FRIEDRICH-ALEXANDER-UNIVERSITÄT ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Introduction

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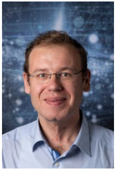
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg
October 18, 2023

Who are we? - Lab Members



Andreas Maier

Zijin Yang

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Merlin Nau

Srikrishna Jaganathan

Alexander Barnhill

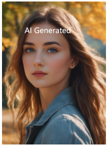
Kai Packhäuser

Noah Maul

Mathias Zinnen

Chang Liu

Who are we? - Student Members



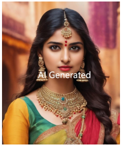
Lisa
Schmidt

Majid
Sharghi

Chengze
Ye

Teena
Tom Dieck

Leyi
Tang



Supraja
Ramesh

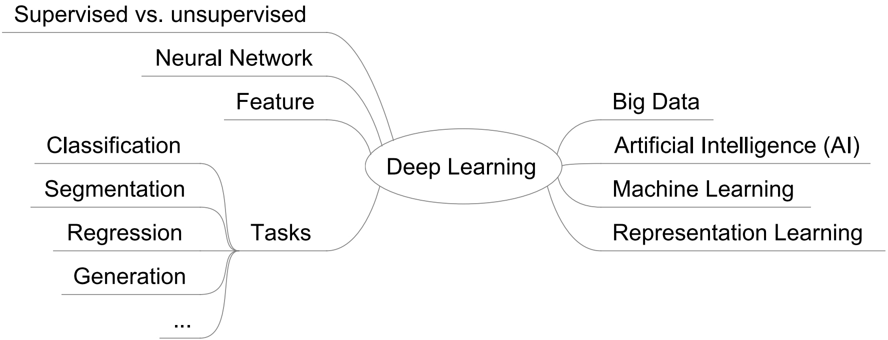
Karlo
Gabriel
Fonseca
Yakovenko

Jingyi
Yao

Anna-
Sophie
Stephan

Philip
Wagner

Deep Learning – Buzzwords



Outline

Motivation

NVIDIA Stock Market

Crypto

Source: https://walletinvestor.com/stock-forecast/nvda-stock-prediction/chart started by challenge - Boom

The Big Bang of Deep Learning

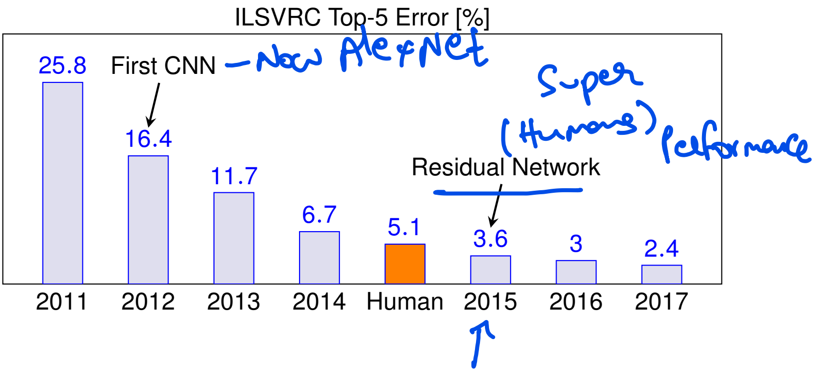
ImageNet [8] Dataset

Before DL impossible

- ≈ 14 mio. images, labeled into ≈ 20.000 **synonym sets**
- **I**mageNet **L**arge **S**cale **V**isual **R**ecognition **C**hallenge using ≈ 1000 classes
- Images downloaded from the Internet, **single** label per image
- **2012: Breakthrough** by Krizhevsky et al. [10]

Source: Krizhevsky et al. 2012

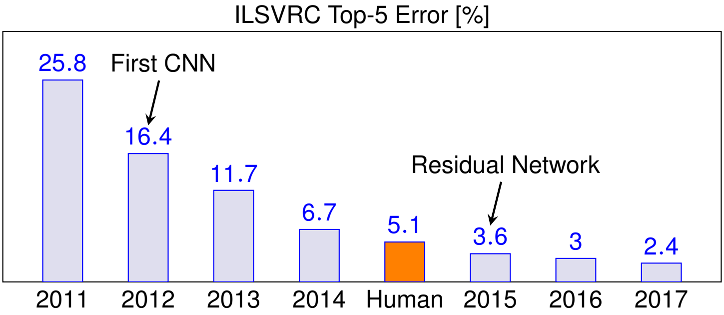
ImageNet Large Scale Visual Recognition Challenge



- First CNN approach now famous as **AlexNet** [10]

Source: image-net.org, Russakovsky et al. 2015

ImageNet Large Scale Visual Recognition Challenge

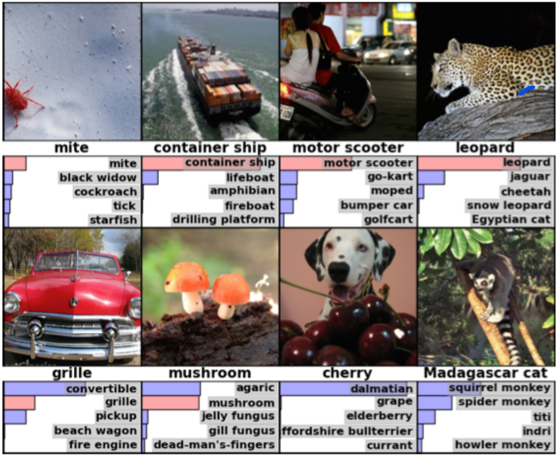


- First CNN approach now famous as **AlexNet** [10]
- “Superhuman” should be Super-Karpathy-an performance

He went through whole set

Source: image-net.org, Russakovsky et al. 2015

ImageNet Large Scale Visual Recognition Challenge



Easy

difficult tasks

Maybe 1 single label is not enough for this challenge

Source: Krizhevsky et al. 2012

Deep Learning Users

Recomendation challenge
(SOLVED)

NETFLIX

Lunit

DAIMLER

SIEMENS

IBM

Google

DeepMind

xerox

SAMSUNG

Microsoft

Playing Go

Chess

- **1997**: Deep Blue beats Garry Kasparov
- **Go** as a next challenge
- Large branching factor

Dictionary →

Brute force

→ Dictionary

Start stage

mid stage

End stage

Source: https://commons.wikimedia.org/wiki/File:FloorGoban.jpg

Playing Go

- **1997**: Deep Blue beats Garry Kasparov
- **Go** as a next challenge
- Large branching factor
- **2016**: AlphaGo [16] beats a professional

Exhausting Search
(Brute-force)
explodes

here easily.

Source: https://commons.wikimedia.org/wiki/File:FloorGoban.jpg

Playing Go

- **1997**: Deep Blue beats Garry Kasparov
- **Go** as a next challenge
- Large branching factor
- **2016**: AlphaGo [16] beats a professional
- **2017**: AlphaGoZero [1] surpasses every human in Go by self-play
- **2017**: AlphaZero [2] generalizes to a number of other board games

Source: https://commons.wikimedia.org/wiki/File:FloorGoban.jpg

Playing Go

- **1997**: Deep Blue beats Garry Kasparov
- **Go** as a next challenge
- Large branching factor
- **2016**: AlphaGo [16] beats a professional
- **2017**: AlphaGoZero [1] surpasses every human in Go by self-play
- **2017**: AlphaZero [2] generalizes to a number of other board games
- **2019**: AlphaStar beats professional StarCraft players

Source: https://commons.wikimedia.org/wiki/File:FloorGoban.jpg

Google DeepDream

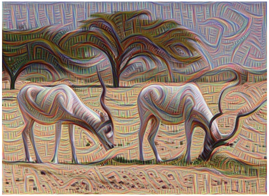
Attempt to understand the inner workings of the network: What it "dreams" about when presented with images

Attempts → Inner working

Idea:

- Arbitrary image or noise as input
- Instead of adjusting network parameters, tweak image towards high activations
- Different layers enhance different features (low or high level)

