Deep Learning for Computer Vision

UCA Master 2 Data Science

INRIA Sophia Antipolis – **STARS team**

S3.2 : **10 December / 25 February**

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STARS Inria Research Team

Objective: designing vision systems for the recognition of human activities

Challenges:

- Perception of Human Activities : **robustness**
  - Long term activities (from sec to months),
  - Real-world scenarios,
  - Real-time processing with high resolution.

- Semantic Activity Recognition : **semantic gap**
  - From pixels to semantics, uncertainty management,
  - Human activities including complex interactions with many agents, vehicles, …
  - Fine grained facial expressions, rich 3D spatio-temporal relationships.

- **Applications** : Safety & Health (CoBTeK from Nice Hospital : Behavior Disorder)

Toyota Smart-Home
Large scale daily living dataset

Related Courses @ UCA

MSc Data Science and Artificial Intelligence

http://univ-cotedazur.fr/en/idex/formations-idex/data-science/

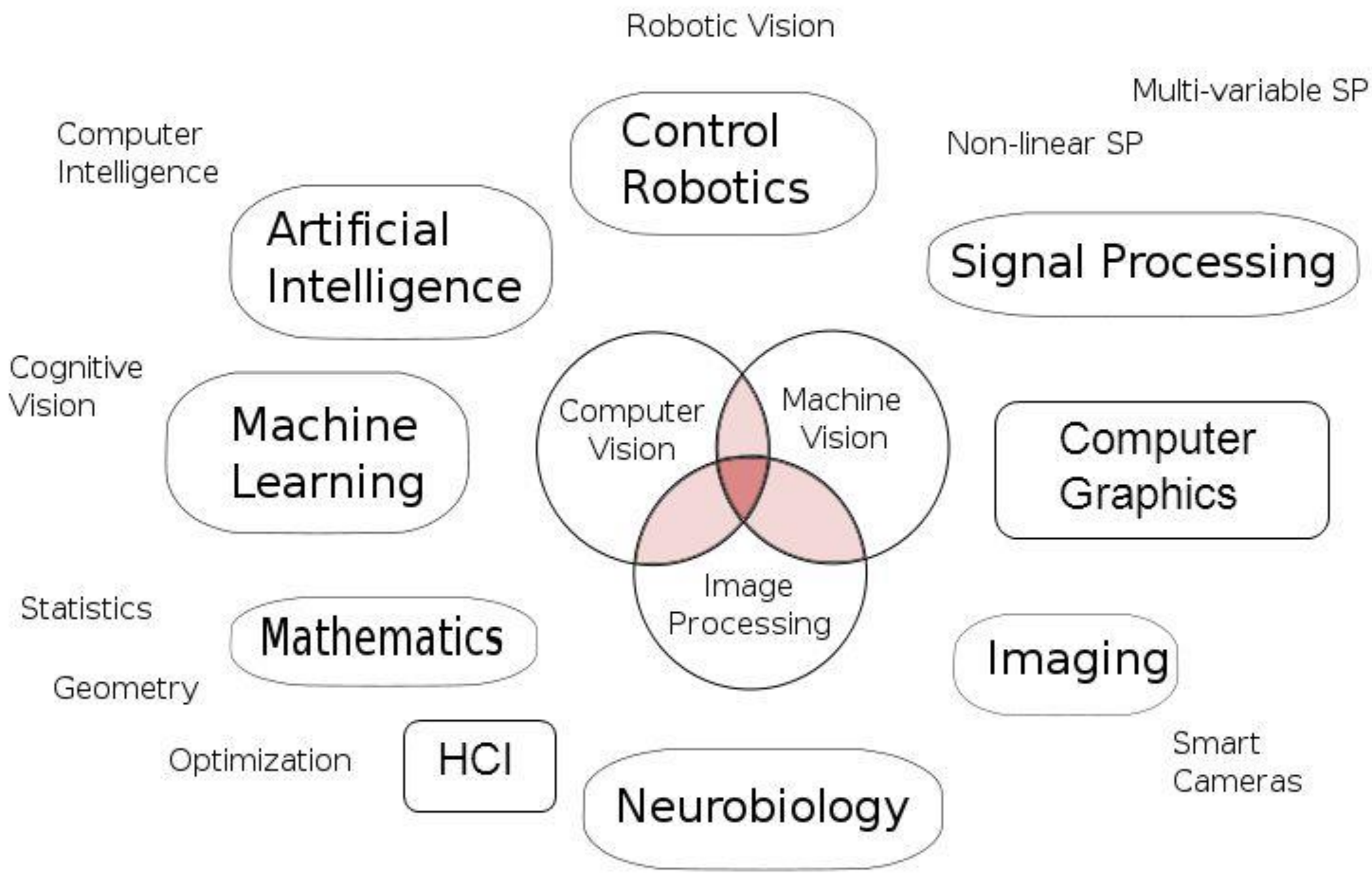
Master 1:

