Lecture Notes to

Big Data Management and Analytics
Winter Term 2018/2019

DBS

Course Logisitics

- **Course website:** http://www.dbs.ifi.lmu.de/cms/studium_lehre/lehre_master/bigdata1819/index.html
- **Registration for course & exams via:** https://uniworx.ifi.lmu.de/?action=uniworxCourseWelcome&id=1011
- **Organization:**
    - Lecture: Prof. Dr. Matthias Schubert
    - Assisting: Daniyal Kazempour, Evgeniy Faerman
- **Exam:** 02.10.2018 14:00-16:00 in M218/A240 (main building)

Component	When	Where	Starts at
Lecture	Tue, 13.00 - 16.00 h	Room S 004 (Schellingstr. 3)	16.10.2018
Tutorial 1	Wed, 16.00 - 18.00 h	Room D Z007 (HGB)	24.10.2018
Tutorial 2	Wed, 18.00 - 20.00 h	Room D Z007 (HGB)	24.10.2018
Tutorial 3	Thu, 16.00 - 18.00 h	Room D Z007 (HGB)	26.10.2018
Tutorial 4	Thu, 14.00 - 16.00 h	Room D Z007 (HGB)	26.10.2018

What is Data Analytics and AI?

- Foundations of Data Analytics and AI
- Drivers of modern Data Science
- The Knowledge Discovery Process
- Big Data Management
- Typical Data Mining Tasks
- Deep Learning
- Artificial Intelligence and Data Analytics
- Reinforcement Learning

Foundations: Prediction and AI

How to make decisions?

- What do you know about the current situation ?
- What are your options ?
- Which option is the best?
- How many decisions do I have to make until reaching my goal?

Problems:

- Parts of your current situation might be unknown or not modeled
- Considering all options is often not possible
- Considering all possible impacts of choosing an option is often not possible.

Foundations: Data Analytics and AI

Uncertain situation:

- Impact of fracking to ground water
- True population of a species

Uncertain impacts :

- What would be the impact of grants for renewables in Alberta?
- What are the long term effects of fracking/oil sand usage?

Considering all options:

- Which kinds of grants and funds should be provided?
- What are the newest technical solutions?

Foundations: Data Analytics and AI

So where does data analytics and AI help?

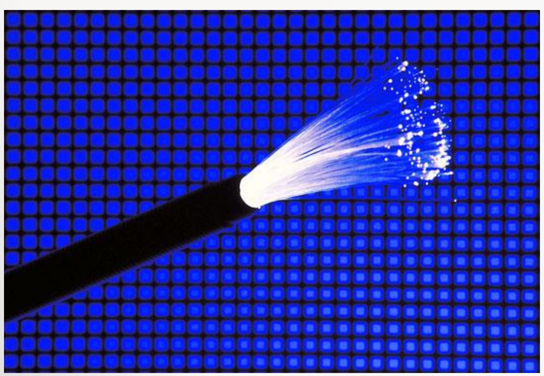
- Modelling uncertain situations and results (Data Analysis)
    - Predict latent situation parameters
    - Predict uncertain outcomes
- Consider possible long-term impacts of decisions (both)
- Develop strategies for achieving long-term goals (AI)

Foundations: Data Analytics

- Statistics (ca. 1663 /some claim even 5 century B.C.)
- Neural Computing (ca. 1943)
- Artificial Intelligence (ca. 1955)
- Machine Learning (ca. 1959)
- Pattern Recognition (ca. 1990 Begriff 1950)
- Data Mining and Knowledge Discovery (ca. 1996)

Drivers of Modern Data Sciences

- Preconditions to Big Data Analytics and modern AI:
- Internet and broadband connections: allowed to publish information easily, access information from a huge amount of sources
- Data Storage: hard drives became larger and cheaper. SSDs make background storage faster. Larger/faster main memory
- Mobile devices: collect personal and spatial data



http://www.ubergizmo.com/2013/01/china-policy-demands-new-residences-have-fiber-optic-connections/

http://blog.rentacomputer.com/2012/09/18/dont-ever-lose-your-data-again-with-a-storage-server-rental/

Drivers of Modern Data Sciences

- Cloud computing: distributed computations on thousands of commodity machines
- Commodity GPUs: dedicated numerical processing power Cheaper sensors/camera: affordable monitoring
- IoT and sensors: monitoring installations and environments
- RC and autonomous mobile units: UAVs, rovers,..

