightarrow \text{ around } \frac{n^2}{\beta \varepsilon}$

Direct : Pay like β^n to observe one A_0 in A_n

. . .

examples Matchings (add more and more edges) $\mu(G + \{e\}) \leq 2\mu(G)$, forests, colorings with more than Δ colors, knapsacks with cost less than *C*

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Approx + Randomized + couting + generating The #P Class A Variant of Cook Theorem Toda Theorem Non proof ??

Some formalism : The $\sharp P$ Class

What contains $\sharp P$?

Unformaly:

Any Counting problem that can be associated to successful computations of a Non Deterministic Turing Machine (in Polynomial time)

Counting Prob in *P*

Elements of a Set S(x) Bijection $\{y \mid TM(x, y) \text{ says ok }\}$ Elements of a Set S(x) Bijection Correct proofs that $(x, y) \in S$

Example

Ham. Cycle : x = (V, E), $S(x) = \{$ Ham. Cycles of $(V, E)\}$, the proof is the cycle itself. For *SAT* where *x* is the instance (the graph), *y* is the variable assignement (set of edges) and the machine checks that it works.

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Cook theorem and $\prescript{P-completeness}$ of 3SAT

Theorem (Fake)

#3SAT is #P - complete.

Proof. Almost a tautology.Correctness of a NdetTM computation can be captured by a (big) 3SAT formula.It's Cook's Theorem, mostly says computation is local3SAT variablesbijection3SAT SolutionsbijectionSucessfull Choices of the NdetTM

Remarque

Indeed One says that Cook reduction is parsimonious.

Counting Solutions of NP-hard problems ?

- Not really interesting, Almost immediately $\sharp P complete$
- No approximation theory (deciding 0 or 1 is hard, ∞ ratio).
- Easy to amplify the number of solutions (add k fake binary clauses $\times 2^k$)

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Counting exactly is way too strong and complicated

Theorem (Toda 25-AM/1998)

Any problem in the Polynomial hierarchy can be solved using a counter. Fancy Madmen notation is

 $PH \subset P^{\sharp P}$

madness pays off

Let us be silly and get the godel prize !

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Valiant Vazirani, isolation lemma [11AM]

Theorem

If you can solve problem when they have unique solution you can solve SAT (up to some randomization)

Detecting unique solutions

- 0 solution \rightarrow says 0
- 1 solution \rightarrow says 1
- > 1 output garbage, anything.

Idea :

- Add linear constraints (see prob. in Z_2^n).
- $\bullet\,$ Dichotomy, one contraint \rightarrow Should divide the solution state by 2
- turn linear constraints into extra clauses (silly but needed)

Isolation Lemma (2)

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Theorem (Isolation)

- S any set of Z_2^n
- pick constraints $H_i = \{x \mid v_i . x = 0\}$ randomly,
- *let* $S_0 = S, S_{i+1} = S_i \cap H_i$.

Then with probability $P \geq \frac{1}{4}$ we have $\exists i, |S_i| = 1$.

So with positive probability once can construct a SAT instance that is stonger (more constrained) than the original one and that admits a single solution.

Toda proof 3

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Sorry No Godel Prize for you !

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Let's try something simpler

Case of trackatable problems Case of trackatable problems Valiant Result about counting Matchings Valiant's reduction :Simulating counting 3Covers

We may still do something for ...

- simple Path, trees
- Matchings
- Polytopes

About Matchings ? Fun situation

Counting exactly Matching is #P-complete [Valiant 6-AM/79] One can approx count (and generate) Matchings [Jerrum 21-AM/95]

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Permanent, One factor, Matchings

Definition (Permanent, determinant)

 $Perm(A) = \sum_{\pi \in \mathfrak{S}_n} a_{i,\pi(i)} | Det(A) = \sum_{\pi \in \mathfrak{S}_n} sign(\pi) a_{i,\pi(i)}$

Term of the sum = 0 \iff some edge $(i, \pi(i))$ does not exist. Term of the sum = 1 if all the edges $(i, \pi(i))$ exist \Rightarrow The permanent counts *One Factors* of *G*

It also counts Matchings in [G, G].



Weigthed version : Instead of 1 we count $\prod_{e \in F} w(e)$ for a factor (a matching) $F \subset E$

Formal version : Multivariate Generating serie of the Matchings

Proof Structure

Case of trackatable problems Case of trackatable problems Valiant Result about counting Matchings Valiant's reduction :Simulating counting 3Covers

Proof Organisation

- # Weigthed Matchings regular reduction # Exact Covers by Triples
- # Weighted Perfect Matchings \rightarrow Exact couting for Weigthed Matchings
- Emulating integral weights.
- #Perfect Matchings int. weigths \rightarrow Can count with any weights.