- Statistical inference: theory and practice I & II
- Processing large datasets with R
- Data visualization
- A general introduction to Data Mining
- Technologies for Big Data with Python
- Computer Vision: Foundations and Applications

Master 2:

- Computer Graphics
- Optimization for Data Science
- Medical Imaging
- Deep Learning
- **Computer Vision**

Vision is multidisciplinary



- Computer Vision is a subfield of artificial intelligence and machine learning.
- Techniques in machine learning and other subfields of AI (e.g. NLP) can be borrowed and reused in computer vision.

Computer Vision: many Tasks

Computer Vision is an interdisciplinary scientific field that deals with how computers can be made to gain high-level understanding from digital images or videos.

From the perspective of engineering, it seeks to automate tasks that the human visual system can do. [Wikipedia]

Computer Vision Tasks:

- Recognition : Objects or Events
  - Classification
  - Detection
  - Retrieval
- Motion analysis
  - Tracking
  - Optical flow
- Image synthesis
- Image restoration
- Biometrics
- etc...

Video Analytics (or VCA) applies CV & ML algorithms to extract/analysis content from videos

Video Analytics: many Domains

- Smart Sensors: Acquisition (dedicated hardware), thermal, omni-directional, PTZ, cmos, IP, tri CCD, RGBD Kinect, FPGA, DSP, GPU.
- Networking: UDP, scalable compression, secure transmission, indexing and storage.
- Image Processing/**Computer Vision**: feature extraction, 2D object detection, active vision, tracking of people using 3D geometric approaches
- Multi-Sensor Information Fusion: cameras (overlapping, distant) + microphones, contact sensors, physiological sensors, optical cells, RFID
- Event Recognition: CNN, Probabilistic approaches HMM, DBN, logics, symbolic constraint networks
- Reusable Systems: Real-time distributed dependable platform for video surveillance, OSGI, adaptable systems, Machine learning
- Visualization: 3D animation, ergonomic, video abstraction, annotation, simulation, HCI, interactive surface.

Video Analytics Applications

- Strong impact in transportation (metro station, trains, airports, aircraft, harbors)
- Traffic monitoring (parking, vehicle counting, street monitoring, driver assistance, self-driving car)
- Control access, intrusion detection and Video surveillance in public places, building
- Store monitoring, Retail, Aware House, Bank agency
- Health (HomeCare) patient monitoring,
- Video communication (Mediaspace, 3D virtual realty)
- Sports monitoring (Tennis coach, Soccer analytics, F1, Swimming pool monitoring)
- Other application domains : Robotics, Drones, Teaching, Biology, Animal Behaviors, Risk management …

➢ Creation of start-up

  ➢ Keeneo: http://www.keeneo.com/

  ➢ Ekinnox: https://www.ekinnox.com/

Video Analytics : Issues

Practical issues

Video Understanding systems have poor performances over time, can be hardly modified and do not provide semantics

Video Analytics : Issues

V1) Acquisition information:

- V1.1) Camera configuration: mono or multi cameras,
- V1.2) Camera type: CCD, CMOS, large field of view, colour, thermal cameras (infrared), Depth
- V1.3) Compression ratio: no compression up to high compression,
- V1.4) Camera motion: static, oscillations (e.g., camera on a pillar agitated by the wind), relative motion (e.g., camera looking outside a train), vibrations (e.g., camera looking inside a train),
- V1.5) Camera position: top view, side view, close view, far view,
- V1.6) Camera frame rate: from 25 down to 1 frame per second,
- V1.7) Image resolution: from low to high resolution,

V2) Scene information:

- V2.1) Classes of physical objects of interest: people, vehicles, crowd, mix of people and vehicles,
- V2.2) Scene type: indoor, outdoor or both,
- V2.3) Scene location: parking, tarmac of airport, office, road, bus, a park,
- V2.4) Weather conditions: night, sun, clouds, rain (falling and settled), fog, snow, sunset, sunrise,
- V2.5) Clutter: empty scenes up to scenes containing many contextual objects (e.g., desk, chair),
- V2.6) Illumination conditions: artificial versus natural light, both artificial and natural light,
- V2.7) Illumination strength: from dark to bright scenes,

Video Analytics : Issues

V3) Technical issues:

- V3.1) Illumination changes: none, slow or fast variations,
- V3.2) Reflections: reflections due to windows, reflections in pools of standing water, reflections,
- V3.3) Shadows: scenes containing weak shadows up to scenes containing contrasted shadows (with textured or coloured background),
- V3.4) Moving Contextual objects: displacement of a chair, escalator management, oscillation of trees and bushes, curtains,
- V3.5) Static occlusion: no occlusion up to partial and full occlusion due to contextual objects,
- V3.6) Dynamic occlusion: none up to a person occluded by a car, by another person,
- V3.7) Crossings of physical objects: none up to high frequency of crossings and high number of implied objects,
- V3.8) Distance between the camera and physical objects of interest: close up to far,
- V3.9) Speed of physical objects of interest: stopped, slow or fast objects,
- V3.10) Posture/orientation of physical objects of interest: lying, crouching, sitting, standing,
- V3.11) Calibration issues: little or large perspective distortion,

Video Analytics : Issues

V4) Application type:

- V4.1) Tool box : primitive events, enter/exit zone, change zone, running, following someone, getting close,
- V4.2) Intrusion detection: person in a sterile perimeter zone, car in no parking zones,
- V4.3) Suspicious behaviour: violence, fraud, tagging, loitering, vandalism, stealing, abandoned bag,
- V4.4) Monitoring: traffic jam detection, counter flow detection, activity optimization, homecare,
- V4.5) Statistical estimation: people counting, car speed estimation, data mining, video retrieval,
- V4.6) Simulation: risk management,
- V4.7) Biometry and object classification: fingerprint, face, iris, gait, soft biometry, license plate, pedestrian.
- V4.8) Interaction and 3D animation: 3D motion sensor (Kinect), action recognition, serious games.
- V4.9) Robotics, Drones

Video Analytics : Issues

Successful application: right balance between

- Structured scene: constant lighting, low people density, repetitive behaviours,
- Simple technology: robust, low energy consumption, easy to set up, to maintain,
- Strong motivation: fast payback investment, regulation,
- Cheap solution: 120 to 3000 euros per smart camera.
- Availability of Knowledge or large video datasets with annotation

Commercial products:

- Intrusion detection: ObjectVideo, Keeneo, Evitech, FoxStream, IOimage, Acic,…
- Traffic monitoring: Citilog, Traficon,…
- Swimming pool surveillance: Poseidon,…
- Parking monitoring: Ivisiotec,…
- Abandoned Luggage: Ipsotek,…
- Biometry: Sagem, Sarnof,…,SenseTime, MegVii (face++),
- Integrators: Honeywell, Thales, IBM, Siemens, GE, …, CVTE, Huawei,
- Camera providers: Bosh, Sony, Panasonic, Axis, …, HIK Vision,
- Game industries: Microsoft, Nitendo,...
- Retail: Amazon,… Tencent YouTu Lab, CloudWalk, Baidu, Alibaba, Tencent
- Self-driving Cars: Tesla, Google, Uber,…Argo AI,

Video Analytics : Issues

Performance: robustness of real-time (vision) algorithms

Bridging the gaps at different abstraction levels:

- From sensors to image processing
- From image processing to 4D (3D + time) analysis
- From 4D analysis to semantics

Uncertainty management:

- uncertainty management of noisy data (imprecise, incomplete, missing, corrupted)
- formalization of the expertise (fuzzy, subjective, incoherent, implicit knowledge)

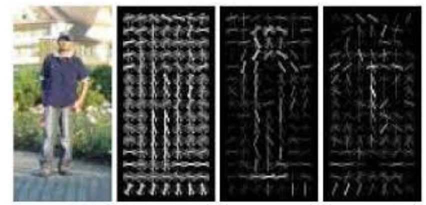
Independence of the models/methods versus:

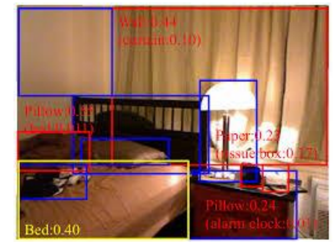
- Sensors (position, type), scenes, low level processing and target applications
- several spatio-temporal scales

Knowledge management :

- Bottom-up versus top-down, focus of attention
- Regularities, invariants, models and context awareness
- Knowledge acquisition versus ((none, semi)-supervised, incremental) learning techniques
- Formalization, modeling, ontology, standardization

A brief history of Computer Vision





David Lowe, 1999
SIFT

Sivic & Zisserman, 2003
Bags of words

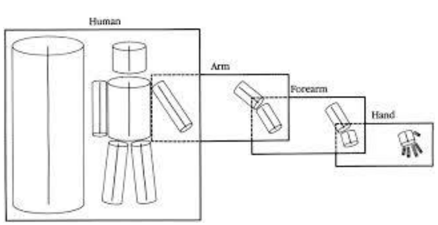
Dalal & Triggs, 2005
HOG

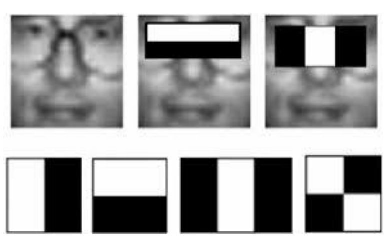
Everingham, 2012
PASCAL Challenge

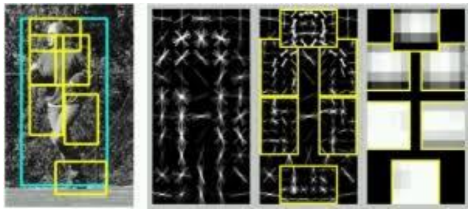
David Marr, 1970s
from images to geometric
blobs, edges, 3-D models

Viola & Jones, 2001
Face Detection

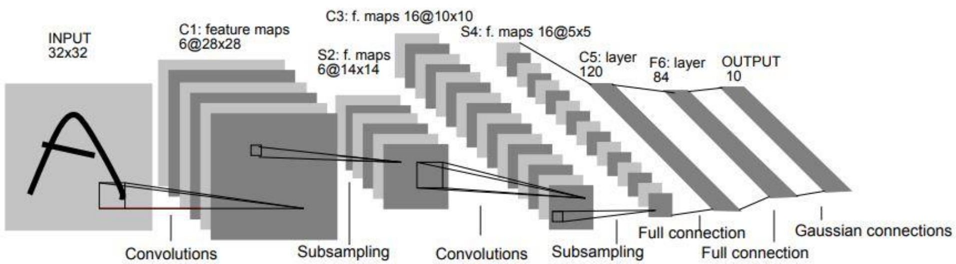
Felzenswalb & Ramanan, 2009
Deformable Part Model

