

# INTRODUCTION TO BIG DATA AND ARTIFICIAL INTELLIGENCE

# Introduction

## Learning objectives



### BD & AI: What and why?

- ▶ Basic definitions
- ▶ Why AI and why now?
- ▶ Real world applications
- ▶ Bosch use cases



### Data as an asset: Value creation

- ▶ Relevance of data
- ▶ Data mining
- ▶ Big Data handling



### Technical foundations: Machine Learning

- ▶ What is machine learning?
- ▶ Strategies and tasks
- ▶ Method focus on Deep Learning overview



### Implementation: Data mining in your BU

- ▶ Value of data
- ▶ Data-driven mind-set
- ▶ Roles and competences
- ▶ Trainings and platforms
- ▶ Discuss & exchange

Depositphotos, Bosch License

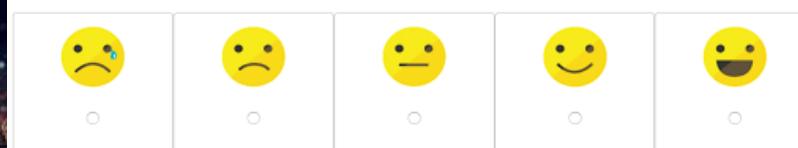
# Introduction

## Now it's your turn!

1. Who are **you** and where do you work?
2. What is your **expectation** of this day?
3. What is your **connection to AI** and how do you feel about AI on a **scale from worried to enthusiastic**?