A small Gadget

Case of trackatable problems Case of trackatable problems Valiant Result about counting Matchings Valiant's reduction :Simulating counting 3Covers

Main property

$$Perm(G(x_2, x_2, x_3)) = \frac{1 + x_1 x_2 x_3}{3}$$

No term with degrees $1, 2 \rightarrow \forall A \subset \{x_1, x_2, x_3\}$

The Gadget (uses negative weigth)



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Just Checking Perm(G(1, 1, 0)).

- 1) *M* contains two edges, two cases : $\frac{-5}{3} \times 1$ and $\frac{1}{6} \times 1$ (tot. $\frac{-9}{6}$)
- 2) *M* contains one edge (4 cases) : $-\frac{5}{3} + 1 + 1 + \frac{1}{6}$ (tot. $\frac{3}{6}$)
- 3) *M* is empty 1 (tot. +1)

total contribution is zero similarly: $P(1,1,1) = \frac{-5}{3} + 1 + 1 = \frac{1}{3}$







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Consequence

Property

When we attach the gadget *H* with its 3 ends to a graph, computing Perm(G + H) compute the "number" of matchings that either contain $\{e_1, e_2, e_3\}$ or do not intersect it.

Gadgets behave like a triple

S: Instance of cover-with-triples , 3m elements (ground set). Triples and gadgets (Bijection) What do we count ? The Exact covers ? No! We count triple-disjoint partial cover

k disjoints triple (+stuff): $\left(\frac{1}{3}\right)^k$

 $Perm(H(S)) = \sum \frac{N(k)}{3^k}, N(k)$ number of disjoint *k* covers.



Gadget Gadget Gadget Gadget

Case of trackatable problems Case of trackatable problems Valiant Result about counting Matchings Valiant's reduction :Simulating counting 3Covers

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Getting ride of partial Covers

Add pending leaves to vertices of the ground set.

Edge weight is $-1 \Rightarrow$ Graph H'(S)

We count now 0 for a partial Cover. We still count $\frac{1}{2m}$ for a perfect cover.



 $Perm(H'(S)) = \frac{\text{number of exact covers}}{3^m}$

Case of trackatable problems Case of trackatable problems Valiant Result about counting Matchings Valiant's reduction :Simulating counting 3Covers

Some More gadgets

• Matching \rightarrow Perfect Matching



• At the end 4 bad weights $x = \frac{1}{6}$, $y = \frac{5}{3}$, z - 1 Polynomial on a bounded number (k = 4) of variables, degree *n* (polynomial), n^4 coefficients \rightarrow can be computed.

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Even couting Simple walk is Difficult

Unless P = NP

Assume we can approx. Generate Simple Walk

Amplify probability of long walks

 \rightarrow Can Solve Hamilton cycle.

Proposition

Generating unbiased (even very approx) simple walk, or couting them (even very badly) is NP-hard

Weaker reduction (to NP) but similar idea can work for much more problems.

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General framework

Ideas

- Move randomly in the state space (form Use Markov Chains)
- Ensure that moves are fair (the station. distribution is uniform)
- Want to be random fast (Ensure Rapid-Mixing)

Theorem (Perron Frobenius + some Folks)

A stochastic matrix M admits a unique fixed point (eigenvector with eigenvalue 1) and everything else decays fast. i.e if u.1 = 0 (noise), then $M^t u \to 0$

More or less: eigenvalues $1 = \lambda_1, \lambda_2, \dots, \lambda_n$

$$|\boldsymbol{M}^t(\boldsymbol{u}) - \boldsymbol{u}_0| \leq (1 - \lambda_2)^t$$

Where $\lambda_2 < 1$ depends on the structure of the chain *M*. State space *S* it converges in $\frac{\log |S|}{\log_2(1-\lambda_2(M))}$

Limitation, Difficulties

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Design a Good Enough Chain ...