↓

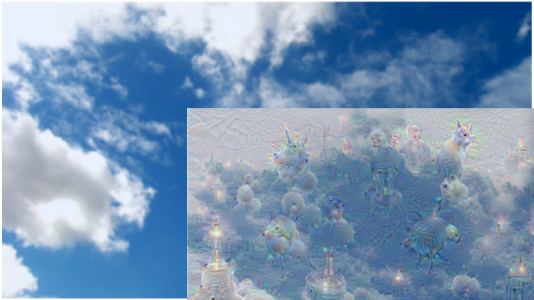


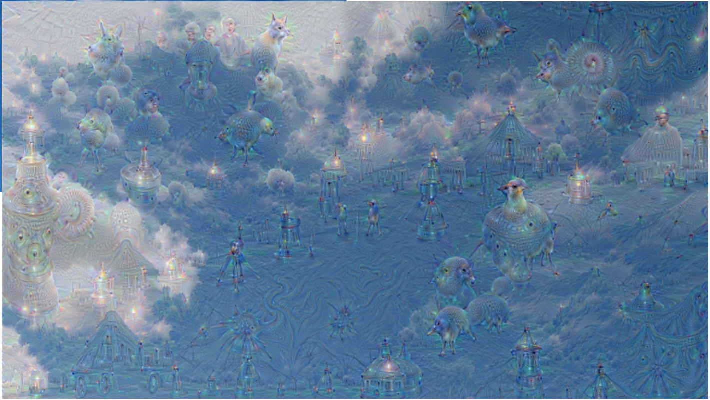
Source: https://research.googleblog.com

Google DeepDream

Source: https://research.googleblog.com

Google DeepDream

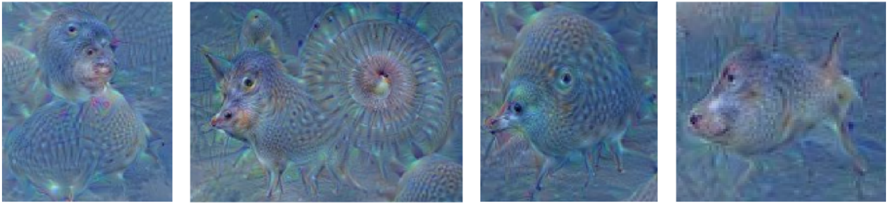




Source: https://research.googleblog.com

Google DeepDream

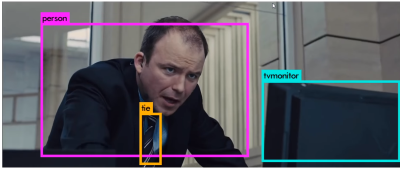
Looking for new animals in the clouds

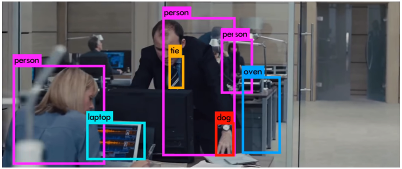


"Admiral Dog!" "The Pig-Snail" "The Camel-Bird" "The Dog-Fish"

Source: https://research.googleblog.com

Real-Time Object Detection: YOLO, YOLO9000, YOLOv3 [11]–[13]





Click for video

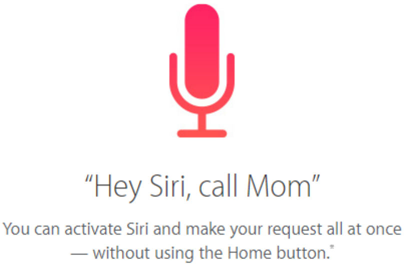
- YOLO: You only ~~live~~ look once
- Prior systems ➔ Use classifiers at multiple locations and scales
- YOLO ➔ Simultaneous regression of bounding box and label
- FAST: 40-90 frames/second on a NVIDIA Titan X

Source: www.youtube.com, Redmon and Farhadi 2016

Every Day Use

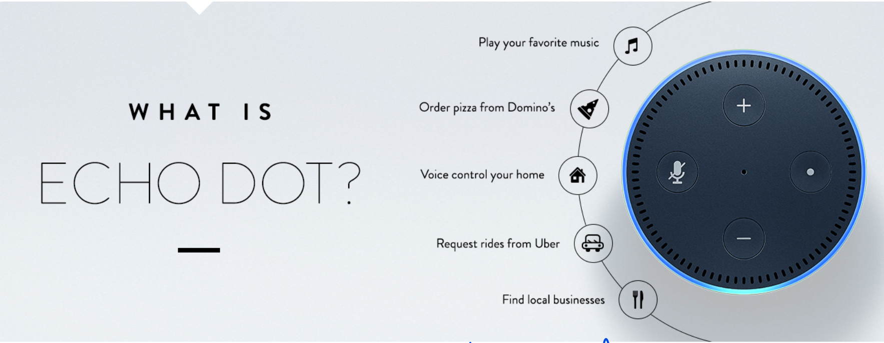
Siri

Siri: Speech Interpretation and Recognition Interface



Source: www.apple.com/ios/siri/

Google Echo & Amazon Alexa Voice Service



Accent - problems

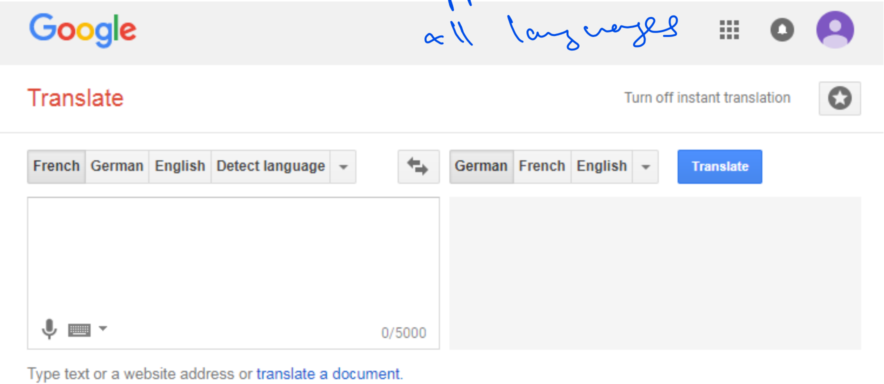
Source: www.amazon.com

Earlier

↳ text → text

Google Translate

Now DL Approach across all languages



Source: translate.google.de

NEXT TIME

ON DEEP LEARNING

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Introduction - Part 2

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April 8, 2020

Research at the Pattern Recognition Lab

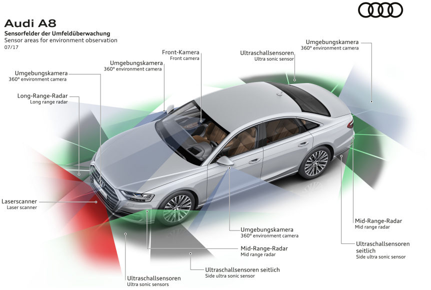
Assisted and Automated Driving

(Audi)

Goal

Find new ways to train and update deep learning mechanisms in environments with high safety requirements

- Assisted and automatic driving relies on sensor data
- Cameras to detect dynamic objects, driving lanes and free space
- Detection and segmentation tasks
  ➔ deep learning



Source: Audi AG

Assisted and Automated Driving

- Currently: neural networks trained and thoroughly tested before deployment

➔ Requires huge amounts of manually labeled data

- Regular test drives cannot verify system reliability in all traffic scenarios

Click for video

Source: Mobileye N.V.

Assisted and Automated Driving

- Currently: neural networks trained and thoroughly tested before deployment

➔ Requires huge amounts of manually labeled data

- Regular test drives cannot verify system reliability in all traffic scenarios
- **Challenge**: New ways to test algorithms in simulated environments and utilize data collected in production cars equipped with appropriate hardware

Click for video

Source: Mobileye N.V.