*Poll:*



CC0



# INTRODUCTION

# EXAMPLES

# What AI demonstrates today



# Introduction

## Examples in everyday life



All CC0



# Introduction

## AI application in major industries

New Retail

Medical

Manufacturing

Development Visual Inspection

Predictive maintenance

AI

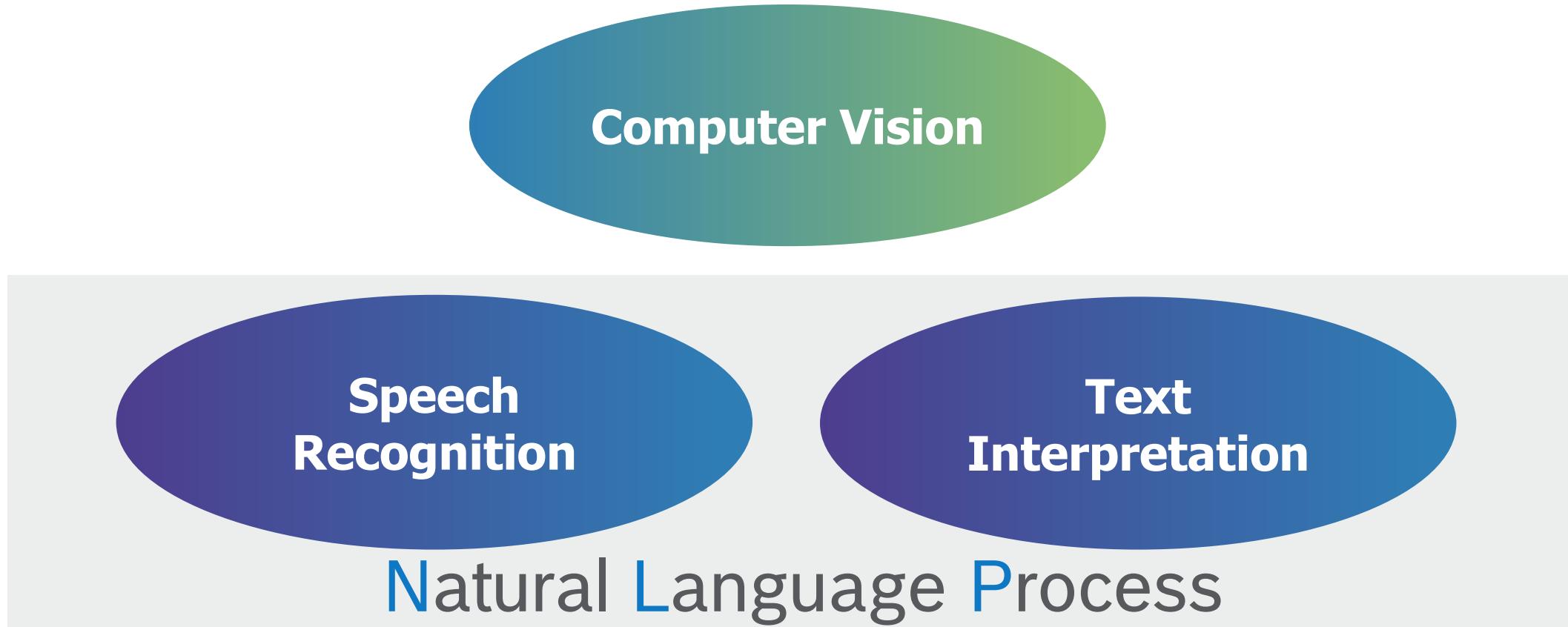
Education

Agriculture

Finance

# Introduction

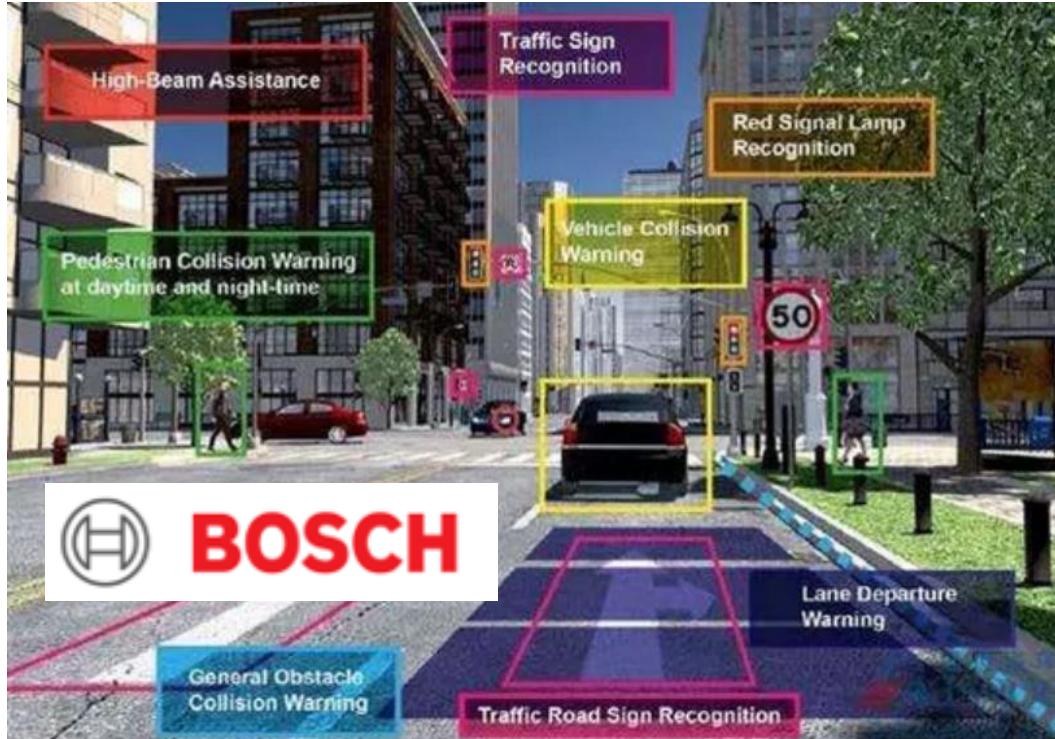
## Major application/technology



# Introduction

## Major application/technology

Computer  
Vision



# Introduction

## Major application/technology

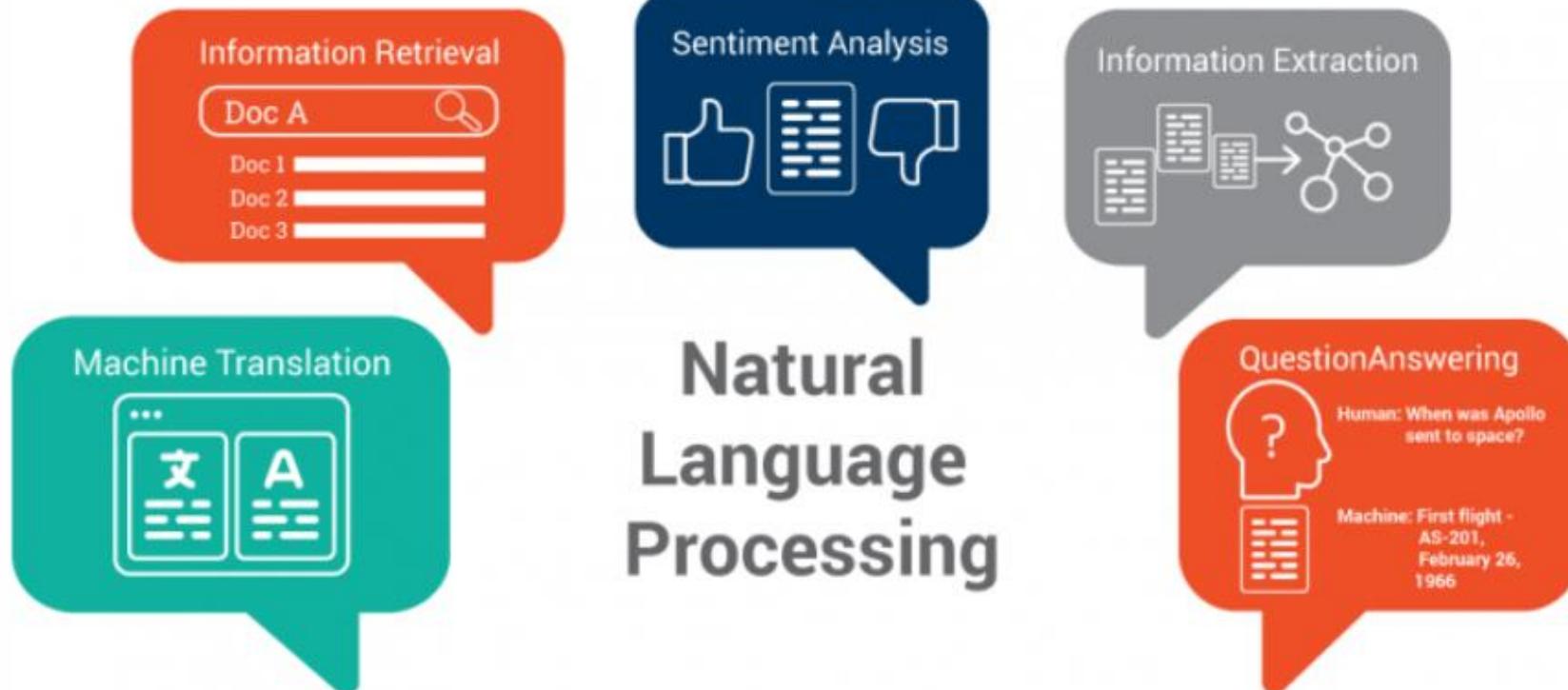
NLP-Speech  
Recognition



# Introduction

## Major application/technology

NLP-Text  
Interpretation



# Introduction

## Examples at Bosch: Smart Agriculture Solution

### Project Description



To develop a disease risk prediction model for tomato crops using data from greenhouse environmental conditions. The solution aims to protect farmers from yield loss and to optimize the use of chemical spray.

### Impact

- Received cumulative orders of over 4,000 devices in Japan
- The solution is being extended to the Korean markets.

### Data used

- Sensors installed inside the greenhouses are used to collect data at 10 minutes interval i.e. temperature and relative humidity.
- Metadata from the greenhouses such as crop stage, planting medium etc. are also used for model development
- Ground truth based on farmers' inputs on disease occurrence.



### AI solution concept

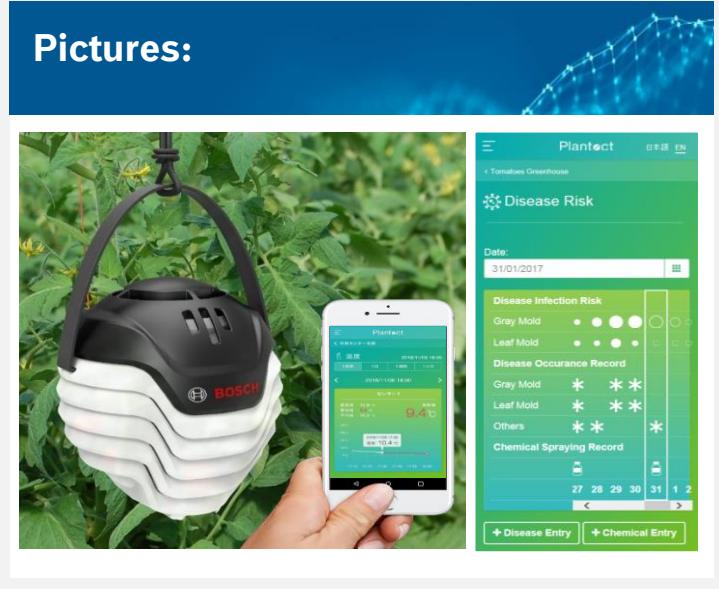
- Raw Data from sensors is extracted and stored in a structured database.
- Agriculture domain and statistical based features are derived from raw data.
- ML model is developed using above mentioned features.
- To perform daily prediction, raw data coming from sensors is processed to get features and is fed to the ML model to get the prediction.
- The result is showcased on the Plantect App.

### Goal of BCAI collaboration



The goal of this project is to establish collaboration with the FUJI team in Japan to develop smart AI-based solutions for the agricultural domain.

### Pictures:



# Introduction

## Examples at Bosch: Sales Forecasting

### Context



Forecasting solution using an ensemble of 30+ state of the art models

User friendly interface via PowerBI. The solution is fully automated and applicable in all Bosch Business Units.

Monthly forecasts currently delivered to 7 GBs. Cloud onboarding Q4/19

### Impact

Improved efficiency, objectivity, accuracy, and transparency

More frequent forecasts with higher or equivalent accuracy

### Data used

- Historical revenue data from GBs
- Business hierarchy data

### Goal of project



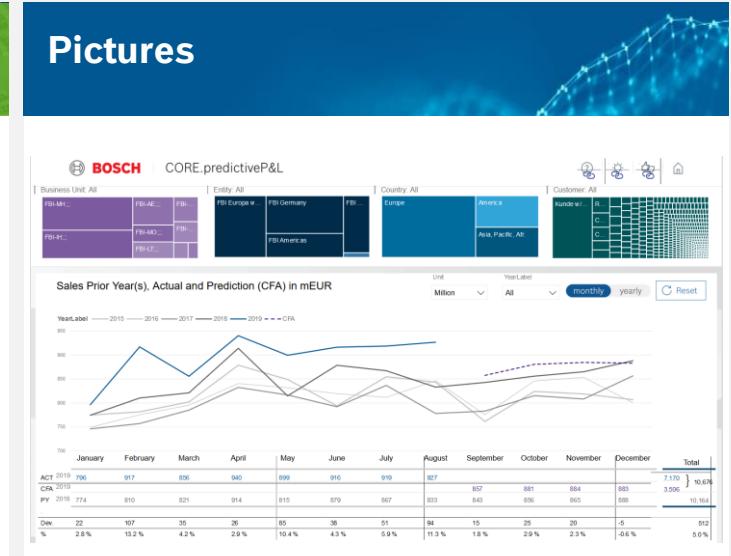
Automatically generated sales forecast integrated into the new Bosch wide Finance Business Intelligence (FBI) platform.

Leverage domain knowledge of FBI team in controlling and BCAI in learning systems to create a scalable AI product.

### AI solution concept

- 30+ forecasting models
- Feature-based model selection and combination using random forests
- Distributed computing using spark and kubernetes
- Hierarchical forecast based on business requirements
- Probabilistic forecasting (forecast distribution vs. point forecast)

### Pictures



# DEFINITION AI

# Introduction

## Basic definition

**Artificial intelligence** is a subfield of computer science that models intelligent behaviour.



# What is Artificial Intelligence?

## Definitions of AI

AI addresses problems which can be solved by humans, but for which we don't have good algorithms for solving.

Defining artificial intelligence isn't just difficult; it's impossible, not the least because we don't really understand human intelligence.

AI is a moving target; once a task solved by algorithms, it's no longer perceived as AI!

Artificial intelligence is the science of making machines do things that would require intelligence if done by men.

# Introduction

## A bold assumption

Dartmouth Conference (1956):

“Every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it.”