Prove that it converges fast

No way to compute λ_2 numerically

State Space is of exponential size

Works only for symmetric chains (but you design it)

Stupid condition (non bipartite), solved making chain Lazy, loop half of the time

Typical Fake-chain

• Pick $\frac{|V|}{2}$ edges,

if they form a matching return it else play again

- Mathematically sound, return unbiased matching
- Mixes slowly (loops forever)

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Bad Guy: Cycle

- Totally random moves, takes $\theta(n^2)$ to get random (unbiased random walk with *t* steps move away from zero lie $\theta(\sqrt{t})$.
- actual time to mix is $\frac{n^2}{2\pi^2}$.
- Very bad expansion, $\frac{2}{n}$



Good Girl: De Bruijn

- Binary chains, length *n*, shift and inject a new bit.
- random moves, takes *n* to exactly anywhere with probably ¹/_{2ⁿ}
- actual time to perfectly mix is $\log_2 |S| = n$.

• Good expansion,
$$\sim \frac{1}{\log_2 n}$$



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Why do Liner Algebra Matter How does the discrepancy evolve ?

- Look how non uniform is a distribution $X \to \delta(X) = \sum_{e=(u,v) \in E} |X_u X_v|^2$
- I an Incidence matrix of the graph
- $\delta(X) = |IX|^2 = XI^t IX$
- $\mathcal{L} = II^t$ is the Laplacian of *G*
- $\mathcal{L} = \Delta(G) M$ (*M* adjacency matrix, Δ diagonal of the degrees)
- **G** is regular : $\mathcal{L} = \Delta Id II^t$.
- Normalisation : divide by Δ
- $1 \lambda_2$ is the largest eigenvalue of $\frac{ld-M}{\Delta}$ which is a SDP matrix.

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Link with congested cuts

- X indicator vector for $S : X_u = 1, u \in S, X_u = -1 u \in \overline{S}$
- $\rightarrow I^t I X = 4 | [S, \overline{S}]$

Definition (isoperimetric constant, conductance)

$$\phi = Min\frac{[S,\overline{S}]}{|S|}$$

High Conductance = Rpid Mixing

$$rac{\phi^2}{2} \leq 1 - \lambda_2 \leq 2\phi$$

(Cheeger inequality)

To prove rapid-mixing \rightarrow Prove that conductance is high.

Hum ? Need to have an idea of the ??

still complicated

The cannonical Path Idea

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Define a cannonical path between any pair of states

Hum ? just a routing indeed

Get low congestion of the edges of G

Here low means logarithmic in the state space size |S| (i.e indeed polynomial).

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A "fast" Chain for matchings

M curent solution, select $e \in E$ Randomly.

- 1) No extremity covered $\rightarrow M \cup \{e\}$
- 2) 1 extremity cov. (by f) $\rightarrow M \setminus \{f\} \cup \{e\}$
- 3) 2 extremities cov., $e \notin M \rightarrow M$
- 4) $e \in M \rightarrow M \setminus \{e\}$



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A good routing

Take the symetric difference of the two matchings.

Order the vertices, induce order on the components

Process by component : for each start from the "first" vertex and do the augmenting path thing.



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Case of Trees

Ney formula : labeled trees on K_n (comp.graph)

Induction is $\forall e = (u, v)N(G) = N(G \setminus \{e\}) + N(G[u = v]).$ Generalizes as a determinant for general *G*.

Markov Chain

- Potentialy Rapidly Mixing Chain : Take an edge and flip it (like when you look for the Min Cost Spanning Tree)
- Prob. Mixes fast (need to check)
- But there is Better ...

Super Smart Generator

Move in *G* randomly add edges to your tree unless it makes a cycle.

Mixes perfectly

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Sampling from inside a Polytope (Lovasz & Simonovits)

We are given a "Nice" Polytope (the solutions of a linear program)

Random Walk inside P

discrete : Divide into cells, make a discrete randomwalk.

conti: $x \rightarrow$ Move randomly inside $B(x, \rho) \cap P$

Complicated :

If ρ big we haven't done anything ρ small \rightarrow No move (mixes slowly)

Continuous space, uniformity ? Mixing time :



Poincaré Inequality

Up to some conditon, for a convex body diameter D:

Congestion
$$\leq \Theta(\frac{D^2n}{\delta})$$

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Stuff to Remember (Ubiquitous Take Home Slide)

Very few things we can do practically Markov chains may work, hard to construct

More ?

David Aldous Book (future book) http://www.stat.berkeley.edu/~aldous/RWG/book.pdf Lázló Lovász papers, monographies : http://matmod.elte.hu/~lovasz/randwalk-papers.html Marc Jerrum & Alistair Sinclair work. Fan Chung book (spectral graph theory) Karp & Luby for DNF (easy, just cond. expectation), coupling from the Past (exact simulation),