Smart Devices

Problem statement

Renewable energy power $\neq$ energy demand

- Underproduction ➔ backup power plants
- Overproduction ➔ energy lost

➔ Real-Time-Pricing to match energy demand and supply (not Great idea)

- Needs *smart devices* to shift workload automatically

Smart Devices

Goal

Establish energy equilibrium by predicting energy consumption

- Example: Interrupt fridge cooling cycle when price is high, start washing machine when price is low
- Dependencies between tasks, user information and action necessary (e.g., washer/dryer)
- Task: Identify time-shiftable loads and assess appropriate time frame
- Approach: Train **recurrent neural networks** to identify usage patterns and dependencies between devices

↳ Prev K built on top

Cloud Detection for Power Forecast [4]

Goal

Power forecast for solar power plants with a high temporal and spatial resolution

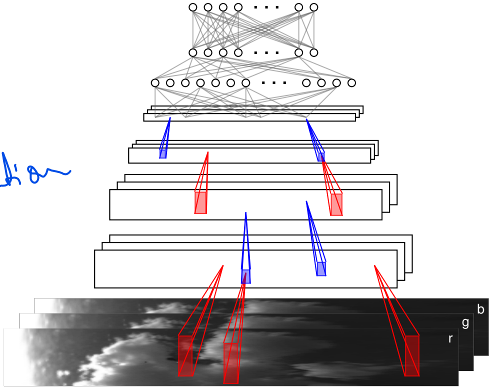
Approach

1. Monitor the sky
2. Detect clouds
3. Estimate the cloud motion
4. Establish power forecasts

How will power will be generated in next 10 minutes by looking at cloud images

Cloud Detection for Power Forecast [4]

Use NN to learn cloud representation



Input: Sky moving towards the sun

Output: Clear Sky Index = values betw. 0 (overcast sky) to 1 (clear sky)

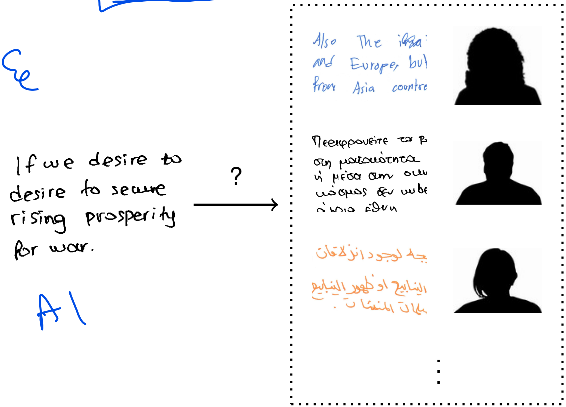
Writer Recognition

Goal

Writer identification with limited training data (few pages per writer)

Identify

Imitate

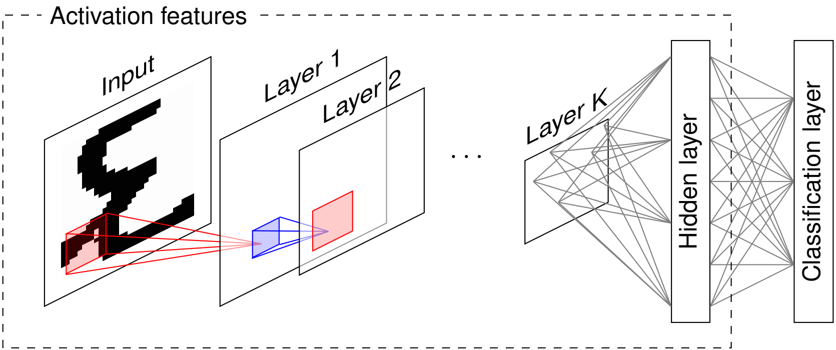


Ethics in AI

Source: ICDAR'13 dataset, QUWI'15 dataset, freepik.com

Writer Recognition using CNN Activation Features [6]

Use Neuronal Network for feature extraction



Medical Applications

Cell Classification for Tumor Diagnostics [3]

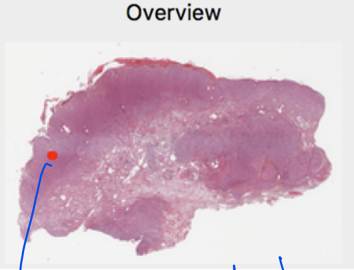
That shows tumor or NOT.
more mitosis → more cells.

Goal

Identify cells undergoing mitosis to asses tumor proliferation and aggressiveness in histological images

Challenge

- Histological images: large number of cells
- Full annotations not feasible
- Sparse annotations
- Cells vary significantly in size/shape/etc



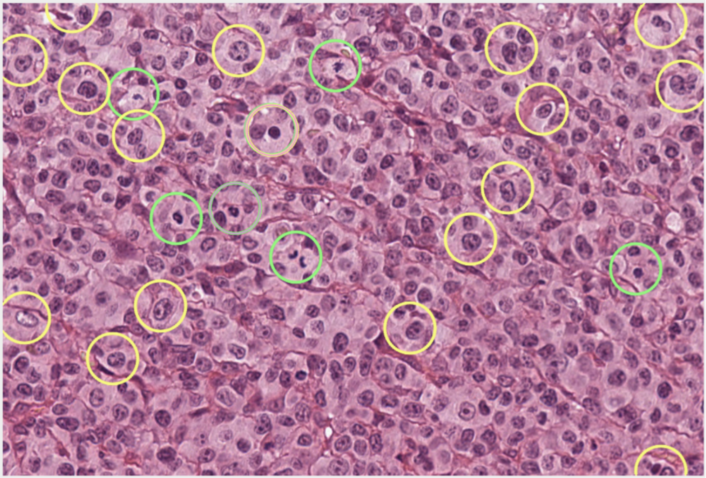
Difficult to identify on microscope

(Similar also available. Tumor / Non-tumor cells.

Source: Aubreville et al. 2017

Only look at high power regions

Cell Classification for Tumor Diagnostics [3]



typically → 10 High power fields

Source: Aubreville et al. 2017

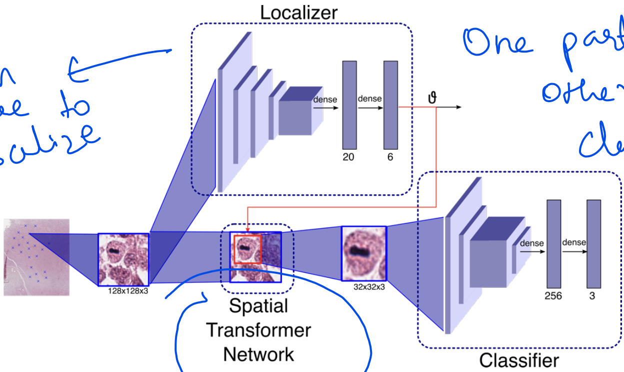
Cell Classification for Tumor Diagnostics [3]

Approach

Use *spatial transformer networks* (STNs) to learn affine transformation **and** classification

learn where to localize

One part localises other part classifies



learn what to classify

Source: Aubreville et al. 2017

Defect Pixel Interpolation

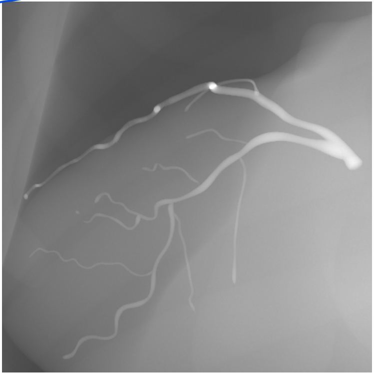
Iodine based contrast agents.