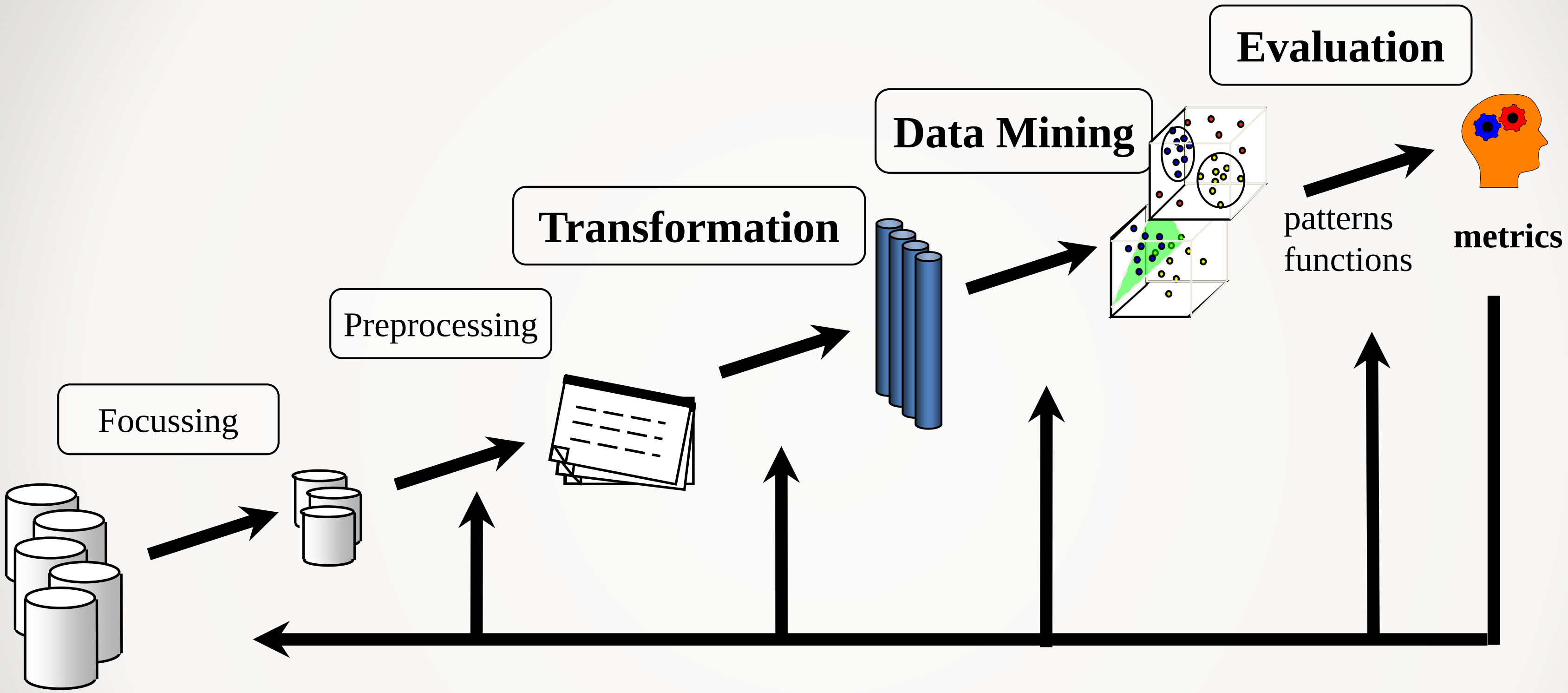
Drivers of Modern Data Sciences

- Impacts on data analytics and AI:
- more data: complex problems become feasible:
    - **before**: available samples only allowed simple models
    - **now**: complex models can be trained because sample sets become huge (several millions+)
- more computational power:
    - **before**: complex models did not finish training
    - **now**: models with several thousand parameters on millions of samples are possible
- scalability:
    - **before**: predictors where done for dedicated cases
    - **now**: building personalized models for millions of cases is possible

Summary

- Some applications already worked out fine centuries before.
- A lot of ideas where created in the 1950 with the first computers, but did not work out.
- Recent breakthroughs in classical problems
  - Image processing
  - Speech recognition
  - Automatic translation
  - AI for board games (e.g. AlphaGo)
- New possibilities and tasks due to:
  - more available data
  - complex prediction networks

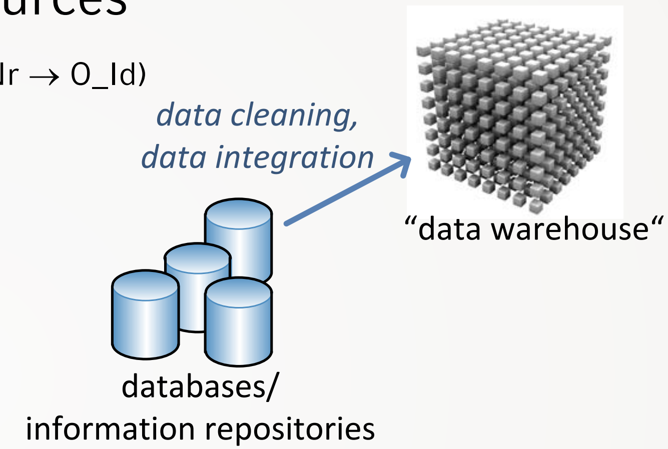
The Knowledge Discovery Process



- Knowledge Discovery is the technical process of knowledge generation
- process is iterative: If results are not satisfying, change the process and try again. (change parameters, more data, different data representations, a simpler goal,..)

Data Cleaning and Integration

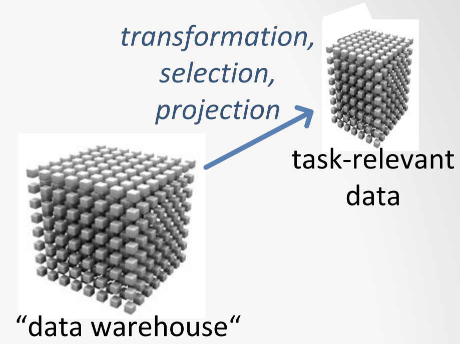
- …may take 60% of effort
- integration of data from different sources
  - mapping of attribute names (e.g. C_Nr → O_Id)
  - joining different tables
    (e.g. Table1 = [C_Nr, Info1]
    and Table2 = [O_Id, Info2] ⇒
    JoinedTable = [O_Id, Info1, Info2])



- elimination of inconsistencies
- elimination of noise
- computation of Missing Values (if necessary and possible)
- fill in missing values by some strategy (e.g. default value, average value, or application specific computations)

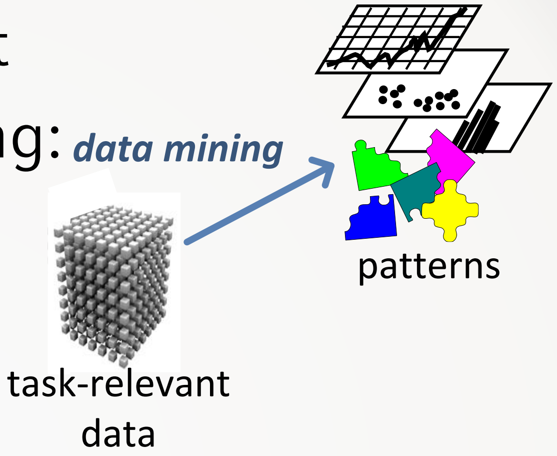
Focusing on Task-Relevant Data

- Find useful features, dimensionality/variable reduction, invariant representation
- creating a target data set
- selections
  - Select the relevant tuples/rows from the database tables (e.g., sales data for the year 2001)
- projections
  - Select the relevant attributes/columns from the database tables (e.g., “id”, “date” “amount” from (Id, name, date, location, amount))
- transformations, e.g.:
  - normalization (e.g., age:[18, 87] → n_age:[0, 100])
  - discretization of numerical attributes (e.g., amount:[0, 100] → d_amount:{low, medium, high})
  - computation of derived tuples/rows and derived attributes
  - aggregation of sets of tuples (e.g., total amount per months)
  - new attributes (e.g., diff = sales current month – sales previous month)



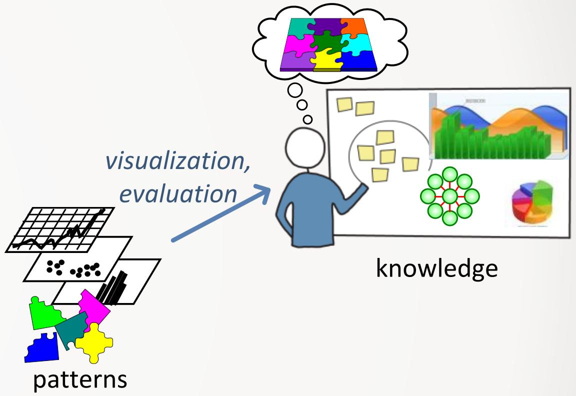
Basic Data Mining Tasks

- searching for patterns of interest
- choosing functions of data mining:
  - Clustering
  - Classification
  - Frequent Patterns
  - Other methods
    - outlier detection
    - sequential patterns
    - trends and analysis of changes
    - methods for special data types, e.g., spatial data mining, web mining
    - …
- choosing the mining algorithm(s)