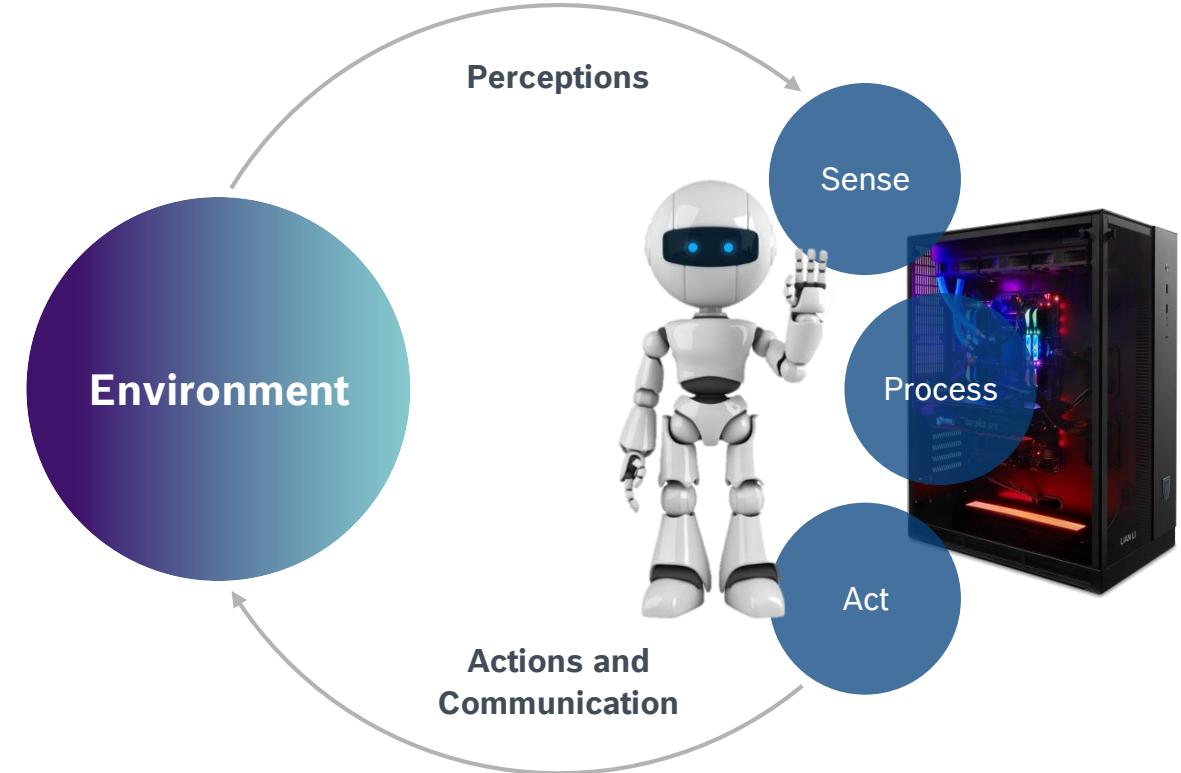
# Introduction

## What is necessary for Artificial Intelligence?

*Poll:*

*“Which skills make humans intelligent?”*

Which tasks do we have to model to make machines behave intelligently?



# Introduction

## A brief look at history



1950s

1960s

1970s

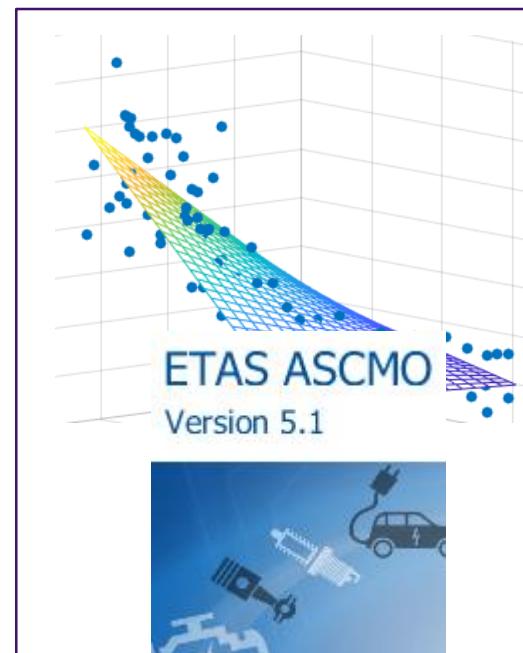
1980s

1990s

2000s

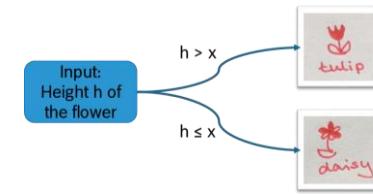
2010s

2016



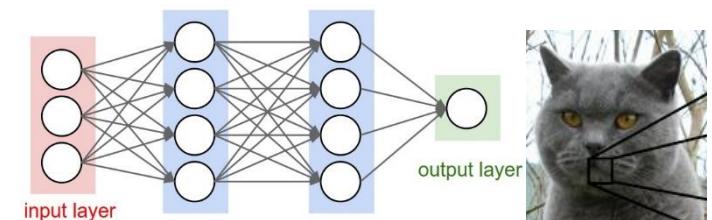
Artificial Intelligence

Machine Learning



Deep Learning

Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT)



# WHY NOW?

# Introduction

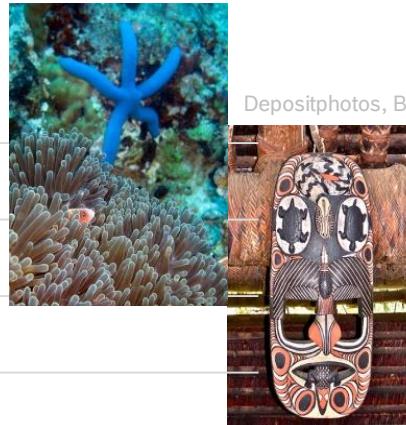
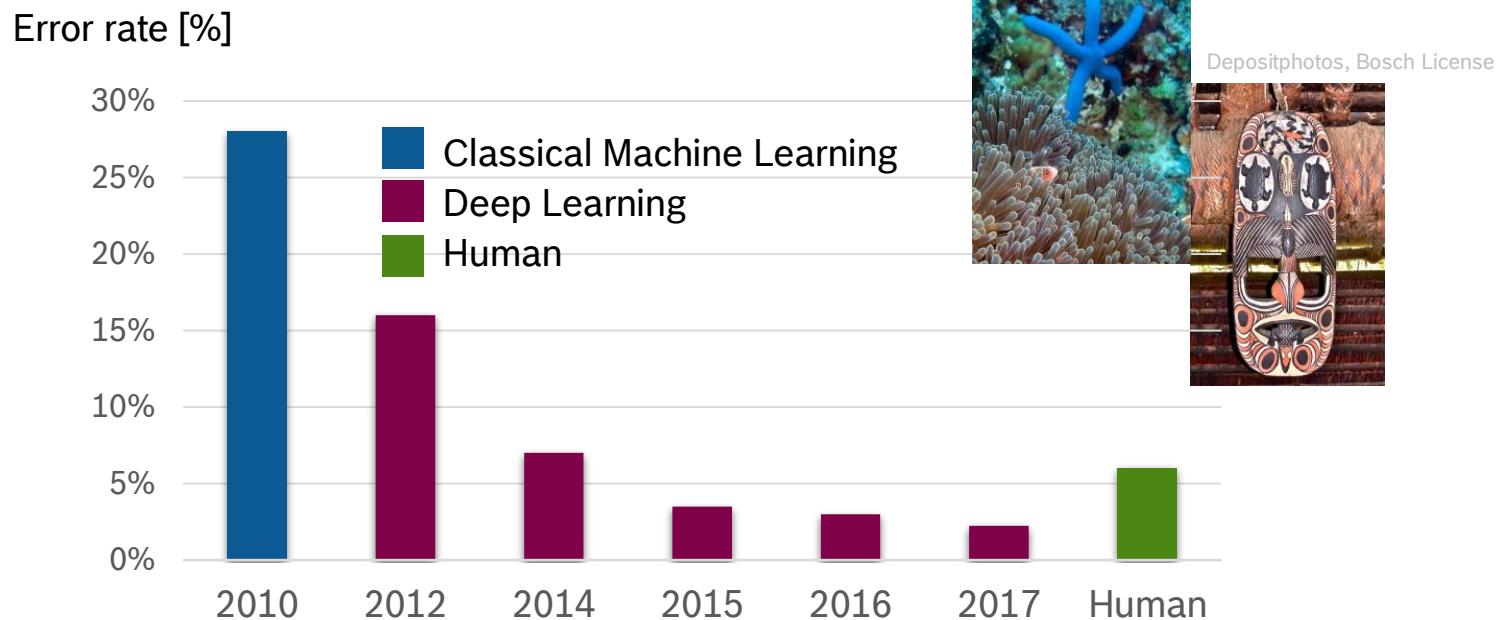
## Why now?



# Introduction

## Why now? – Improved algorithms

### 1. Algorithmic advances, especially in the area of deep learning



Depositphotos, Bosch License

- Error rate of image recognition “imagenet challenge”. In 2015, algorithms surpassed human image recognition error rate.