Goal

- Reconstruction of coronaries based on truncated X-ray images
- Create "virtual" digital subtraction angiography

Approach

1. Segment coronary vessels
2. Mask fluoroscopic image
3. Inpaint using U-net
4. Subtract inpainted image to get untruncated data



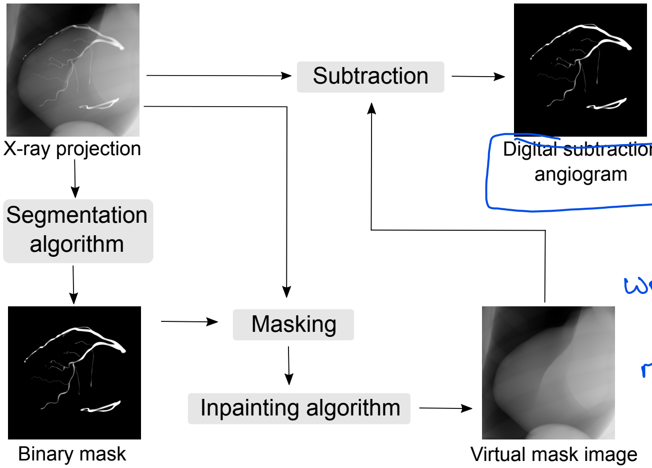
Because Heart → Moves → Very Difficult

Defect Pixel Interpolation

with Contrast agent
without contrast agent

Processing pipeline

DL technique

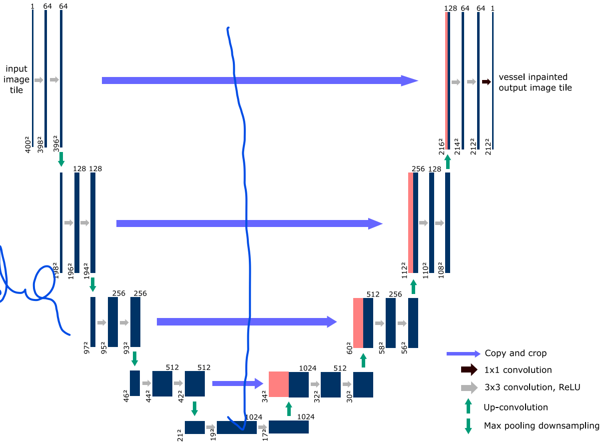


works Even with motion

Defect Pixel Interpolation

UNET ;
General Image
transformer

Deep learning for inpainting



Encoder

Decoder

Organ Search [7]

Localize parts

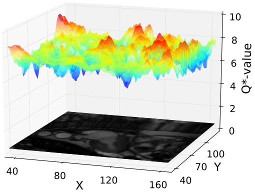
Start somewhere
→ Predict where you would want to Go

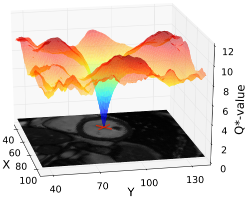
Goal

Locate anatomic structures automatically

Approach

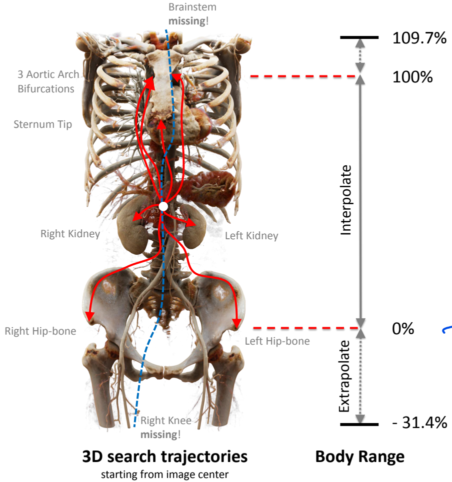
- Deep reinforcement learning
- Learn strategies how to search objects
  ➔ Learn optimal shortest search through image volume to different landmarks
- Hierarchical approach to improve speed and robustness





Source: Ghesu et al. 2016, Ghesu et al. 2017

Organ Search [7]



200 landmarks in 2 seconds.

- Even path finds the not false position.

Organ Search [7]

X-ray-transform Invariant Anatomical Landmark Detection

Goal

- Detect landmarks in X-ray images
- Knowing correspondences enables symbolic reconstruction

→ Classic computervision reconstruction

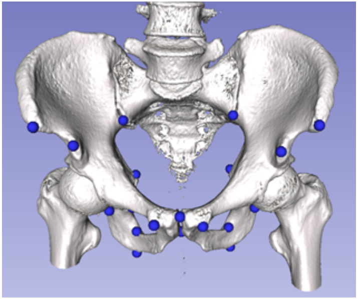
Challenge

- Transmission imaging

→ Overlap/superposition of structures

→ High variance due to projection

→ Artifacts e.g. interventional devices



Source: Bier et al. 2018

X-ray-transform Invariant Anatomical Landmark Detection

Approach: Convolutional Pose Machine (CPM) [17]

CPM

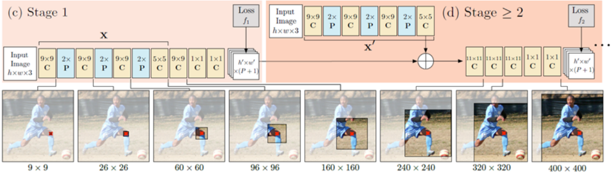
- Sequential prediction framework to detect landmarks

→ Yields 2D belief maps

process each landmark individually & other positions

Properties

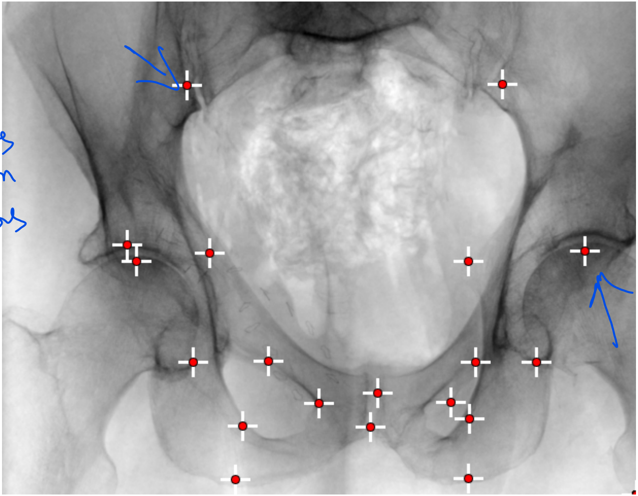
- Large receptive fields enable learning of configurations
- Estimation is refined over stages



Source: Wei et al. 2016

X-ray-transform Invariant Anatomical Landmark Detection

Hipbone locations even on rotations



Source: Bier et al. 2018

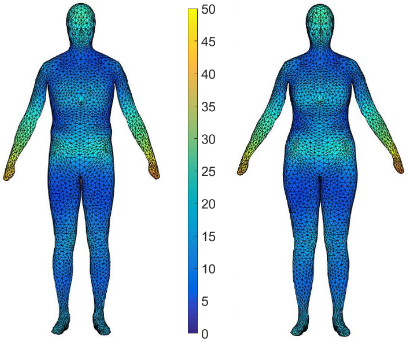
Organ Prediction

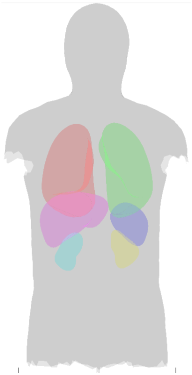
Using a 3D Camera

Goal

Estimation of body and organ shapes based on patient's height and weight for X-ray exposure estimation.

Adjust - Dosage to organs



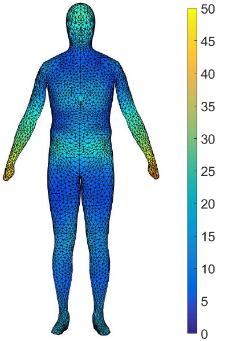


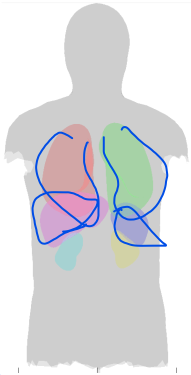
Organ Prediction

only from surface

Goal

Estimation of body and organ shapes based on patient's height and weight for X-ray exposure estimation.





Could we achieve more if we had old CT data of a patient?

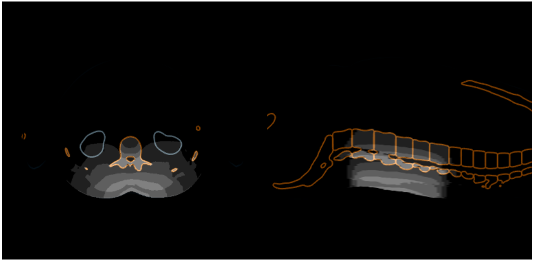
Action Learning for 3D Point Cloud Based Organ Segmentation

Goal: Versatile organ segmentation for:

- Use it in computer aided diagnosis
- Treatment planning
- Dose management

Over dosage ⇒ Cancer.