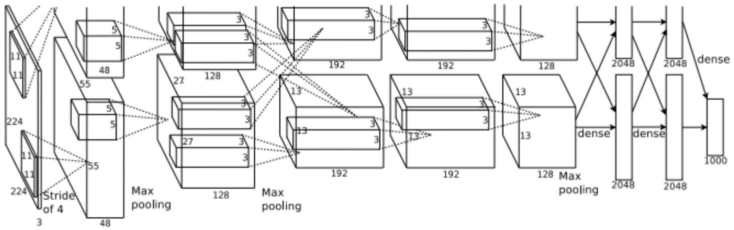






A brief history of Deep Learning





Minsky & Papert, 1969
perceptron

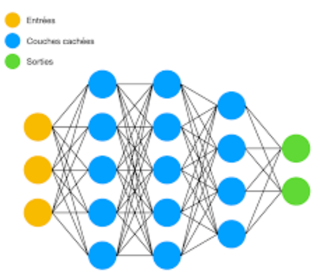
LeCun, 1990
convolutional networks

LeCun, Bengio, 1998
LeNet-5
Gradient-based learning

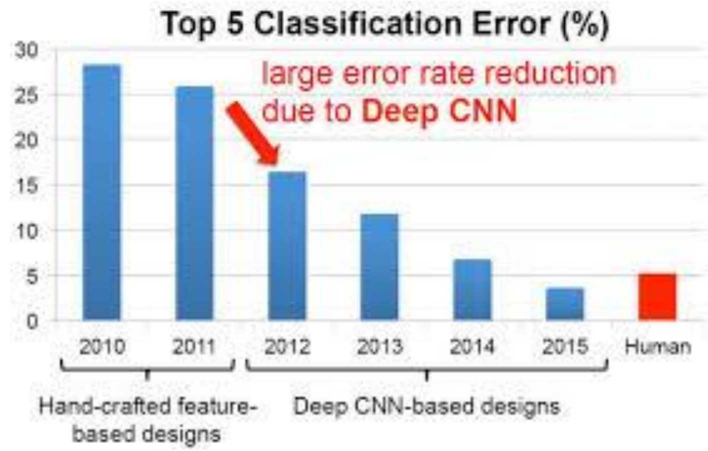
Li Fei-Fei, 2009
Image-net
22K categories and 15M images

Krizhevsky, Hinton, 2012
AlexNet

Ross Girshick, 2016
Faster RCNN



ImageNet Large Scale Visual Recognition Challenge
Russakovsky et al. IJCV 2015



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Components for Deep Learning

3 Components for Deep Learning:

- Software: Deep Learning Algorithms, Libraries
- Data : Images, Videos, Annotation
- Hardware: High Computation

Deep Learning Software

Libraries

- Caffe — (Berkeley Vision Lab)
- **TensorFlow** — (Google)
- CNTK — (Microsoft) - discontinued
- Torch — (Facebook) - discontinued
  - **PyTorch** — (Facebook)
- Theano — (MILA) – discontinued
- MXNet – Apache Software Foundation
- built on top of other libraries:
  - **Keras** — (Individual initiative + Google push)

Models

A complete end-to-end system performing a well-defined vision task

- FRCNN, Mask-RCNN; SSD, YOLO, RetinaNet (detection/segmentation),
- FCNN (Fully Convolutional, segmentation)
- RNN, GRU, LSTM

Networks

A neural network consisting of convolutional or recurrent layers or both, which extracts features from an image.

- VGG16, Alexnet,
- Siamese,
- ResNet, Inception, Inception-Resnet, DenseNet

Data : machine learning

Machine Learning : Data-Driven Approach

- Collect a dataset of images and labels
- Use Machine Learning to train a classifier
- Evaluate the classifier on new images

Machine Learning : Few Approaches

- supervised learning
  - Learn to map an input (data) to a target output (representation), which can be discrete (classification) or continuous (regression)
- unsupervised learning
  - Learn a compact representation of the data that can be useful for other tasks, e.g. density estimation, clustering, sampling, dimension reduction, manifold learning
  - but: in many cases, labels can be obtained automatically, transforming an unsupervised task to supervised
- semi-supervised
  - weakly supervised, ambiguous/noisy labels, self-supervised etc.
- reinforcement learning
  - learn to select actions, supervised by rewards.