Evaluation and Visualization

- pattern evaluation and knowledge presentation:
  Visualization, transformation, removing redundant patterns, etc.
- integration of visualization and data mining
  - data visualization
  - data mining result visualization
  - data mining process visualization
  - Interactive visual data mining



- different types of 2D/3D plots, charts and diagrams are used, e.g.: Box-plots, trees, X-Y-Plots, parallel coordinates
- use of discovered knowledge

Data Management

- **more data** causes **more** handling **problems**:
- data from foreign sources usually has no clear structure (what does a number mean, how is the information related)

  => date exploration to find out what is there?
- data integration data from different sources (integrate once all vs. on demand integration)
- how to structure the data (data variety)
- when is data changed/updated (data volatility)
  - streaming data (data arrives constantly)
  - batch data (data arrives in large bulks)
- selecting and manipulating data should be easy
- data quality must be addressed (missing, synchronization, errors, e.t.c.) (data veracity)

Data Management

handling data volume:

Small data: (data fits into the main memory)

- file system: csv-files, excel files, arff
- read everything from file into memory
- manipulate data in memory (e.g. excel,python)

Medium data: (data fits on machine but not into memory)

- database systems, files
- read only necessary part of the data (replace data in memory)
- manipulate data on disk (e.g. SQL queries, temporary views)

Big data: (data does not fit on one machine)

- NoSQL databases, distributed file systems (e.g. Cassandra,HDFS)
- Manipulate data using cloud frame work (e.g. map reduce, Spark)

What else is Big Data?

Business Perspective: A new business model

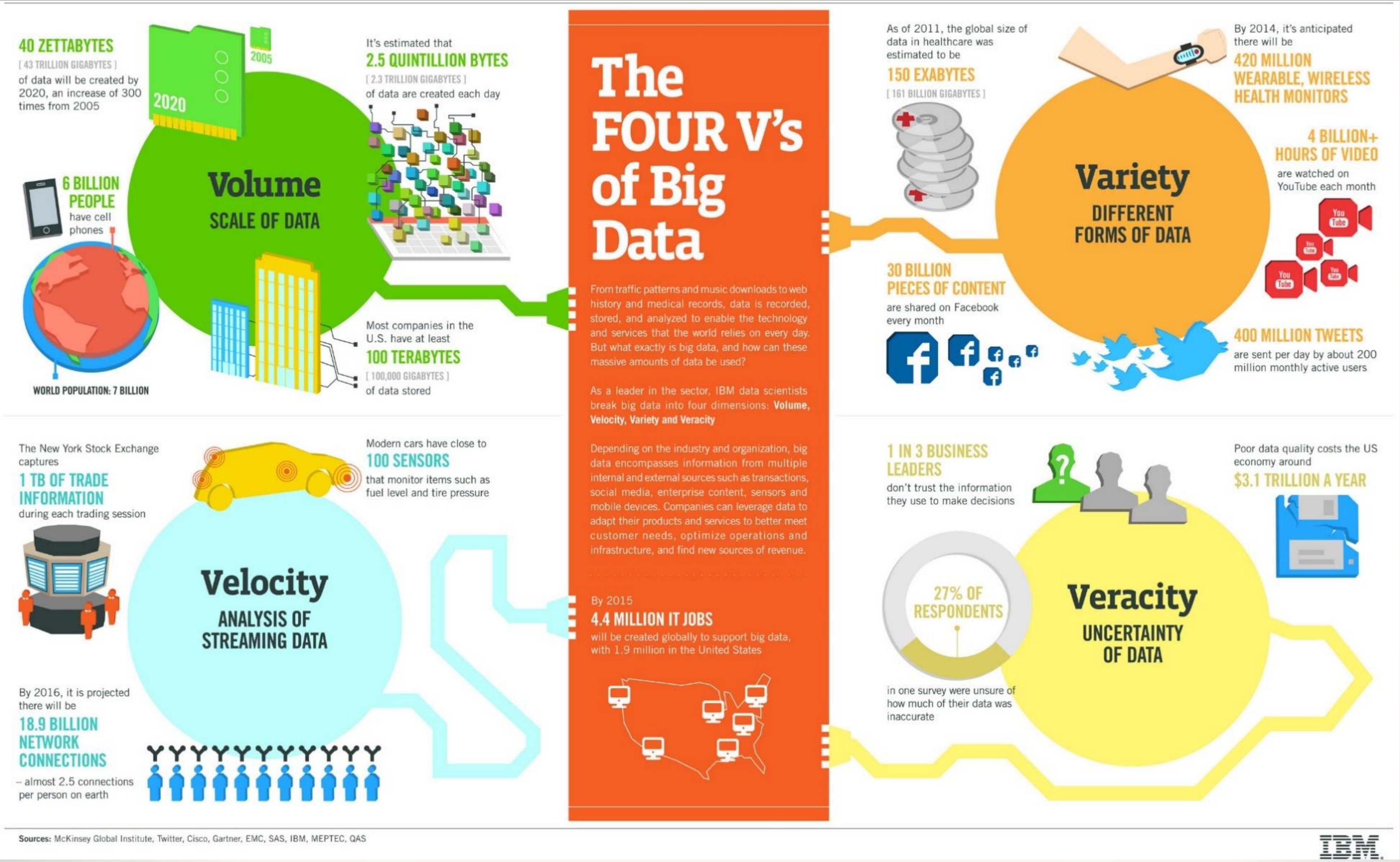
=> People pay with data

- e.g., Facebook, Google, Twitter:
  - use service => provide data
  - data is used for target advertisement
  - (you pay indirectly)
- e.g., Amazon:
  - pay service + give data
  - sells data and uses data to improve service

Four V's of Big Data

- **Volume:** integrated data from many sources
  - volume on disk
  - number of instances or features
- **Velocity:** data is changing/new data is arriving
  - sensors constantly produce data
  - communication is constantly going on
- **Variety:** not all data is the same
  - data can have different structures: vectors, sequences, graphs, tensors
  - different sources rely on different formats
- **Veracity:** the meaning of the data is unsecure
  - inputs may be noisy, manipulated or misinterpreted
  - consider data objects as samples not facts

Four V's of Big Data



Alternative Definitions

Literature does not agree upon the # of Vs defining Big Data

Examples:

- **Laney 2001**
  Laney D. 3D data management: controlling data volume, velocity, and variety, META Group, Tech. Rep. 2001. http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf.