Dose estimation in interventions with overlays

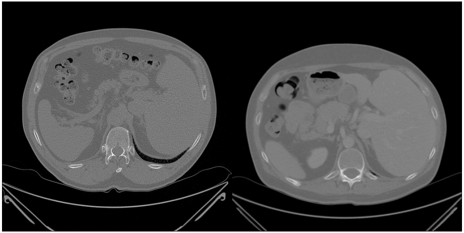


Action Learning for 3D Point Cloud Based Organ Segmentation

Challenges for clinical applications

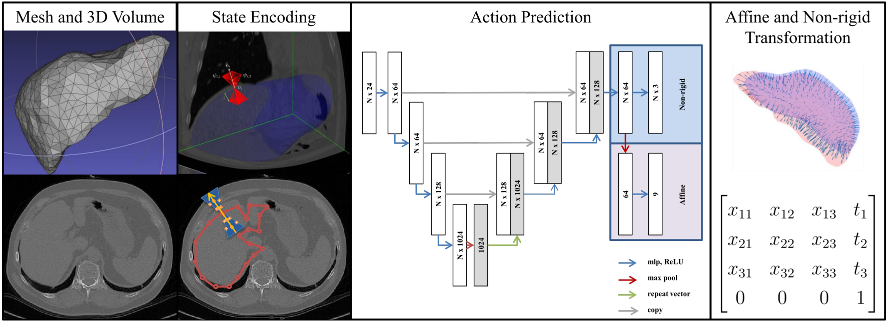
- Robustness w.r.t.
    1. Individual anatomy
    2. Scan protocols
- Time constraints

Pre-operative CT (left) and contrast enhanced CT (right)



Action Learning for 3D Point Cloud Based Organ Segmentation

- Reinforcement learning
- Predict the transformation at given state



Action prediction pipeline for 3D point cloud based organ segmentation

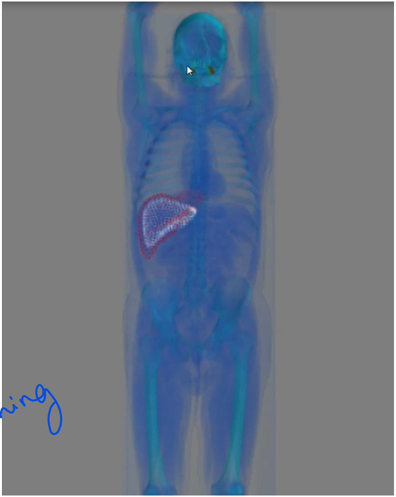
Source: Zhong et al. 2018

Action Learning for 3D Point Cloud Based Organ Segmentation

- Runtime:
  1. **0.3 - 2.6s per volume**
  2. **50 - 100 speedup** from U-net [5]
- Very accurate
- Robust to:
  1. scan protocol
  2. contrast agent
  3. organ initialization

Trained on CT but works on low-level as well

Pre sizes are given so only matching



Source: Zhong et al. 2018

NEXT TIME

ON DEEP LEARNING

Introduction - Part 3

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April 8, 2020

Limitations

Image Captioning

(old)

Image captioning (e.g., Karpathy et al. 2014 [9]) often yields impressive results:

"baseball player is throwing ball in game."

"girl in pink dress is jumping in air."

"man in black shirt is playing guitar."

(impressive)

Source: http://cs.stanford.edu/people/karpathy/deepimagesent

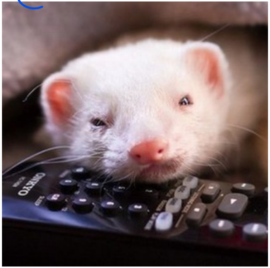
Image Captioning

(Very bad)

"Straightforward" errors:

(misunderstanding)

"a young boy is holding a baseball bat."



"a cat is sitting on a couch with a remote control."

"black cat is sitting on top of suitcase."

Source: http://cs.stanford.edu/people/karpathy/deepimagesent

Image Captioning

Plainly wrong: (totally Gone)

"a horse is standing in the middle of a road."

"a woman holding a teddy bear in front of a mirror."

Source: http://cs.stanford.edu/people/karpathy/deepimagesent

Challenges with Training Data

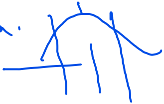
- Deep learning applications often rely on **huge**, manually-annotated data sets
- Hard to obtain, time-consuming, expensive, ambiguous
- To err is human: Mislabeled ground-truth annotation

➔ May cause a significant drop in performance

ImageNet challenge
(Dual Labels)

Peak distributions
Good/Common labels

Broad distribution
Multiple label dilemma.



Challenges with Training Data

- Deep learning applications often rely on **huge**, manually-annotated data sets
- Hard to obtain, time-consuming, expensive, ambiguous
- To err is human: Mislabeled ground-truth annotation

➔ May cause a significant drop in performance

- Question: How far can we get with simulations?

Challenges with Trust and Reliability

- Verification is mandatory for high risk applications

➔ End-to-end learning prohibits verification of parts

➔ Largely unsolved

Black Box

Regulators - Govt. / People (CXO)

Challenges with Trust and Reliability

- Verification is mandatory for high risk applications

➔ End-to-end learning prohibits verification of parts

➔ Largely unsolved

- Possible solution: Reformulate classical algorithms

→ Not Concrete

Future Directions

(At Erlangen)

FRIEDRICH-ALEXANDER-UNIVERSITÄT ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Learning of Algorithms

- Computed Tomography
- Efficient solution via filtered back-projection:

$$f(x, y) = \int_0^{\pi} p(s, \theta) * h(s)\big|_{s=x\cos\theta+y\sin\theta} d\theta$$

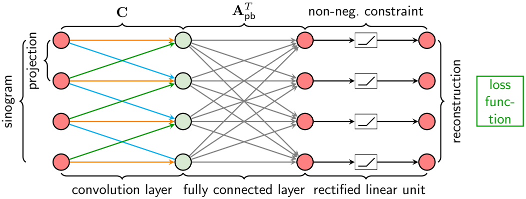
- Three steps:
  - Convolution along s — C
  - Back-projection along θ — F
  - Suppress negative values — ReLU

Reconstruction Networks

Convolve along s ; B.p along θ ; suppress -ve)

(C F Relu)

- All three steps can be modeled as a neural network:



- All weights are known from FBP

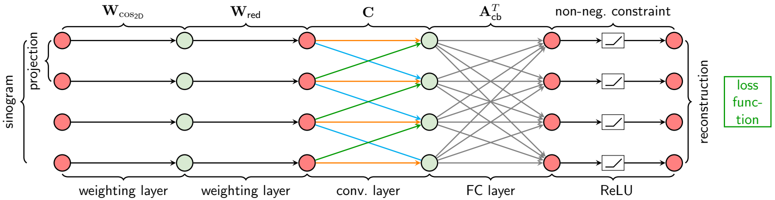
↗ Non negative suppress.

Reconstruction Networks

W W C FC. ReLU

B.P
↳ FC.

- Reconstruction Networks can be expanded



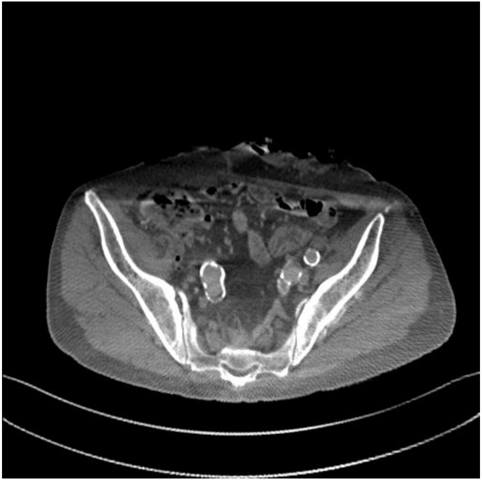
- Embedding of "heuristics" for artifact reduction possible

Re-construction of CT

Application to Incomplete Scans [18]

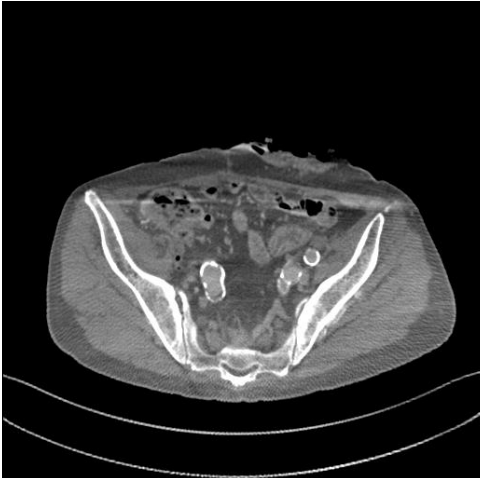
Reconstruction with 360°

Application to Incomplete Scans [18]