# Introduction

## Why now? – Improved algorithms

### 1. Algorithmic advances, especially in the area of deep learning



From <https://medium.freecodecamp.org/chihuahua-or-muffin-my-search-for-the-best-computer-vision-api-cbda4d6b425d>

# Introduction

## Why now? – More data

2. Tremendous growth of data – example: inauguration of the pope



Luca Bruno, AP

**2005**



Michael Sohn, AP

**2013**

# Introduction

## Why now? – Cheaper computing power

3. Technological advancements lead to cheaper computing power, storage and memory



Wikipedia.org, CC BY-SA 3.0 fr

**1985, Cray-2**  
~ \$ 32,000,000  
(2011 dollars)

=



**2010, iPhone 4**  
~ \$ 600

=



**2016, Apple Watch**  
~ \$ 300

# Introduction

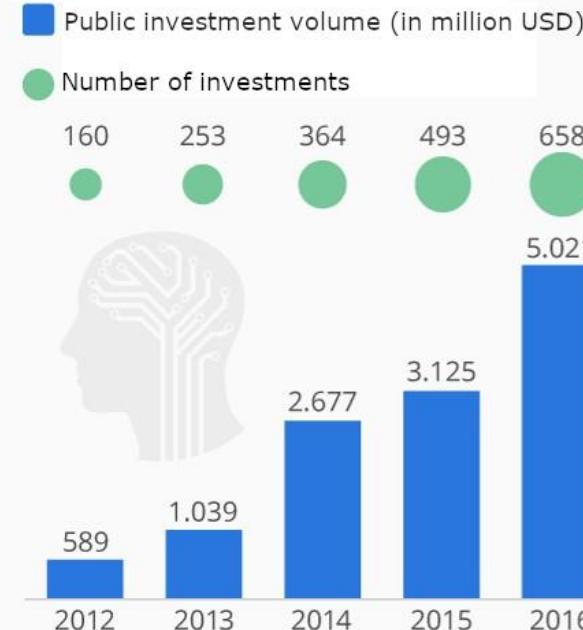
## Why now?



# Introduction Investments

## Artificial Intelligence in upwards trend

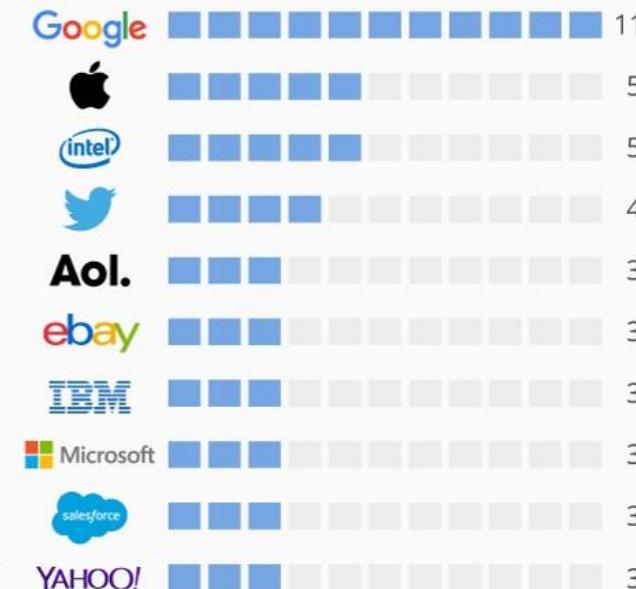
### Investments in AI startups:



@Statista\_com

Source: CB Insights

### Number of major business acquisitions in the area of Artificial Intelligence Nov 2011–Nov 2016



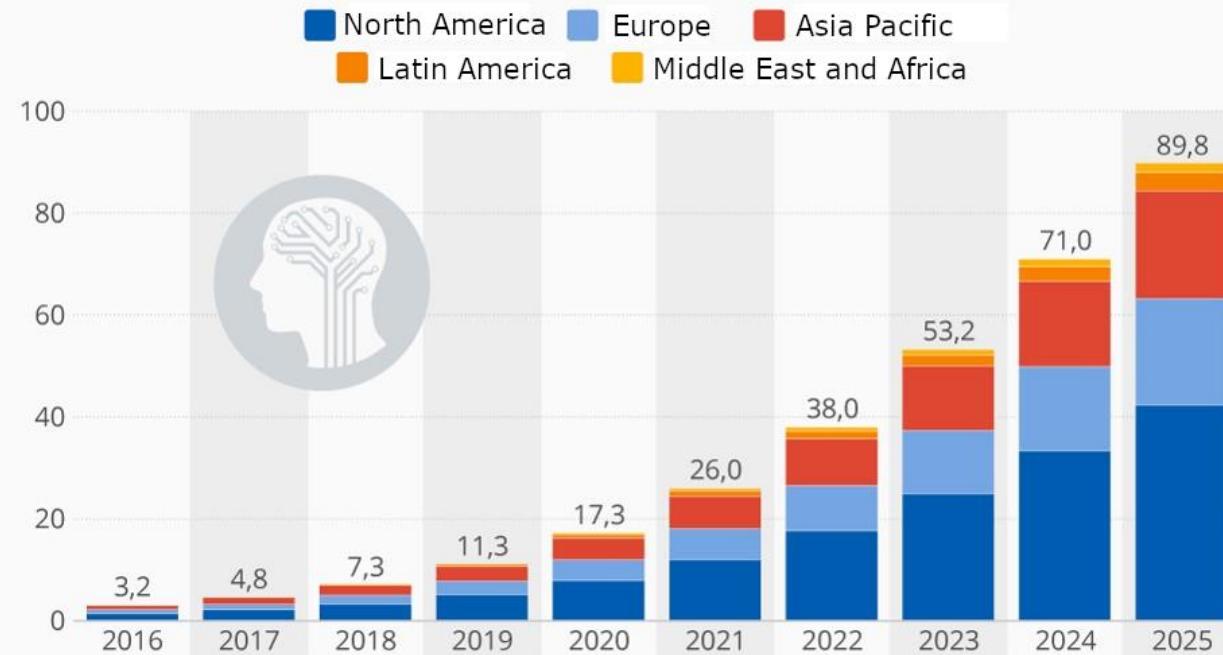
statista

# Introduction

## Projected turnover

### The billion dollar business with Artificial Intelligence

Projected global turnover with AI-applications (in billion USD)



@Statista\_com Source: Tractica

statista

# Introduction

## AI researcher is the new soccer player



Skysports.com

- AI talent is scarce
- Experts expect another intensification in the „war for talent“ in the AI field
- Median income at Facebook \$ 240,000 (Economist)

### Big tech firms' AI hiring frenzy leads to brain drain at UK universities

High demand at companies such as Google could leave fewer talented scientists to teach next generation, academics fear



The Guardian

# DATA

# Data

## Why do we need data?

Big data is to AI what fuel is to engines: If the tank is empty, the engine comes to a halt.



Max Welling (Amsterdam Machine Learning Lab)

<https://www.bosch.com/de/explore-and-experience/thought-leader-max-welling/>

# Data

## Types of data acquisition



**no**  
data acquisition



**passive**  
data acquisition  
(digitization)



**active**  
data acquisition  
(business case driven)



**strategic**  
data acquisition  
(foresight based)

# Data

## Example: Big Data at Waymo

- 32M km (20M miles) driven (as of 01/20)
- 10B miles in simulator (as of 09/19)
- Hand-over to driver every 21,151 km (disengagement report for 2019)
- 82,000 vehicles ordered for robo cab fleet
- Around 2/3 of Waymo's valuation are because of their test miles