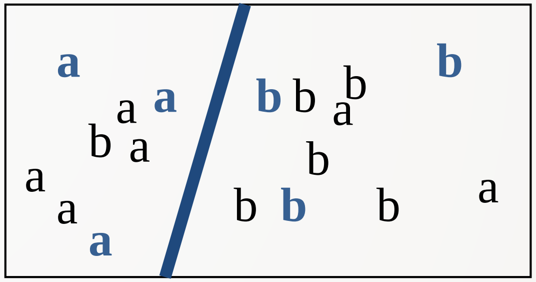
talks about 3 Vs: volume, velocity, and variety

- **later in Van Rijmenam 2014 and Borne 2014**
  van Rijmenam M. Why the 3v's are not sufficient to describe big data, BigData Startups, Tech. Rep. 2013.
  http://www.bigdata-startups.com/3vs-sufficient-describe-big-data/.
  it is pointed out that 3Vs are insufficient.
  In addition to volume, velocity, and variety, further 7 Vs are identified:
  veracity, validity, value, variability, venue, vocabulary, and vagueness

Classification

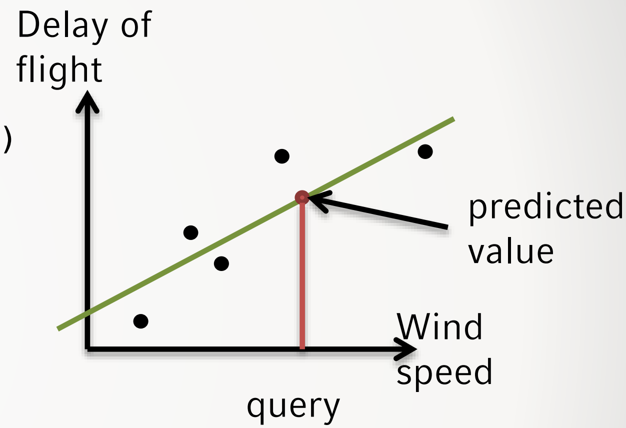
- Class labels are known for a set of "training data":
  Find models/functions/rules (based on attribute values of the training examples) that
  - describe and distinguish classes
  - predict class membership for "new" objects

- Applications
  - image classification
  - document categorization
  - land usage classification from arial images

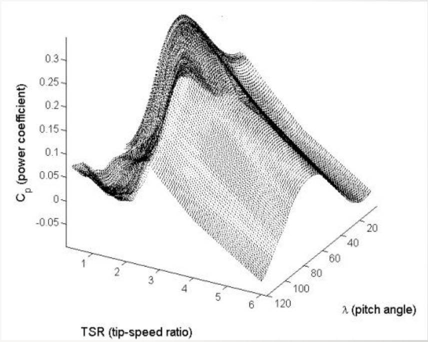


Prediction

- numerical output values are known for a small set of “training data”
- find models/functions (based on attribute values of the training examples) that
  - describe the numerical output values of the training data (Major method for prediction is regression)
  - predict the numerical value for “new” objects



- applications
  - build a model of the housing values, which can be used to predict the price for a house in a certain area
  - build a model of an engineering process as a basis to control a technical system
  - . .

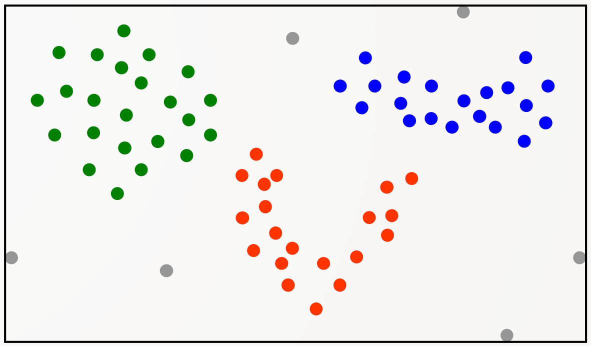


Wind turbine

Clustering

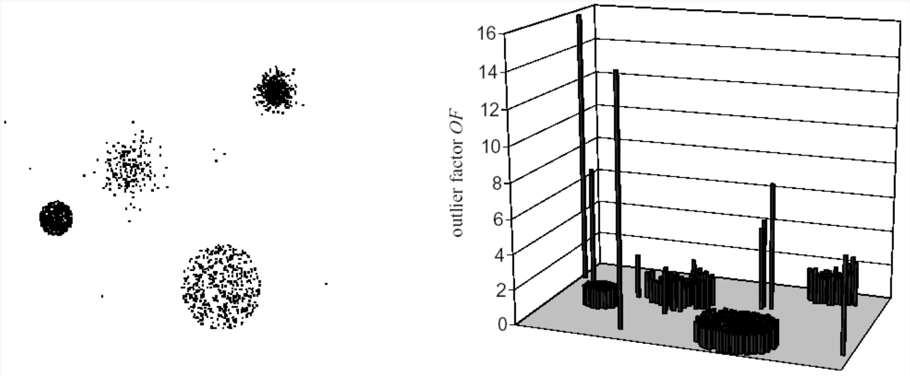
- class labels are unknown:
  group objects into sub-groups (clusters)
  - similarity function (or dissimilarity function = distance) to measure similarity between objects
  - objective: “maximize” intra-class similarity and “minimize” interclass similarity

- applications
  - customer profiling/segmentation
  - document or image collections
  - web access patterns
  - . . .



Outlier Detection

- find data which are uncommon in the given distribution (e.g. measuring errors, critical system conditions, network intrusion, DNS-Attacks to Servers etc.)
- model what is “normal” to the given data distribution:
  - models should be accurate for common cases
  - models might contain varying levels of assumption (kNN-based vs. Statistical Process)
- everything which isn’t normal w.r.t. to the model is an outlier?