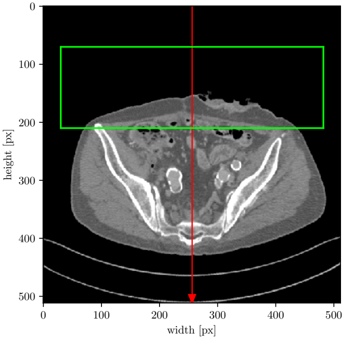
Reconstruction with 180° (FBP)

Application to Incomplete Scans [18]

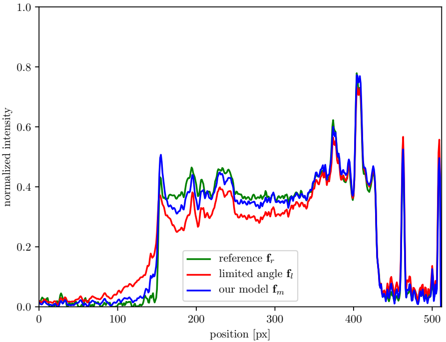


Reconstruction with 180° (NN)

Application to Incomplete Scans [18]

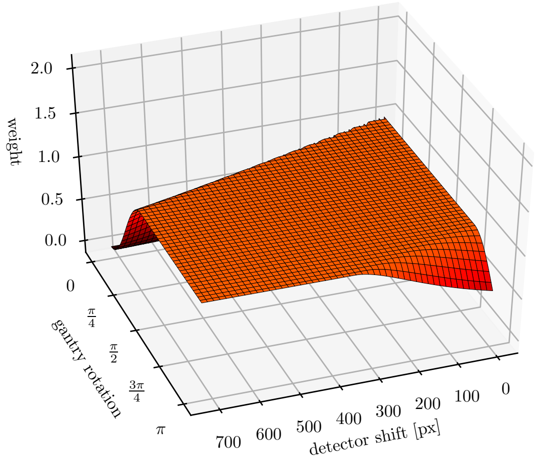


Location of the lineplot



Lineplot

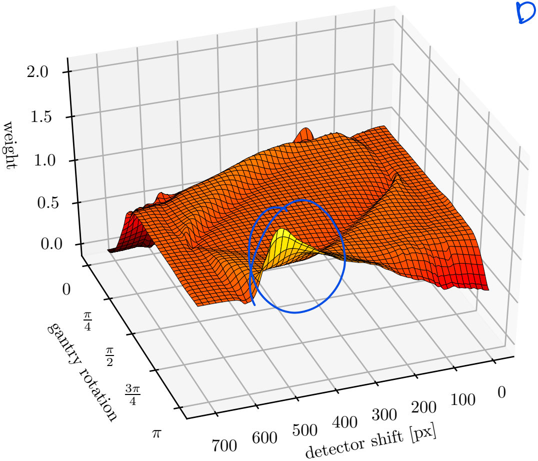
Parker Weights



Parker weights before learning

Parker Weights

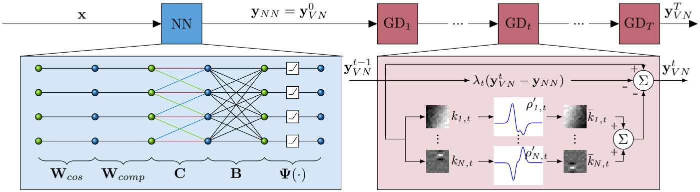
Learning more in Angular limitation directions.



Parker weights after learning

Further Extensions

- Add non-linear de-streaking and de-noising step:

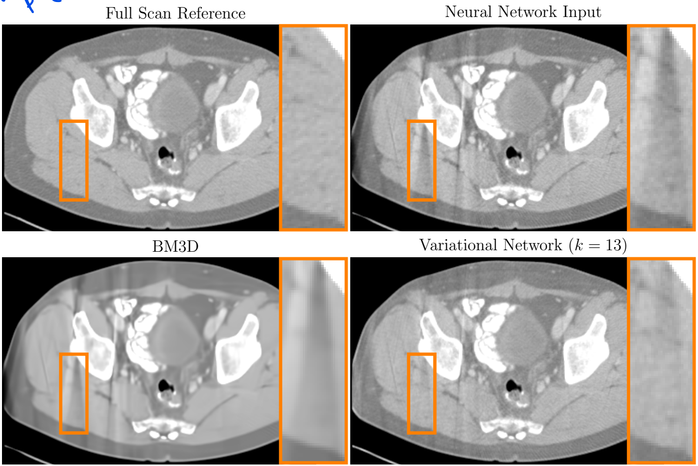


Step 1: Neural network CT reconstruction **Step 2: Variational network non-linear filtering**

Further Extensions

Sample

NN



NEXT TIME

ON DEEP LEARNING

Introduction - Part 4

A. Maier, V. Christlein, K. Breininger, Z. Yang, L. Rist, M. Nau, S. Jaganathan, C. Liu, N. Maul, L. Folle, K. Packhäuser, M. Zinnen
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg
April 8, 2020

Machine Learning and Pattern Recognition

Terminology and Notation

Very important

Throughout these slides, we will use the following notation:

- Matrices: bold, uppercase, e.g., $\mathbf{M}$, $\mathbf{A}$
- Vectors: bold, lowercase, e.g., $\mathbf{v}$, $\mathbf{x}$
- Scalars: italic, lowercase, e.g., y, w, α
- Gradient of a function: ∇, partial derivative: ∂

Terminology and Notation

Throughout these slides, we will use the following notation:

M A
- Matrices: bold, uppercase, e.g., **M**, **A** – M capitals

v x
- Vectors: bold, lowercase, e.g., **v**, **x** – bold; small.
- Scalars: italic, lowercase, e.g., y, w, α
- Gradient of a function: ∇, partial derivative: ∂

Very important

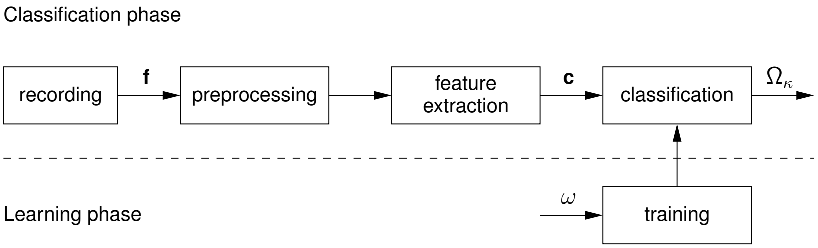
Notation regarding deep learning:

- Trainable parameters ("weights"): w
- Features/input: **x** → vector
- Ground truth label/target: y → scalar
- Estimated output: $\hat{y}$ → $\hat{y}$ scalar.
- Index denoting iteration will be in superscript, e.g., $\mathbf{x}^{(i)}$

iteration index.

The notation and the terminology will be further developed throughout the lecture.