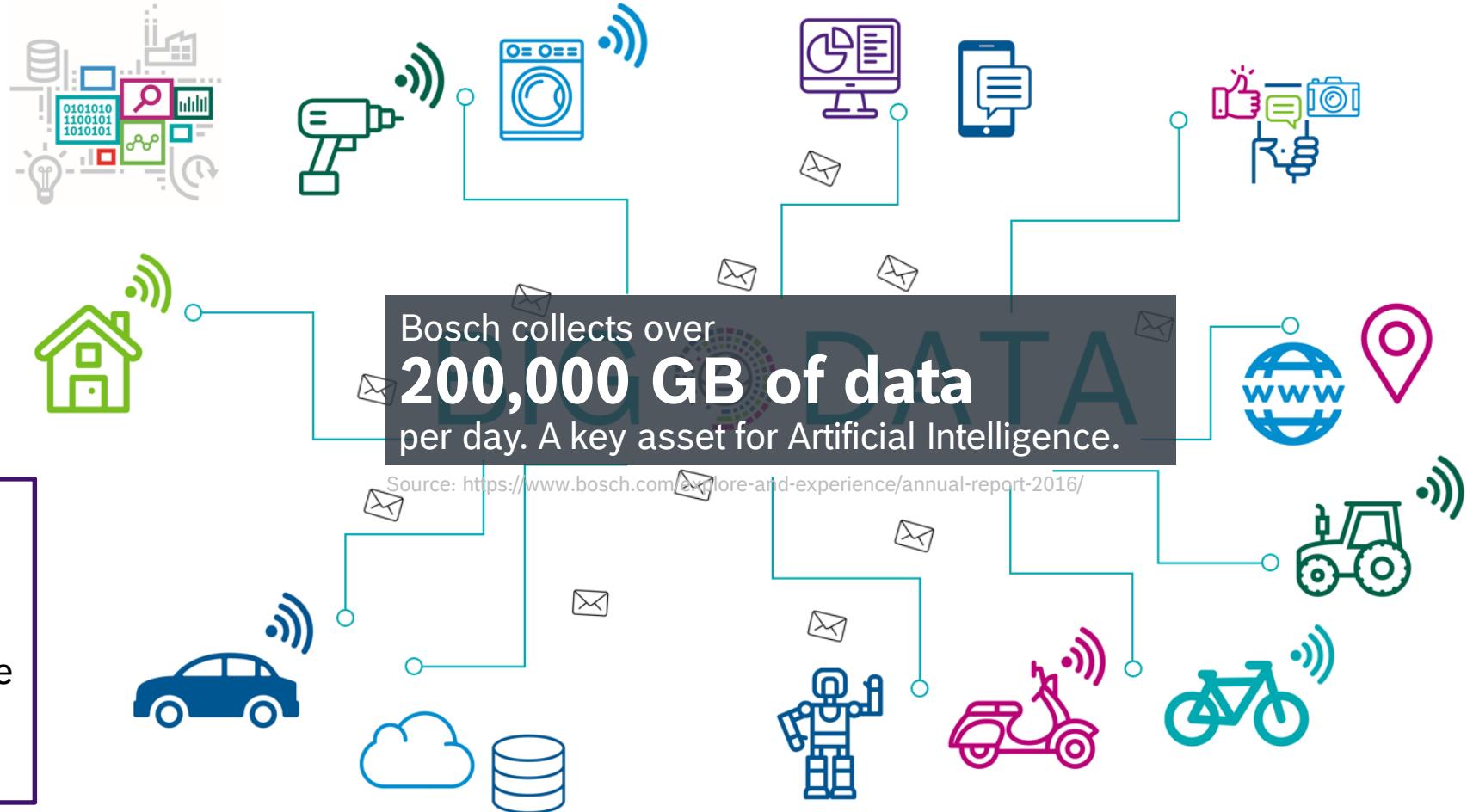
*Poll:*

*“How much data did Bosch produce  
each day in 2016?”*

# Data

## Data at Bosch

**Which data  
do you  
already or  
could you use  
for your  
business?**



# Data Based Value Creation

## Data Mining



Depositphotos, Bosch License

Data mining is the process of discovering hidden, previously unknown and usable information from a large amount of data.

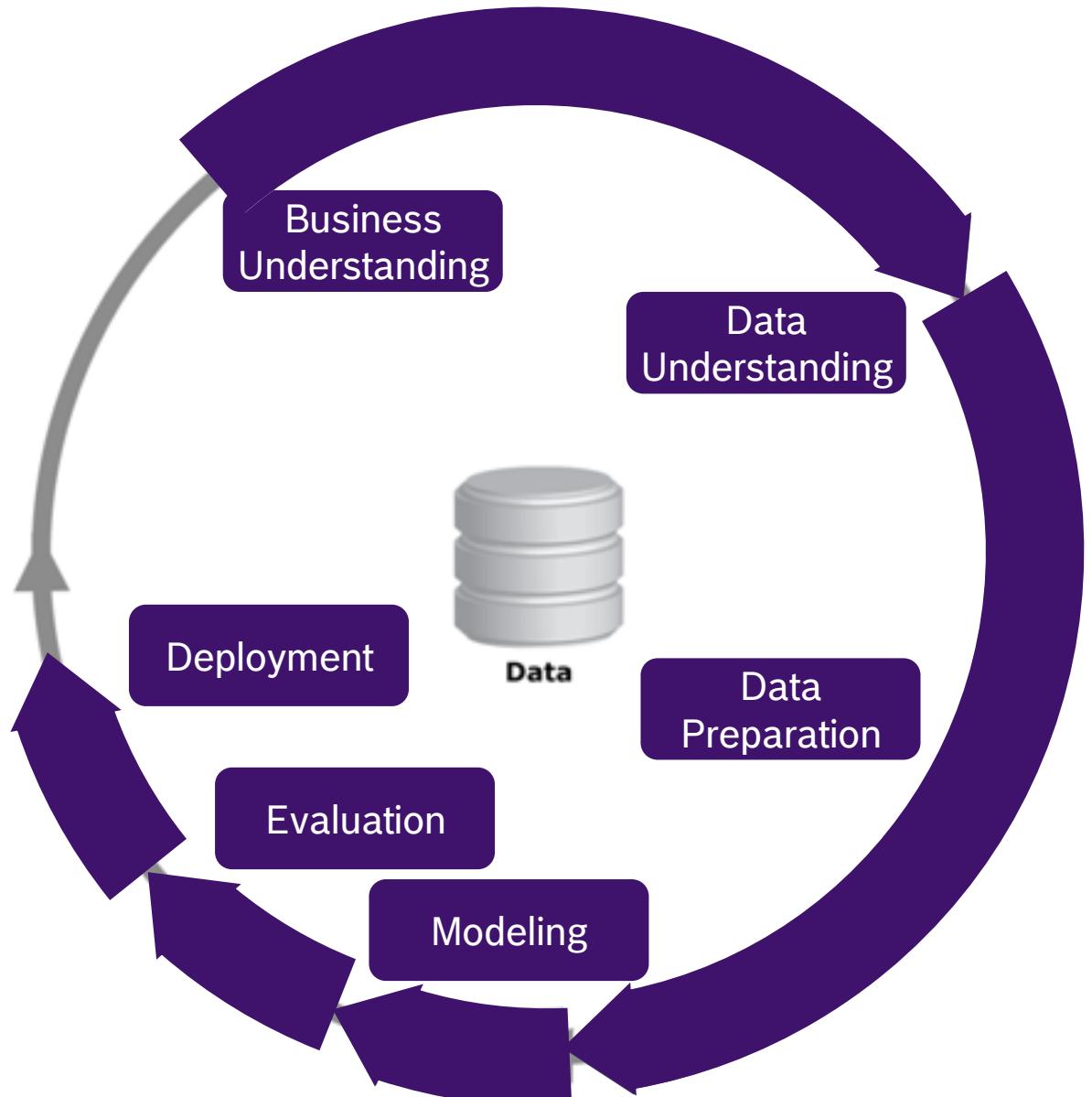
(ISO/IEC JTC1/SC32 WG4 SQL/MM Part 6 WD, 2000)

# Data Based Value Creation

## CRISP-DM

The standard data based value creation process is called CRISP-DM:

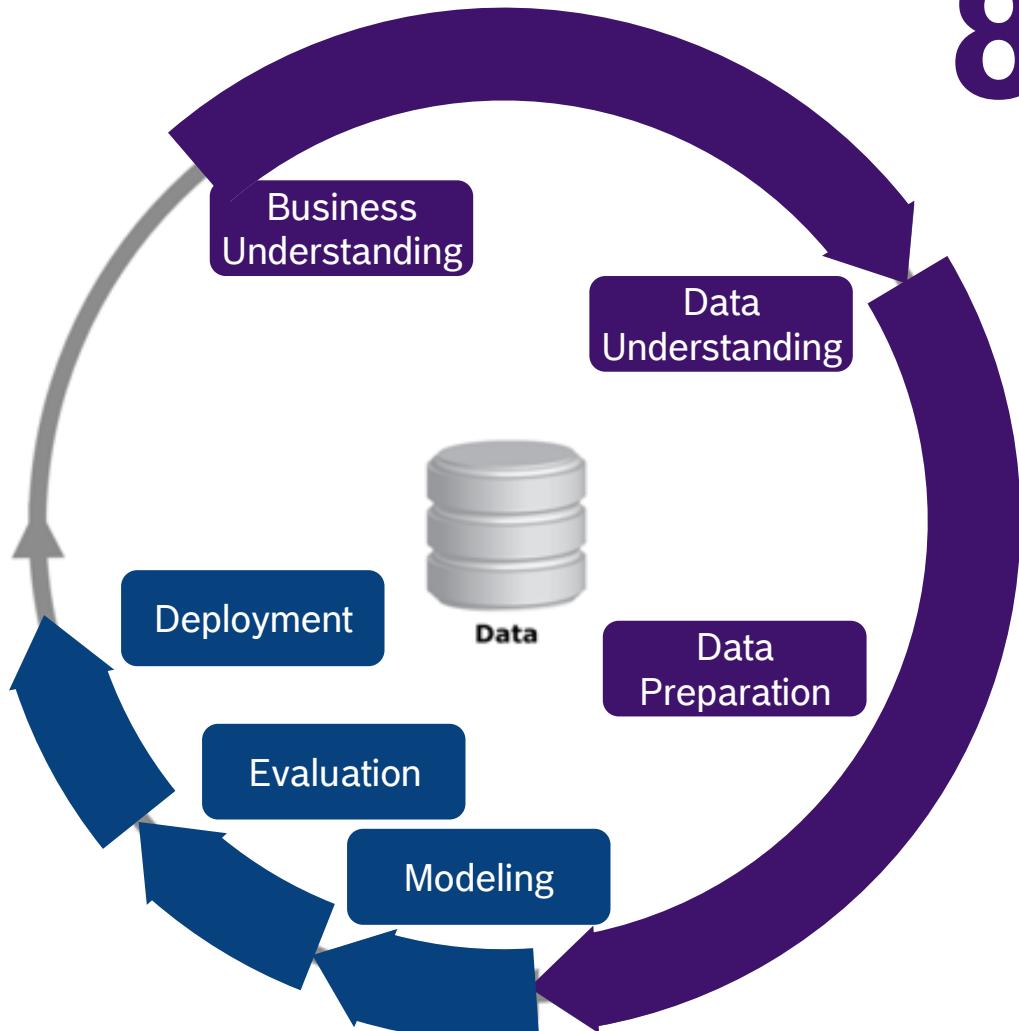
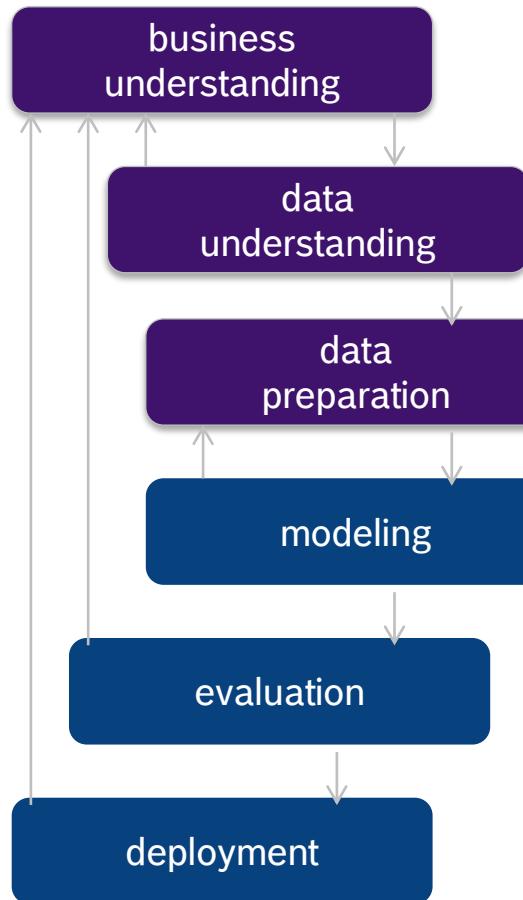
Cross-Industry  
Standard Process  
for Data Mining



# Data Based Value Creation

## CRISP-DM

80%



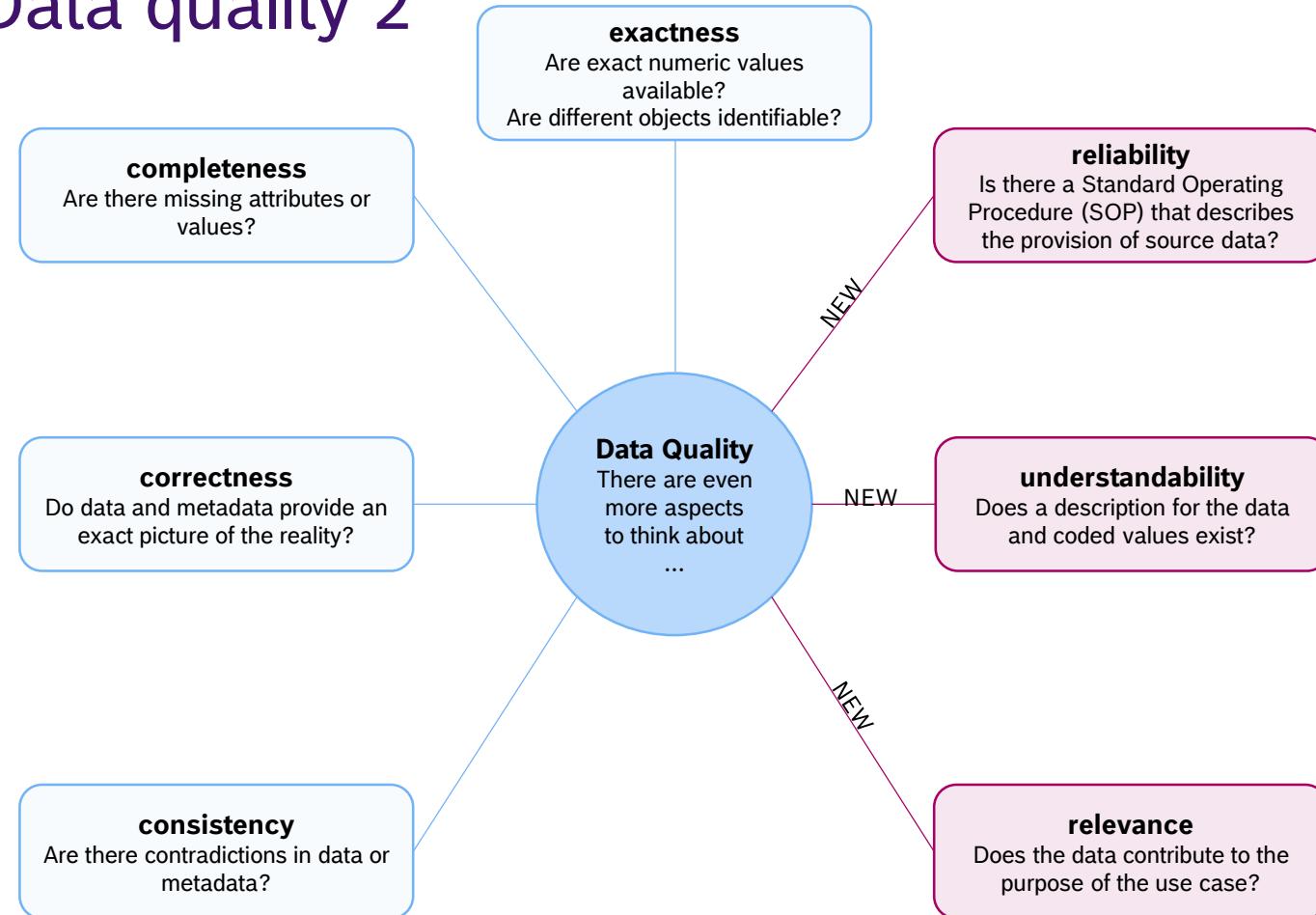
# Data Based Value Creation

## Excursion: Data quality

Schema Level		Instance Level		Schema Level		Instance Level	
- Illegal values (1)		- Missing values (3)		- Structural conflicts (5)		- Inconsistent representations (6)	
- Violated attribute dependencies		- Misspellings		- Naming conflicts		- Inconsistent timing	
- Uniqueness		- Redundancy/duplicates		- ...		- ...	
- Referential integrity (2)		- Contradictory values					
- ...		- Wrong references (4)					