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Data : machine learning

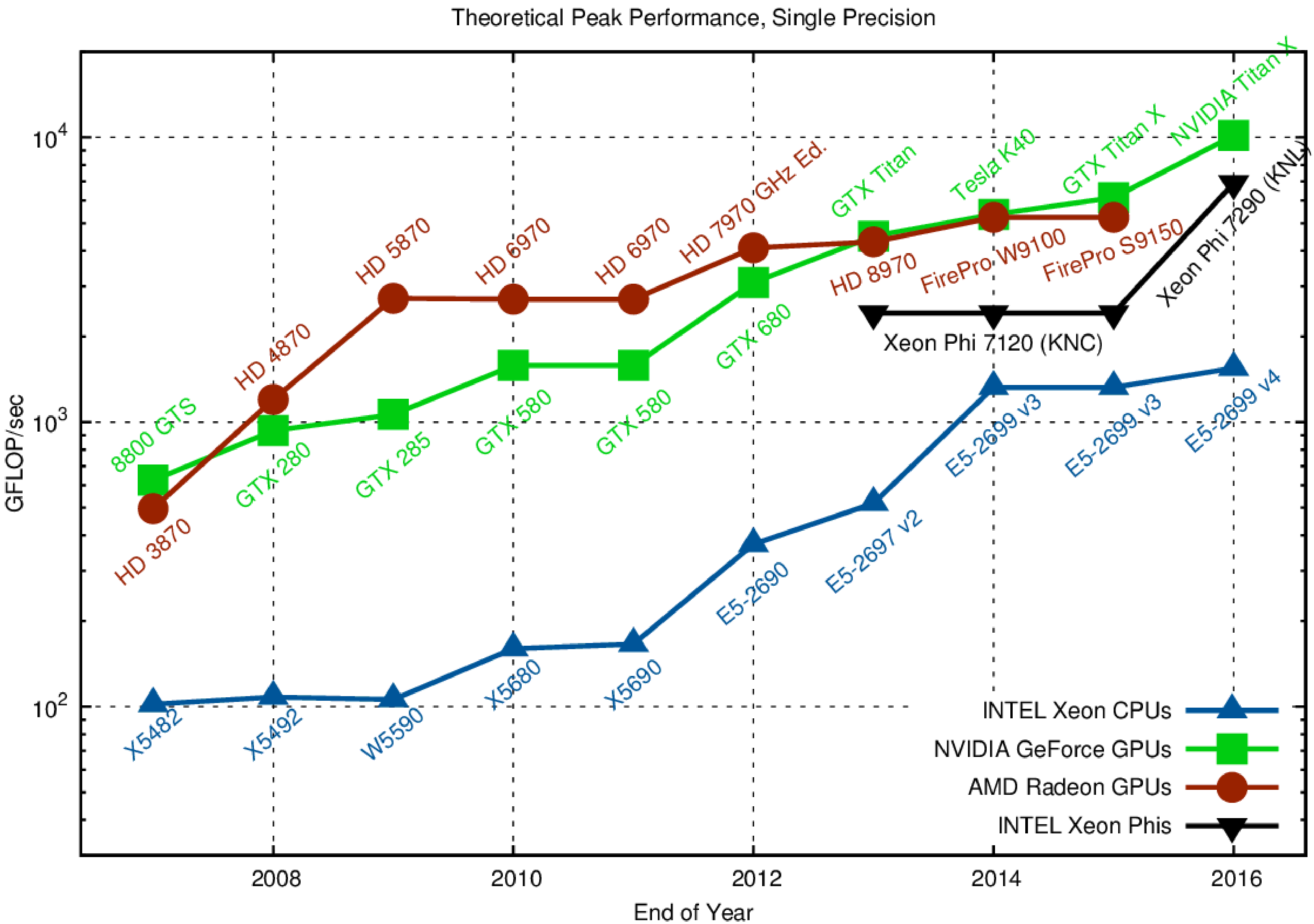
Image DataSets

- CIFAR10 (CIFAR100, MNIST) [1998 - 2006]
  - 10 classes/ 50,000 training images/ 10,000 testing images
- Image-net [2009 – 2012]
  - 22K categories and 15M images; (subset) 1K categories and 1.2M images
- Pascal VOC [2006 - 2012]
  - 20 object categories, 11.5K images, detection + segmentation
- MS COCO [2014]
  - 90 object categories, 183 K images, detection + segmentation + keypoints
- OpenImages
  - 600 object categories, 1.7 M images, detection – weakly annotated