Frequent Itemset Mining

- find frequent patterns in transaction databases
  – Frequently co-occurring items in the set of transactions (*frequent itemsets*): indicate correlations or causalities

Transaction ID	Items Bought
2000	A,B,C
1000	A,C
4000	A,D
5000	B,E,F

- applications:
  - market-basket analysis
  - cross-marketing
  - catalog design
  - also used as a basis for clustering, classification
  - association rule mining: Determine correlations between different itemsets

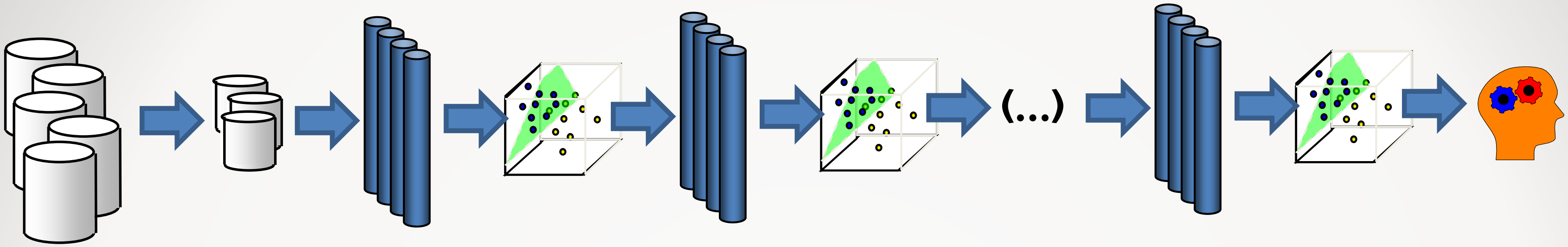
Examples:

buys(x, “diapers”) → buys(x, “beers”) [support: 0.5%, confidence: 60%]
major(x, “CS”) ^ takes(x, “DB”) → grade(x, “A”) [support: 1%, confidence: 75%]

other types of Analysis

- Trends and Evolution Analysis
- Sequential Patterns (find re-occurring sequences of events)
- Spatial Data Mining
  - spatial outlier prediction and clustering
  - spatial prediction
  - trajectory analysis
- Graph Mining:
  - link prediction
  - community detection
  - network centrality
- methods for special data types, and applications e.g.,
  - Natural Language Processing
  - Web Mining
  - Bio-KDD
  - . . .

Deep Learning



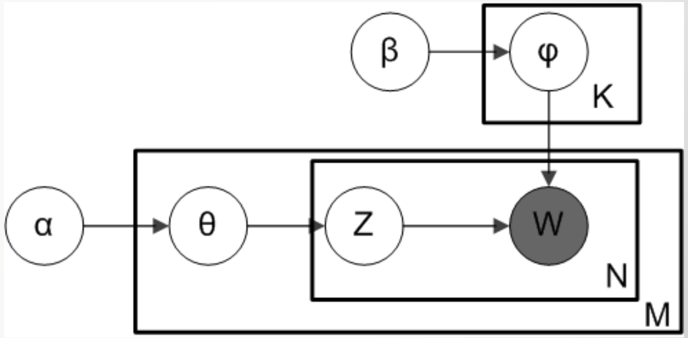
- often a KDD Process involves several transformation and learning task
- combining multiple learners increases the quality

$\Rightarrow$ Deep Architectures

- integrate data transformation and model training (input raw data -> output target variables)
- joint optimization (instead of training each step separately)

Deep Learning

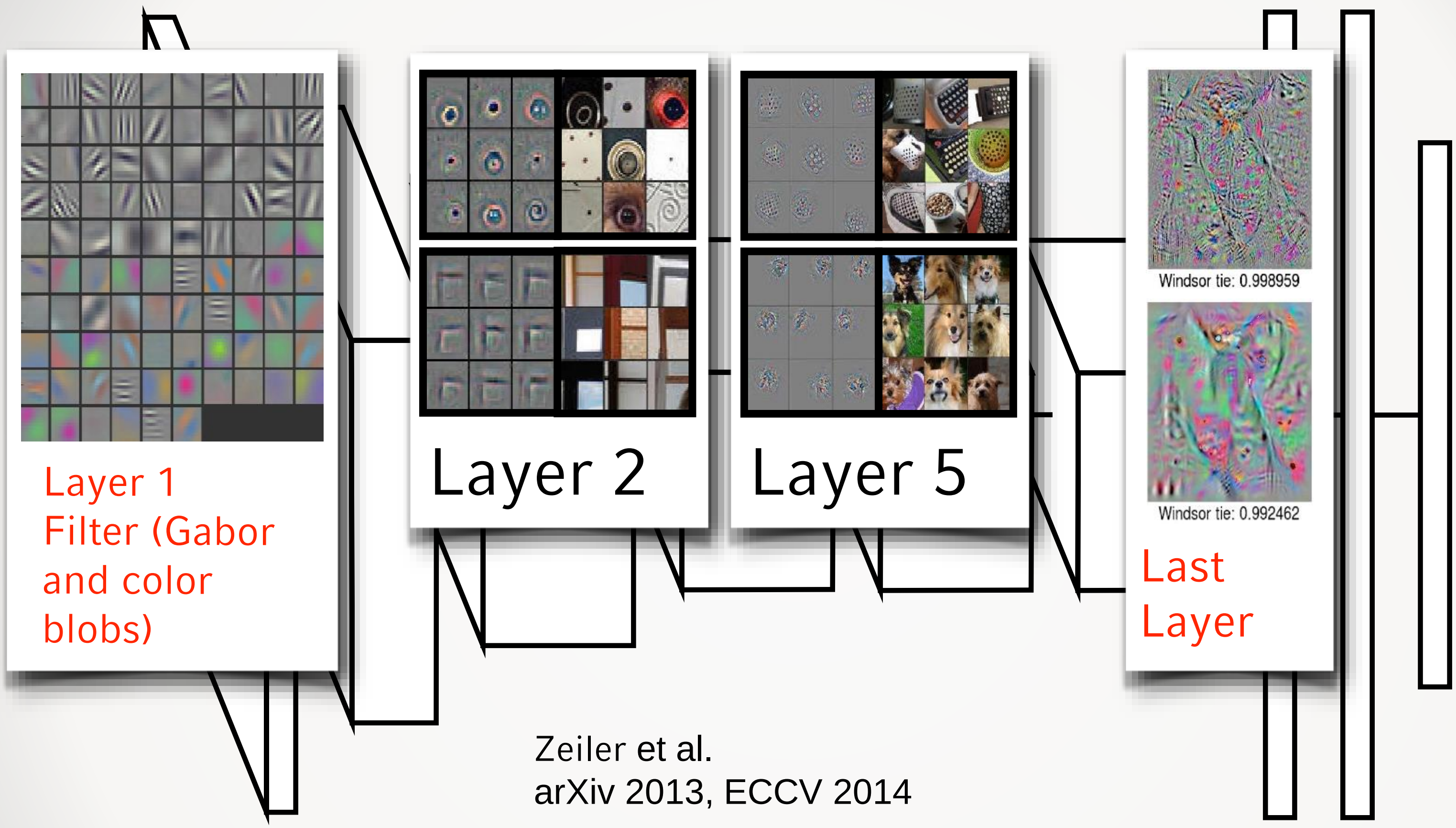
- paradigms for modelling the connection between raw data to abstract results:
- artificial neural networks:
  - connect multiple functions $f_n(f_{n-1}(f\ldots(f_1(x)..)) = y$ (each output is the input of the next step)
  - training by minimizing a loss function $L(f_n\ldots(f_1(x)..), y)$
  - optimization is done by gradient descent
- statistical graphical models
  - generative Bayesian models
  - compute the posterior $p(y|x,\theta)$
  - training by Gibbs Sampling,..