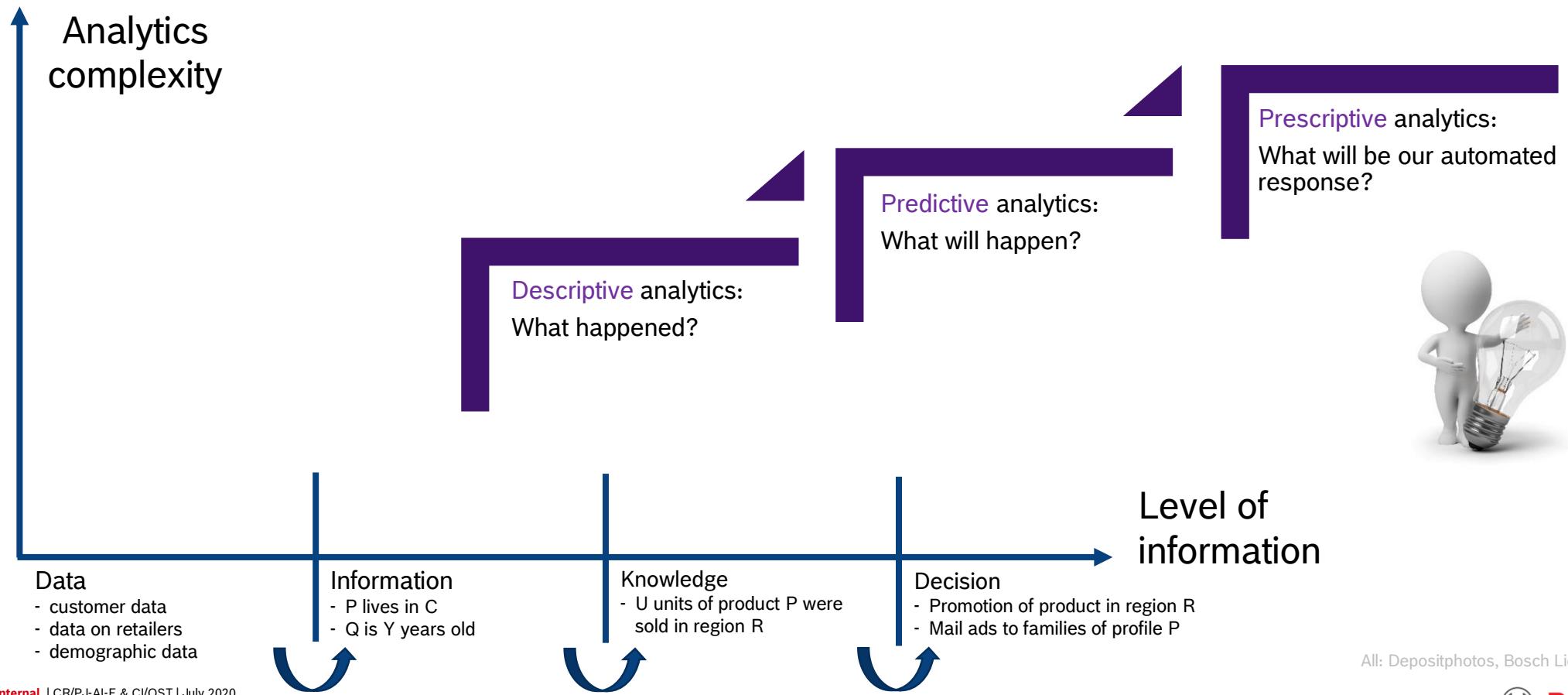
# Data Based Value Creation

## Excursion: Data quality 2



# Data Based Value Creation

## Levels of Data Mining

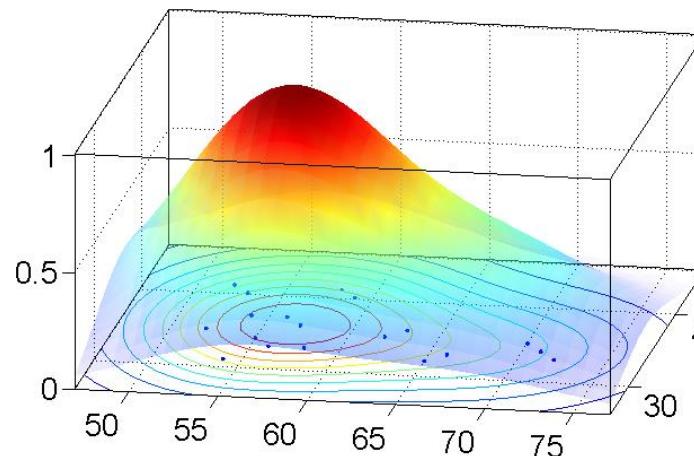


All: Depositphotos, Bosch License

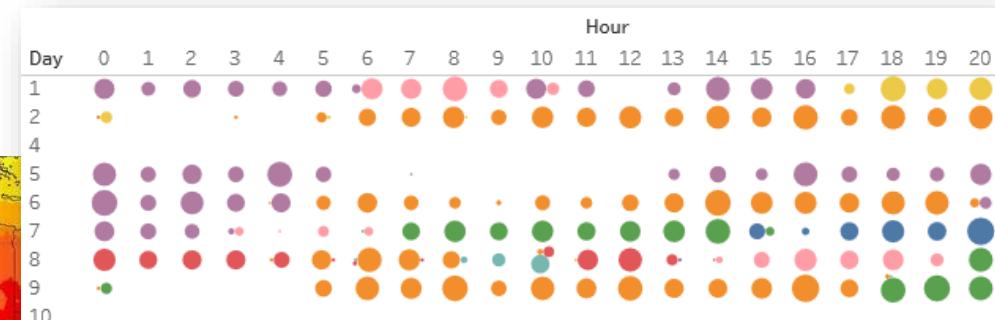
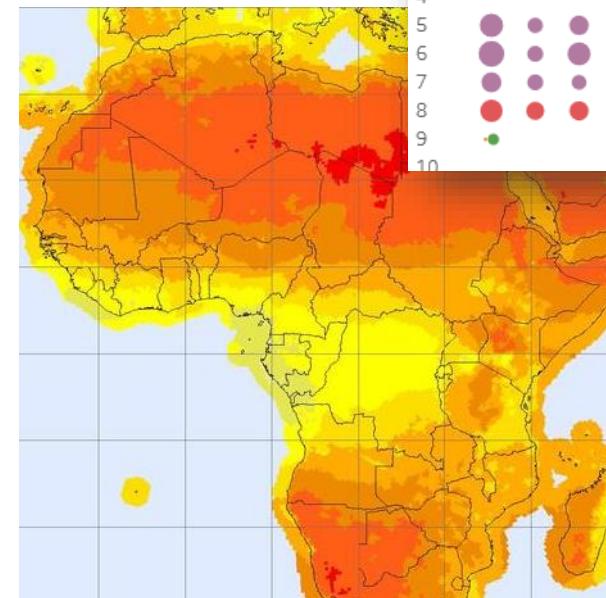
# Data Based Value Creation

## Descriptive analytics

We can gain **data understanding** by the use of **descriptive analytics**:



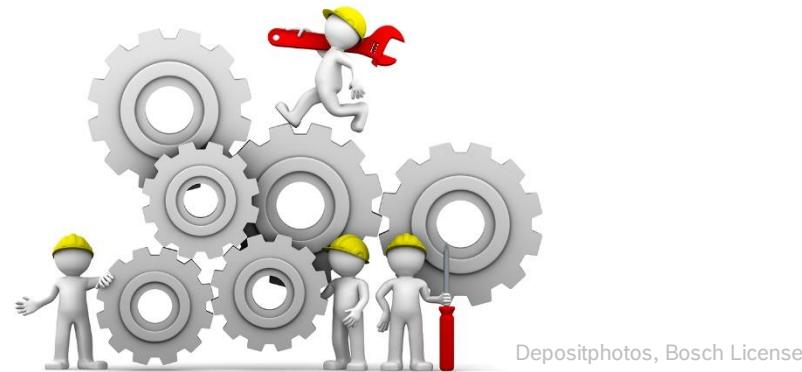
All: CC0



# Data Based Value Creation

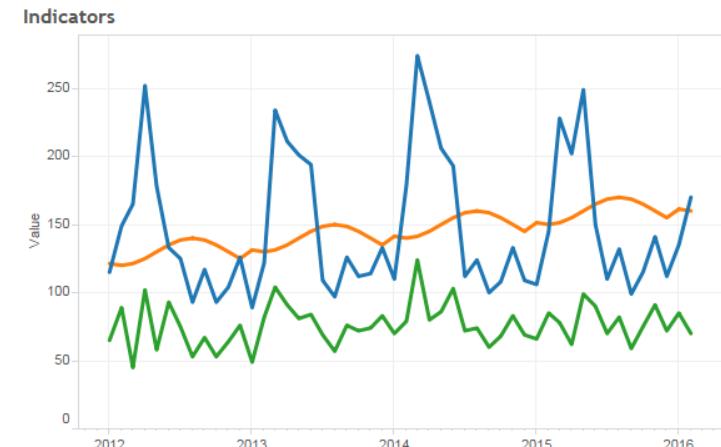
## Predictive analytics

If we really understand the mechanisms behind our data,



we can make **predictions** for the future.