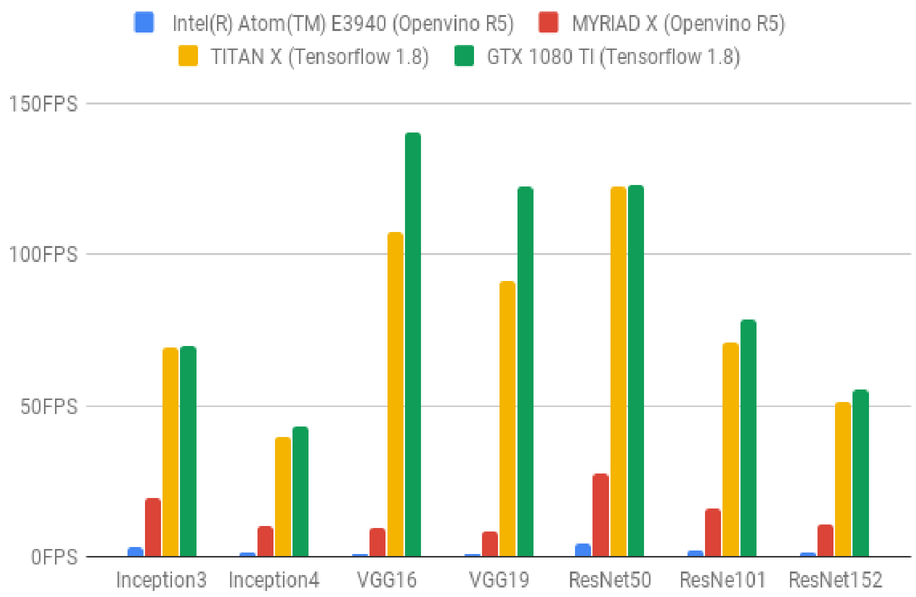
Video DataSets

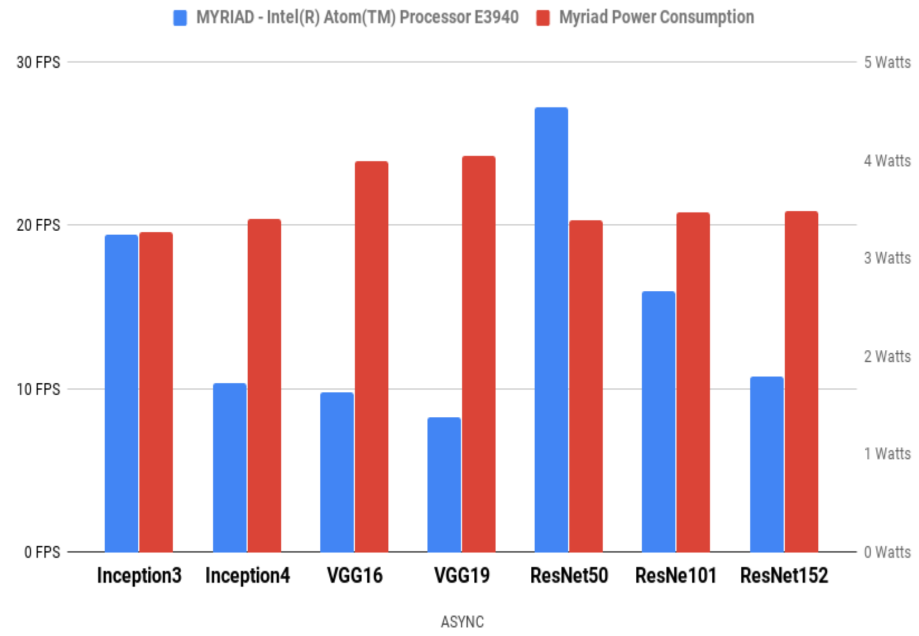
- Kinetics
  - 400-600-700 action classes, 325-650K video clips [2017-2019]
- ActivityNet-200
  - 200 action classes, 20K untrimmed videos, 31K action instances [2016]
- MSRDailyActivity3D:
  - 16 action classes, 320 video clips [2012]
- NTU RGB+D
  - 60 action classes, 56880 videos [2016], 120 action classes, 120K videos [2019]
- Toyota Smarthome
  - 31 action classes, 16129 videos [2019], 53 action classes, 536 videos , 41K action instances [2020]

Deep Learning Hardware



Deep Learning Hardware





Limitations on Nvidia Deep learning on Embedded hardware

- Power consumption : GTX 1080: 250 W > Myriad X: 5 W
- Only 3 years of Warranty (at least 8 needed)

Educational Objectives:

- Discuss well-known methods from low-level description to intermediate representation, and their dependence on the end task
- Study a data-driven approach where the entire pipeline is optimized jointly in a supervised fashion, according to a task-dependent objective
- Study deep learning models in details
- Interpret them in connection to conventional models
- Focus on recent, state of the art methods and large scale applications