example: Image Recognition

- **Conventional Imaging**: Imaging Pipeline handcrafted to a the problem (develop function and chain them)
- **Current Development**: Use Convolutional and Deep Neural Networks on the Raw Pixel data
- Strong performance increase in object recognition
- **Applications**:
  - search engines and data management
  - autonomous driving and robotics
  - remote sensing
  - surveillance tasks
- Works on excessive amount of data and usually requires a lot of Hardware (e.g. GPU computers) for training

Convolutional NN for Image Recognition



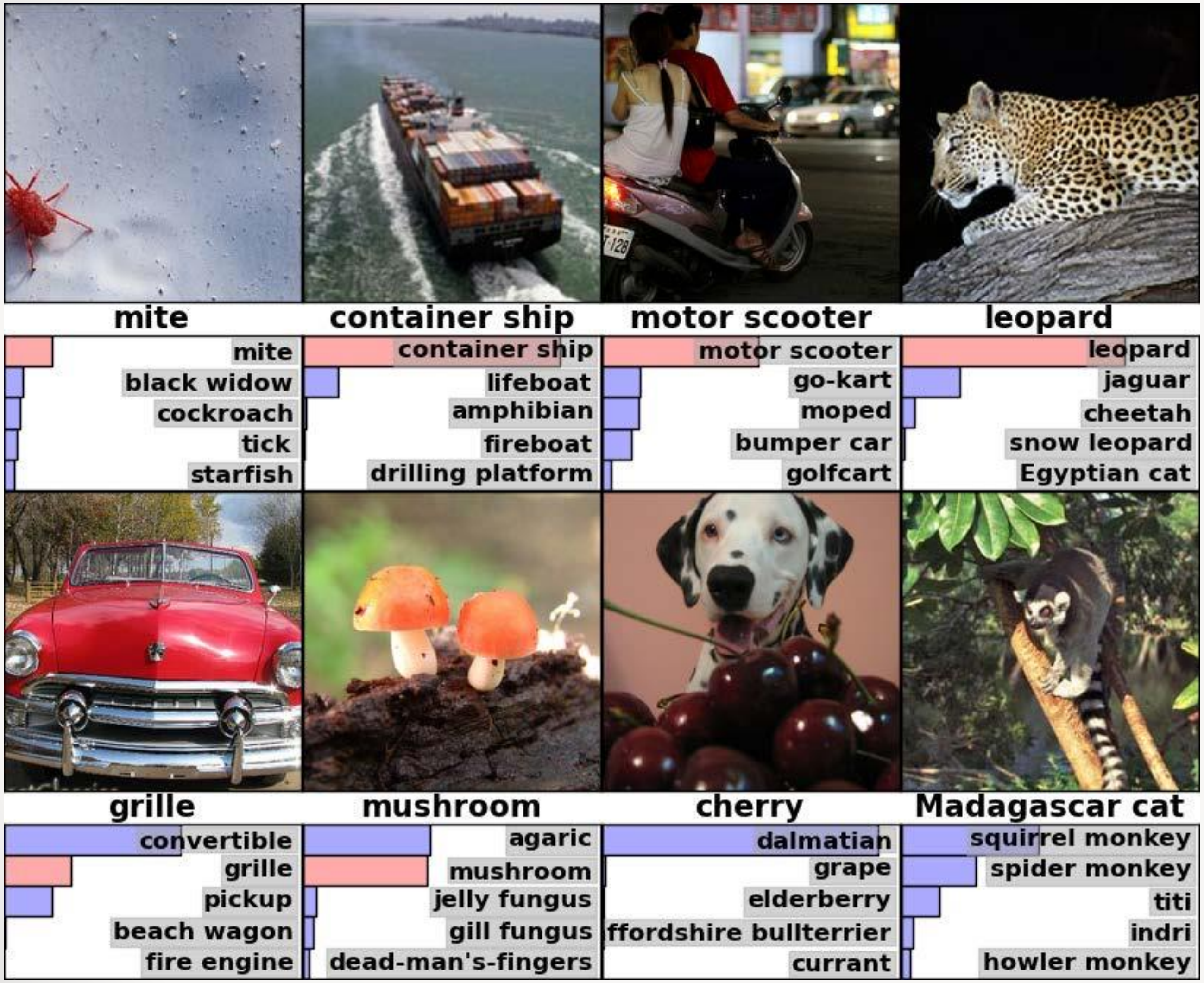
Zeiler et al.
arXiv 2013, ECCV 2014

Nguyen et al. arXiv 2014

Gabor filter: linear filters used for edge detection with similar orientation representations to the human visual system