"Classical" Image Processing Pipeline

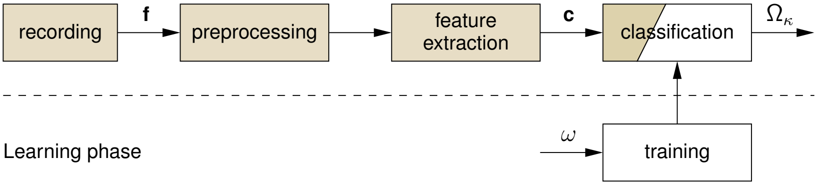


[RPFCT]

“Classical” Image Processing Pipeline

Lecture Introduction to Pattern Recognition

Classification phase

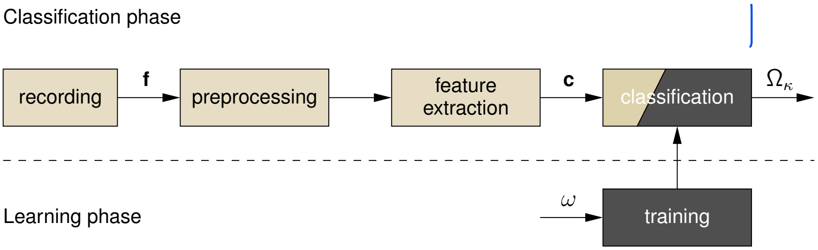


"Classical" Image Processing Pipeline

R P F C

Lecture Introduction to Pattern Recognition

T



Lecture Pattern Recognition

"Classical" Image Processing Pipeline: Apple vs. Pears

Source: https://commons.wikimedia.org

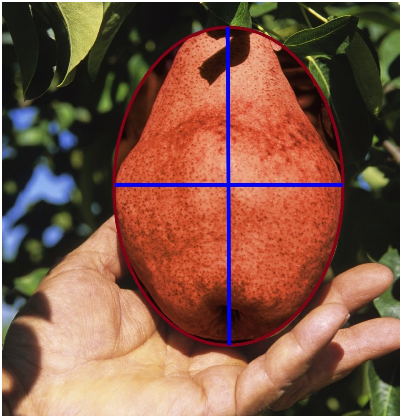
“Classical” Image Processing Pipeline: Apple vs. Pears

Circle

Major Vs Minor Axis

Source: https://commons.wikimedia.org

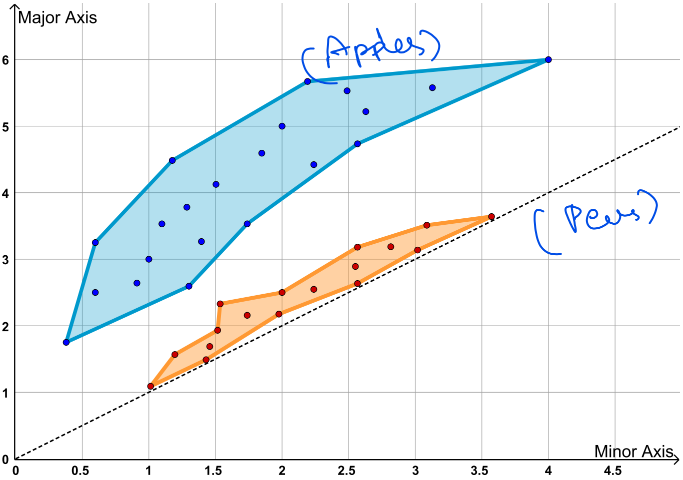
“Classical” Image Processing Pipeline: Apple vs. Pears



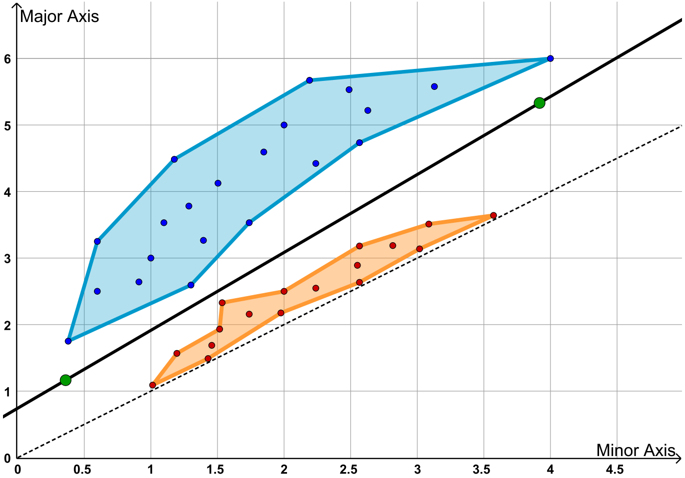
Source: https://commons.wikimedia.org

“Classical” Image Processing Pipeline: Apple vs. Pears

2D Space

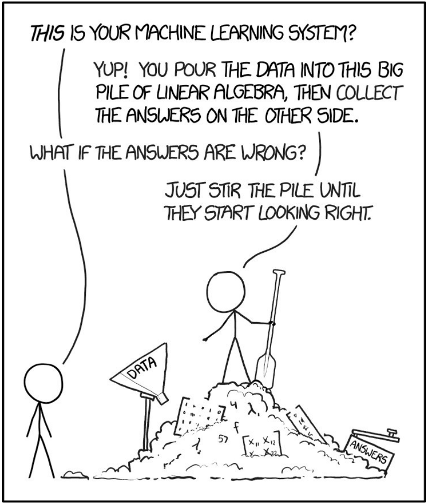


“Classical” Image Processing Pipeline: Apple vs. Pears



Pipeline in Deep Learning

WRONG thought process



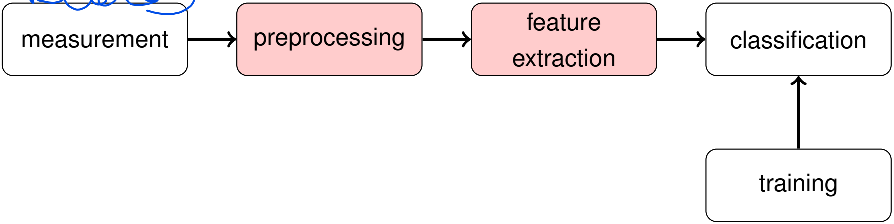
Source: https://xkcd.com/1838/

(MPFCT)

Pipeline in Deep Learning

Reminder

Reality

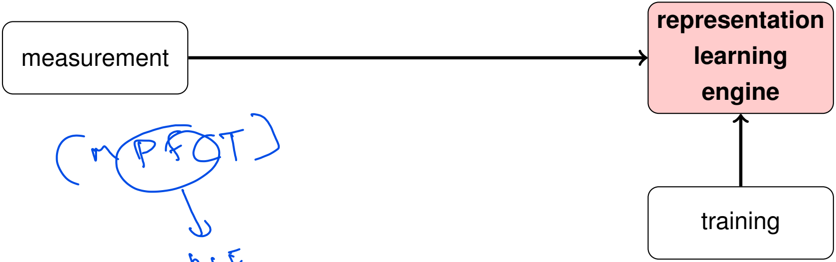


[M RLE T]

Pipeline in Deep Learning

Everything into one

Now



(MPFOT)

RLE

Not Any Data

Right Data

(i.S)

Postulates for Pattern Recognition

6 Postulates:

1. Availability of a **representative sample** ω of **patterns** ${}^i\mathbf{f}(\mathbf{x})$ for the given field of problems Ω

$$\omega = \{{}^1\mathbf{f}(\mathbf{x}), \ldots, {}^N\mathbf{f}(\mathbf{x})\} \subseteq \Omega.$$

new observation → similar to that of Existing.

Postulates for Pattern Recognition

6 Postulates:

1. Availability of a **representative sample** ω of **patterns** ${}^{i}\mathbf{f}(\mathbf{x})$ for the given field of problems Ω

$$\omega = \{{}^{1}\mathbf{f}(\mathbf{x}), \ldots, {}^{N}\mathbf{f}(\mathbf{x})\} \subseteq \Omega.$$

2. A (simple) pattern has **features**, which characterize its membership in a certain class Ω_κ.

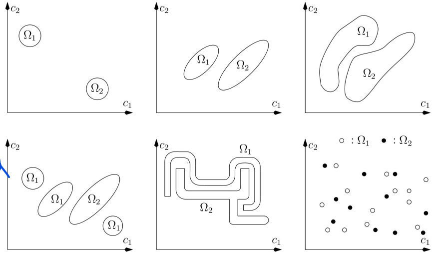
data ⇒ derive abstract representation
↓
classify.

Postulates for Pattern Recognition (cont.)

3. Compact domain of features of the same class; domains of different classes are (reasonably) separable.
   - small **intra-class distance**
   - high **inter-class distance**

Example of an increasingly less compact domain in the feature space:

(Same Class) Inter mixed



(Avoid) find better features

Postulates for Pattern Recognition (cont.)

4. A (complex) pattern consists of **simpler constituents**, which have certain relations to each other. A pattern may be decomposed into these constituents.

Comp Pattern ⇐ smaller | simpler constituents

Postulates for Pattern Recognition (cont.)

4. A (complex) pattern consists of **simpler constituents**, which have certain relations to each other. A pattern may be decomposed into these constituents.