Course Planning

Each session : lecture (theoretical) + practice

- **Lecture 1:** Introduction to CV : Francois + Hao
  - Traditional and modern Computer Vision & Artificial Intelligence [FB]
  - Neural Networks for CV : one neuron, activation, loss function, BP [HC]
  - Practice: Back Propagation with Python
- **Lecture 2:** Image Classification : Hao
  - CNN : convolution, pooling, receptive field, normalization [HC]
  - Practice: LeNet-5 for digit recognition with Pytorch
- **Lecture 3,4,5:** Object Detection : Ujjwal
  - Object detection techniques will include Faster-RCNN, SSD and Feature Pyramid Networks.
  - Each will be deeply described and compared.
- **Lecture 6:** Video Classification, RNNs (Vanilla network), LSTM : Srijan
- **Lecture 7:** Action Recognition: Srijan
  - Dense Trajectories, different video aggregation techniques, two-streams, LSTMs for AR, 3D ConvNets
- **Lecture 8:** Attention Mechanism : Srijan
  - spatial attention for image classification, spatio-temporal attention for action recognition.
- **Lecture 9:** GAN and VAE : Yaohui
- **Lecture 10:** Article presentation : all

How to Contact Us

- Course Website:
  - http://www-sop.inria.fr/members/Francois.Bremond/MSclass/deepLearningWinterSchool/index.html
  - Syllabus, lecture slides, schedule, etc
- Emails:
  - Hao Chen: hao.chen@inria.fr
  - Ujjwal: ujjwal.ujjwal@inria.fr
  - Srijan Das: srijan.das@inria.fr
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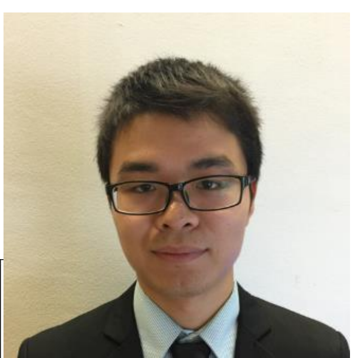

Evaluation Policy

- Engagement while attending class (oral) : 30%
  - Answering questions
  - Practical training

- Article presentation: 70%
  - 5 groups of 2 – 3 students
  - Select 1 article out of 10
  - Last day: slide presentation : 20 min + 10 min questions
    - Motivation (P1)
    - State-of-the-art (P1)
    - Proposed approach (P2)
    - Performance/limitations (P3)
    - Future directions (P3)

Proposed articles

- **Visual explanation [Hao]**
  - Learning Deep Features for Discriminative Localization (CVPR 2016)
- **Object Detection [Ujjwal]**
  - Read the papers of YOLOv1, YOLOv2 and YOLOv3 and make a consolidated presentation explaining the YOLO pipeline along with its historical development
    - YOLOv1 Paper : https://pjreddie.com/media/files/papers/yolo_1.pdf
    - YOLOv2 Paper: https://pjreddie.com/media/files/papers/YOLO9000.pdf
    - YOLOv3 Paper: https://pjreddie.com/media/files/papers/YOLOv3.pdf
  - Read the following two papers and discuss their relative and comparative ideas.
    - http://openaccess.thecvf.com/content_iccv_2017/html/Bodla_Soft-NMS_--_Improving_ICCV_2017_paper.html
    - http://openaccess.thecvf.com/content_CVPR_2019/papers/Liu_Adaptive_NMS_Refining_Pedestrian_Detection_in_a_Crowd_CVPR_2019_paper.pdf
- **Re-ID [Hao]**
  - Beyond Part Models: Person Retrieval with Refined Part Pooling (and a Strong Convolutional Baseline) (ECCV 2018)
- **Action recognition [Srijan]**
  - An End-to-End Spatio-Temporal Attention Model for Human Action Recognition from Skeleton Data (AAAI 2017)
    - Project (optional) - To implement the above framework and validate on a small dataset like MSRdailyActivity3D (Skeleton data will be provided)
    - Expected results - Classification accuracy, ablation studies, attention visualization
  - Can Spatiotemporal 3D CNNs Retrace the History of 2D CNNs and ImageNet? (CVPR 2018)
    - Project (optional) - To implement the above framework and validate on a small dataset like MSRdailyActivity3D (RGB data will be provided)
    - Expected Results - Classification accuracy, analysis of the network (comparison with ResNet, DenseNet)
- **GANs [Yaohui]**
  - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (ICCV 2017)
  - Image-to-Image Translation with Conditional Adversarial Networks (CVPR2017)
- **Biometry [Antitza]**
  - Rössler et al. "Faceforensics++: Learning to detect manipulated facial images." ICCV, 2019.
  - Shi and Jain. DocFace+: ID Document to Selfie Matching. IEEE TRANS. ON BIOMETRICS, BEHAVIOR, AND IDENTITY SCIENCE, 2019

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