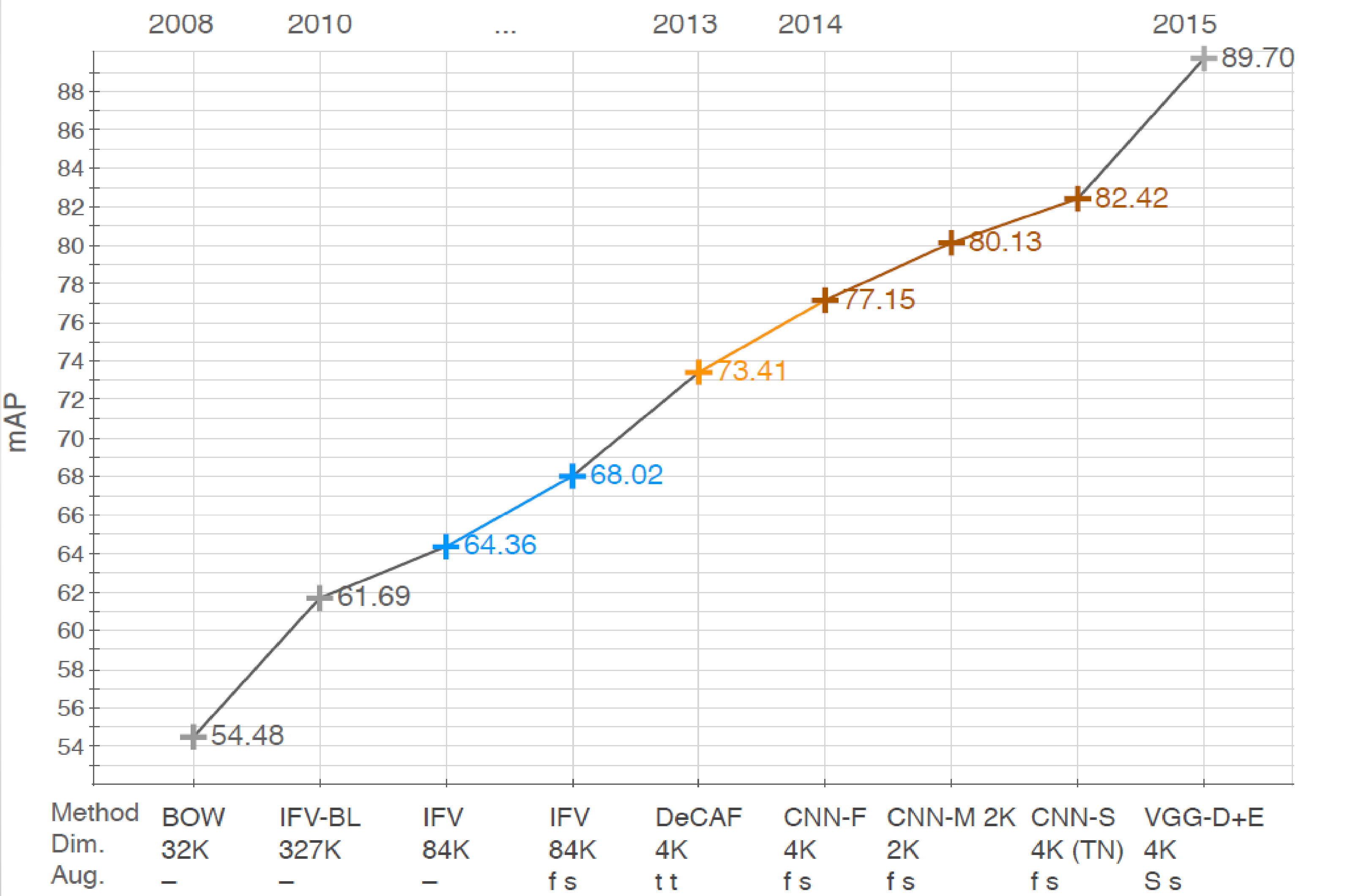
slide credit Jason Yosinski

LeNet5 (Winner ImageNet competition)



Evolution of Performance

PASCAL VOC-2007



other directions in Deep Neural Networks

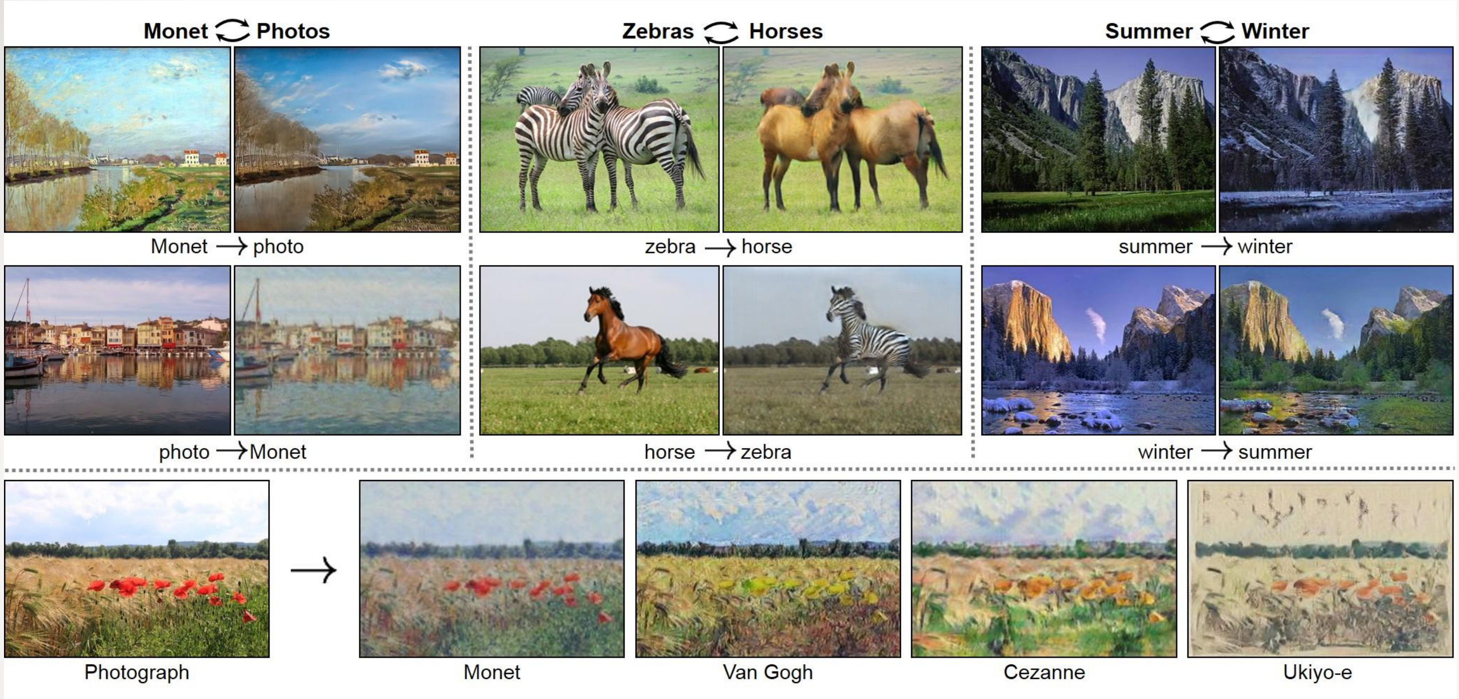
- Recurrent Neural Networks: e.g. long short-term memory
    - models long term dependencies in time series
    - used in speech, text and signal processing

    –(e.g. automatic translation and chat bots)
- Autoencoders: learn compact representations
- Generative Adversarial Networks (GANs): build data generator for based on observed examples
- Deep Dreams: visualize intermediate results to make image detection better understandable
- …

example: Generative Adversarial Networks

https://medium.com/@ageitgey/abusing-generative-adversarial-networks-to-make-8-bit-pixel-art-e45d9b96cee7

Example: Image Fusion



Jun-Yan Zhu*, Taesung Park*, Phillip Isola, and Alexei A. Efros. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", in IEEE International Conference on Computer Vision (ICCV), 2017.