5. A (complex) pattern $\mathbf{f}(\mathbf{x}) \in \Omega$ has a certain **structure**. Not any arrangement of simple constituents is a valid pattern. Many patterns may be represented with relatively few constituents.

Postulates for Pattern Recognition (cont.)

4. A (complex) pattern consists of **simpler constituents**, which have certain relations to each other. A pattern may be decomposed into these constituents.
5. A (complex) pattern $\mathbf{f}(\mathbf{x}) \in \Omega$ has a certain **structure**. Not any arrangement of simple constituents is a valid pattern. Many patterns may be represented with relatively few constituents.
6. Two patterns are **similar** if their features or simpler constituents differ only slightly.

not required,

Complex Pattern

$C_1 \to C_2 \to C_3 \to C_4$

$|C_8 - C_4| \geq 0$

P_1, P_2 Same

$P_2 \cong C_5\ C_6\ C_7\ C_8$

Many still valid in DL

Perceptron

Perceptron Biology - Neural Excitation (simplified)

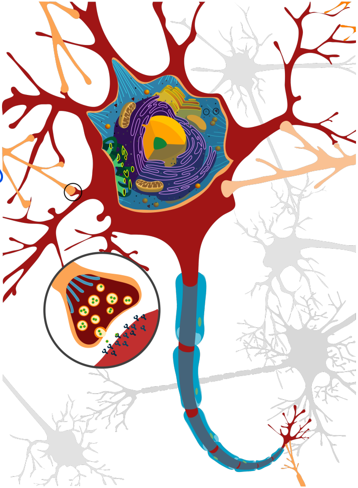
fire / no fire

- Neurons are **connected** by synapses / dendrites
- If the **sum** of incoming (excitatory and inhibitory) **activations** is large enough, an action potential is created

or

Binary

- The action potential activates synapses to other neurons, "transmitting" information
- All-or-none response: A **higher** stimulus does **not** cause a **higher** response
  ➔ "binary classifier"



Source: https://commons.wikimedia.org

franc Rosenblatt.

vector [ ]

$$\begin{bmatrix} w_0 \\ w_1 \\ \vdots \end{bmatrix}_{n+1,1} \qquad [1, x_1 .. x_n]$$

Rosenblatt's Perceptron

- In 1957, Frank Rosenblatt [14] invented the Perceptron
- (scaler) Binary classification $y \in \{-1, 1\}$.
- It computes the function

simplistic

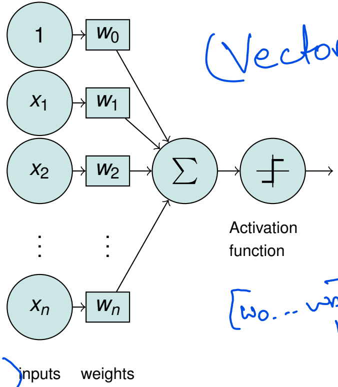
o/p $\hat{y} = \text{sign}(\mathbf{w}^\mathsf{T}\mathbf{x})$,

$\hat{y} = \text{sign}(w^T x)$

where

$\mathbf{w} = (w_0, \ldots, w_n)$: set of weights ($w_0$=bias) $1 \times n+1$

$\mathbf{x} = (1, x_1, \ldots, x_n)$: input feature vector



(Vectors)

$[w_0 \ldots w_n]$ $1 \times n+1$

$\hat{y} = \text{sign}(w^T x)$
$n+1 \times 1 \quad 1 \times n+1$

$$\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}_{n+1 \times 1}$$

[C.S]

Perceptron Objective Function

Task: Find weights that minimize the distance of misclassified samples to the decision boundary

Assumptions

$S = \{(\text{vector}, \text{scalar}), \ldots\} \rightarrow$ (tuples of observables)

- Let $S = \{(\mathbf{x_1}, y_1), (\mathbf{x_2}, y_2), \ldots, (\mathbf{x_m}, y_m)\}$ be a training data set
- Let $\mathcal{M}$ be the set of misclassified feature vectors $y_i \neq \hat{y}_i = \text{sign}(\mathbf{w}^\mathsf{T}\mathbf{x_i})$ according to a given set of weights $\mathbf{w}$
- Optimization problem: $D(w) = -\sum_{x_i \in \mathcal{M}} y_i \cdot (w^T x_i)$

Because of $y = \text{sign}(w^T x_i)$ sign $\Rightarrow$ (-1)

$1 \rightarrow -1$

$-1 \rightarrow 1$

always (-1)

$$\underset{\mathbf{w}}{\text{argmin}} \left\{ D(\mathbf{w}) = - \sum_{\mathbf{x_i} \in \mathcal{M}} y_i \cdot (\mathbf{w}^\mathsf{T}\mathbf{x}_i) \right\}$$

$-(-1)$ = max value

which is why min(max value)

[C.S.]

Perceptron Objective Function – Observations

- Objective function depends on misclassified feature vectors $\mathcal{M}$ → iterative optimization
- In each iteration, the cardinality and composition of $\mathcal{M}$ may change
- The gradient of the objective function is:

$\nabla D(\omega) = - \sum_{x_i \in M} y_i x_i$

$$\nabla D(\mathbf{w}) = - \sum_{x_i \in \mathcal{M}} y_i \cdot \mathbf{x}_i$$

Perceptron Training

(Total) & later

- Strategy 1: Process all samples, then perform weight update
- Strategy 2: Take an update step right after each misclassified sample
- Update rule in iteration $(k+1)$ for the misclassified sample $\mathbf{x}_i$ simplifies to:

$$\mathbf{w}^{(k+1)} = \mathbf{w}^{(k)} + y_i \cdot \mathbf{x}_i$$

- Optimization until convergence or for a predefined number of iterations

Repeat

$$w^{(k+1)} = w^k - \eta \cdot \partial w^k$$
$$= w^k + y_i \, x_i$$

(No. of disadvantages (see later))

NEXT TIME

ON DEEP LEARNING

Introduction - Part 5

A. Maier, V. Christlein, K. Breininger, Z. Yang, L. Rist, M. Nau, S. Jaganathan, C. Liu, N. Maul, L. Folle, K. Packhäuser, M. Zinnen

Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg

April 8, 2020

Organizational Matters

Grading

- Module consists of lecture **and** exercises (together 5 ECTS)
- 90 min. written exam in the semester break, determines grade
- Exercises are **optional**. 100% exercise completion = 10% grade when you pass the exam

Exercise Content

- Python introduction
- Developing a neural network framework from scratch
  - Feed Forward Neural Networks
  - Convolutional Neural Networks
  - Regularization
  - Recurrent Networks
- Using the PyTorch framework
  - Large scale classification

Exercise Requirements

- Basic knowledge of Python and Numpy
- Linear algebra, -
- Image processing, -
- Pattern recognition fundamentals
- Passion for coding
- Attention to detail
- Time

How it works

- Five exercises throughout the semester
- Unit tests for all but last exercise
- Last exercise: PyTorch + Challenge
- Assistance during exercise sessions
- Personal demonstration of every exercise to get bonus points
- Exercise deadlines are announced in the respective exercise sessions

Summary

- Deep learning more and more present in day to day life
- Huge support and interest from industry
- **Very** active area of research!
- Perceptron as binary classifier motivated by biological neurons

NEXT TIME

ON DEEP LEARNING

Next Lecture Block

- Extending the Perceptron to obtain a universal function approximator
- Gradient based training algorithm for these models
- Efficient automatic computation of gradients

Comprehensive Questions

[C.S]

- What are the six postulates of pattern recognition?
- What is the Perceptron objective function? [C.S]
- Can you name three applications successfully tackled by deep learning?

Convolution Pose Machine

UNET - Image Segmentation.

Tumor diagnostic

Spatial Transformer Network

Further Reading

- Link - Deep learning book
- Link - Research and publications at the Pattern Recognition Lab
- Link - Google Research Blog with posts on e.g. Deep dream or Alpha Go

Goal — Net

Writer Recognition — CNN

Defect Pixel Interp. — UNET

Tumor detection — Spatial Transformer network

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UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Questions?

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[16] David Silver, Aja Huang, Chris J. Maddison, et al. "Mastering the game of Go with deep neural networks and tree search". In: Nature 529.7587 (Jan. 2016), pp. 484–489.

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