Artificial Intelligence and Data Analytics

- AI is an extremely broad subject within CS:
- ***tasks***: reasoning, problem solving, knowledge representation, planning, learning, natural language processing, perception, motion and manipulation, social intelligence, creativity, general intelligence

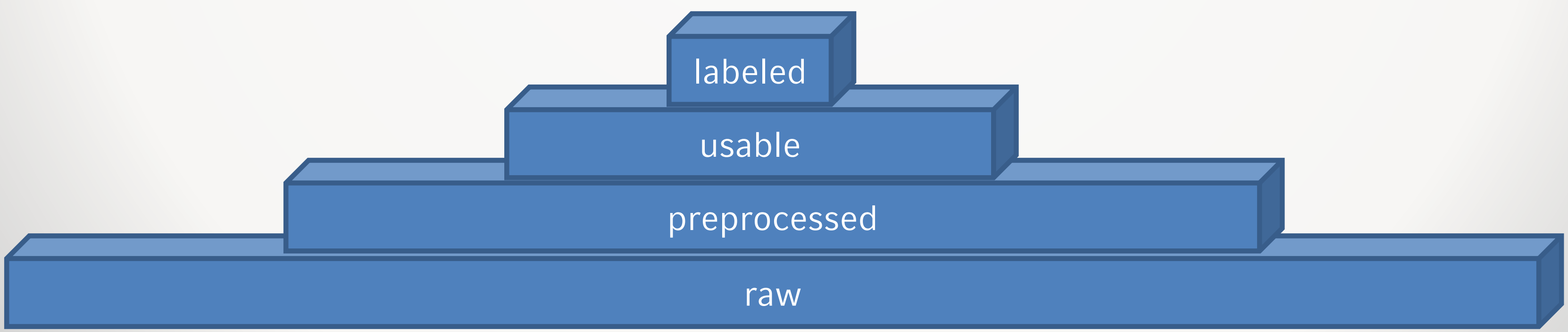
$\Rightarrow$ some major overlap to machine learning and data analytics

- for this talk, I will focus on the following aspects:
- **analytics**: predict unknown values and abstract from given data (What will happen?)
- **artificial intelligence**: (here: strong focus on planning) find the best strategy to optimize a goal (What should I do?)

The data pyramid

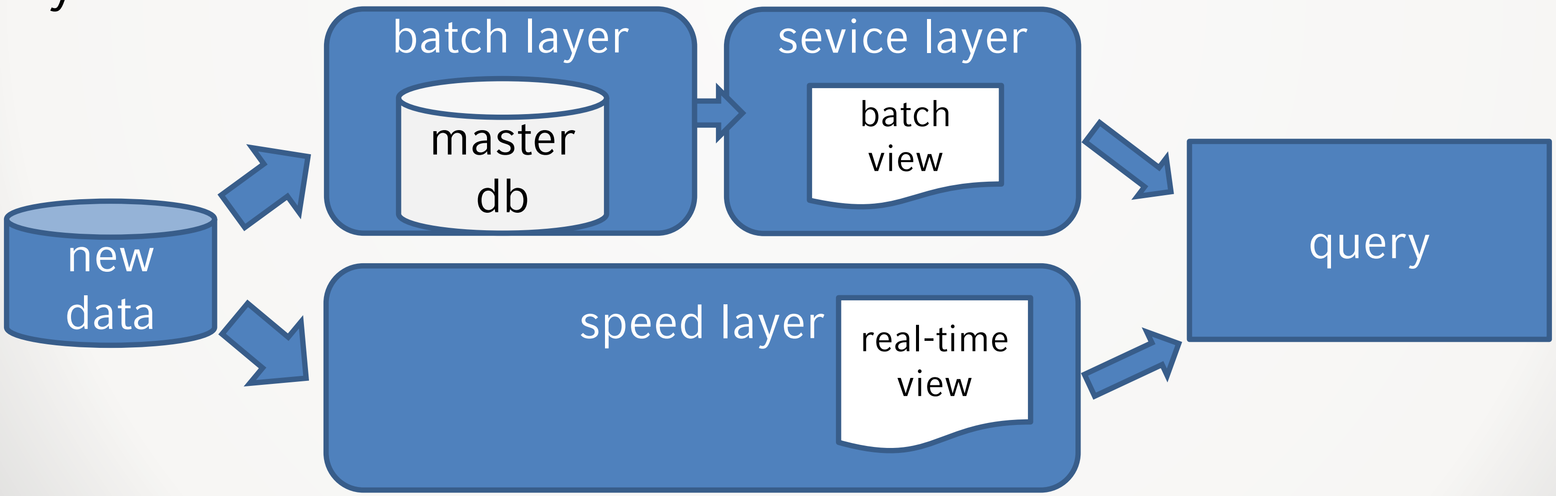
- raw data is often big
- in selection and preprocessing data shrinks
- for complex tasks high-quality data is often still small (e.g. not enough labels, noise, irrelevant, too high resolution)

⇒ Big Data systems often found in the first steps of the of the KDD process where scalability and efficiency play a role



The Lambda Architecture

- never change/delete data, store original and transformed data
- distinguish between speed and batch layer
  - speed layer: indexes batch view for interactive access
  - batch layer: breaks down all data to batch views
  - serving layer: high frequency update/latest data
- any query can be answered by combination service and speed layer



Course Contents

- Data Science: The Big Picture
- NoSQL Systems
- Hadoop / HDFS / MapReduce
- Apache Spark
- Data Streams & Streaming Methods
- Apache Flink
- Stream Analytics
- Text Data
- High-Dimensional Data
- Graph Data

Volume

Velocity

Variety

Literature

- This course is mainly based on a mixture of existing external lectures, Surveys, Papers and Reports on Big Data
- There is NO, or better, I'm not aware of a single book or script that is equivalent to this course (and addresses all issues discussed in this course)
- Since Big Data is a quite new and hot topic, standards and basic concepts are quite dynamic => The Web is a very appropriate source of relevant information
- External lectures basically used for this course:
  - Big Data: Donald Kossmann & Nesime Tatbul, Systems Group ETH Zurich - http://www.systems.ethz.ch/node/217
  - Mining of Massive Datasets: Jure Leskovec, Anand Rajaraman, Jeff Ullman, Stanford University - http://www.mmds.org
- Further material will appear at our web page
  (check for updates during the course / open to further suggestions!)