**Example:** Sales forecasting



# Data Based Value Creation

## Use case: Predictive Analytics Toolbox for Finance

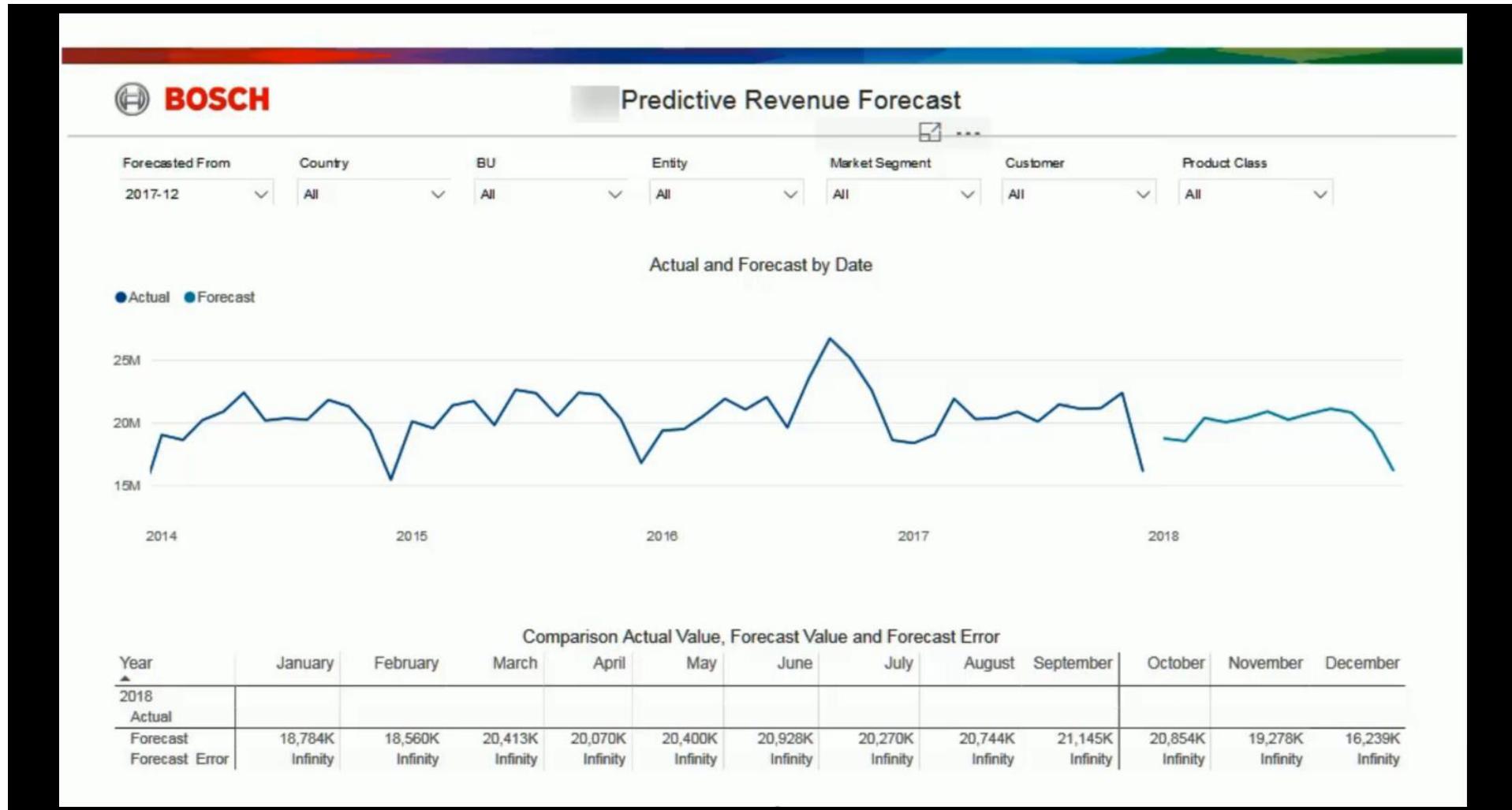
A **forecasting toolbox** for Bosch which can answer questions such as the following:

- ▶ How many sales is a BU expected to generate in the short and mid-term future?
- ▶ Are there **regular sales patterns** in the past from which we are able to **predict future sales** developments?
- ▶ What drives **irregularities** and what can I learn for future predictions?
- ▶ Part of **G2/PJ-FCE** in close collaboration with BCAI and CI



<https://pixabay.com/de/wahrsagen-zukunft-magie-astrologie-1989579/>, CC0

# Video: Predictive Analytics Toolbox for Finance



# Data Based Value Creation

## Use case: Predictive Analytics Toolbox for Finance

- ▶ Tremendous **speed-up** of and more accurate forecast (for regular patterns in the data)
  - ▶ Less bottom-up, **hand-tuned** aggregation and consolidation
    - „90% of time required for number crunching and consolidation, getting it from BUs and sending it to Schillerhöhe“
  - ▶ More time for **strategic decision support**
- ▶ A tool to **understand the past**
  - ▶ Controllers can find out which **extraordinary factors influenced the business**
- ▶ Manual forecasts often have a **political component**
  - ▶ Data Mining is an objective resource and **adjustments have to be justified**

# Data Based Value Creation

## Poll

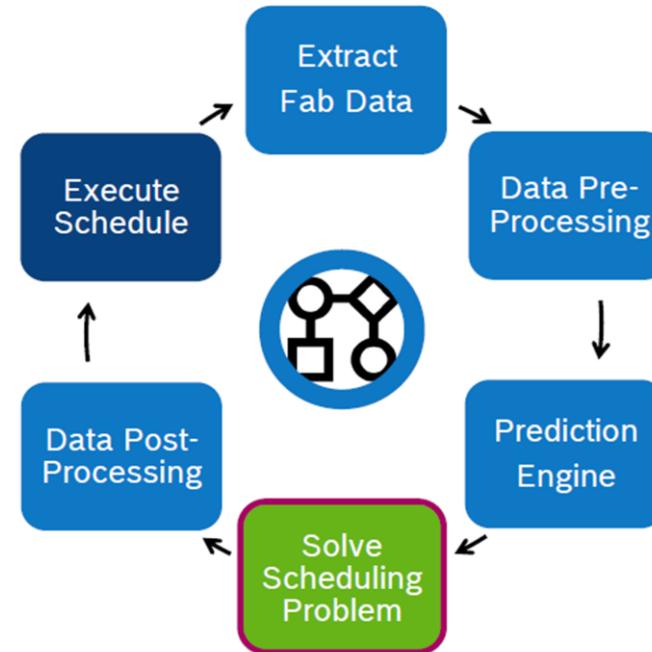
*Poll:*  
*“On what level of data mining is forecasting?”*

# Data Based Value Creation

## Prescriptive analytics

We can expand predictive analytics to prescriptive analytics by automated reactions.

Example: Production Scheduling  
@ Bosch plant in Reutlingen



# Data Based Value Creation

## Use case: Production Scheduling

Target:

Optimal production plan  
also in **varying conditions!**

RtP1 project requirement:  
New optimum production plan  
within **5 minutes!**

Changing job deadlines/priorities

Bicycle production line by clement127, CC0



Changing input provision

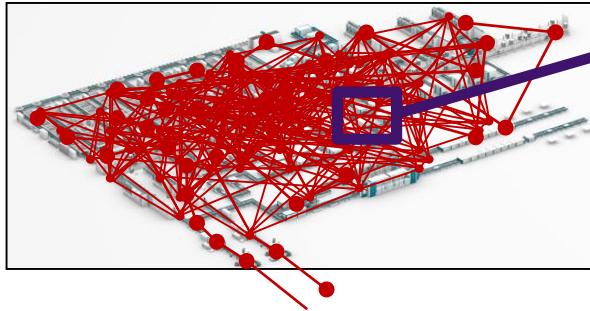
Changing output requirements

Machine stalls

Machine/job-dependent process times

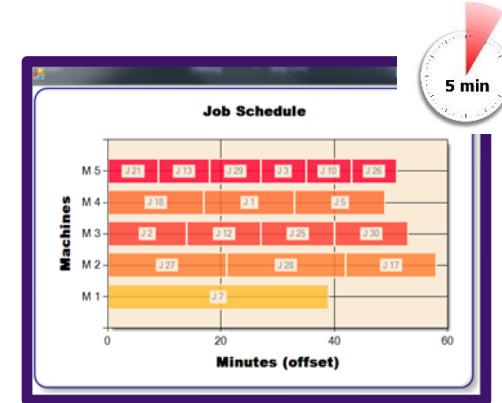
# Data Based Value Creation

## Use case: Production Scheduling



### Rule-Based Dispatching

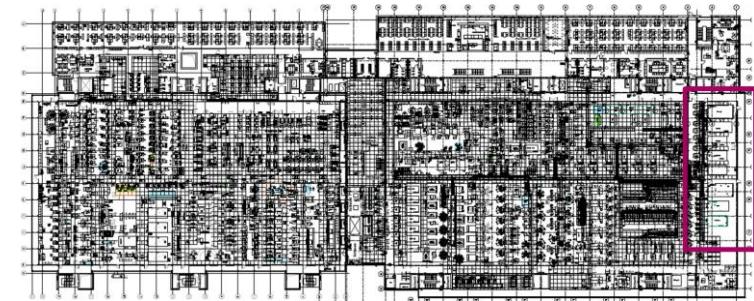
Status quo is production control using rule-based dispatching



### Scheduling with Optimization (Solver)

First scheduling solution deployed in RtP1 production after 6 months (BCAI cooperation)

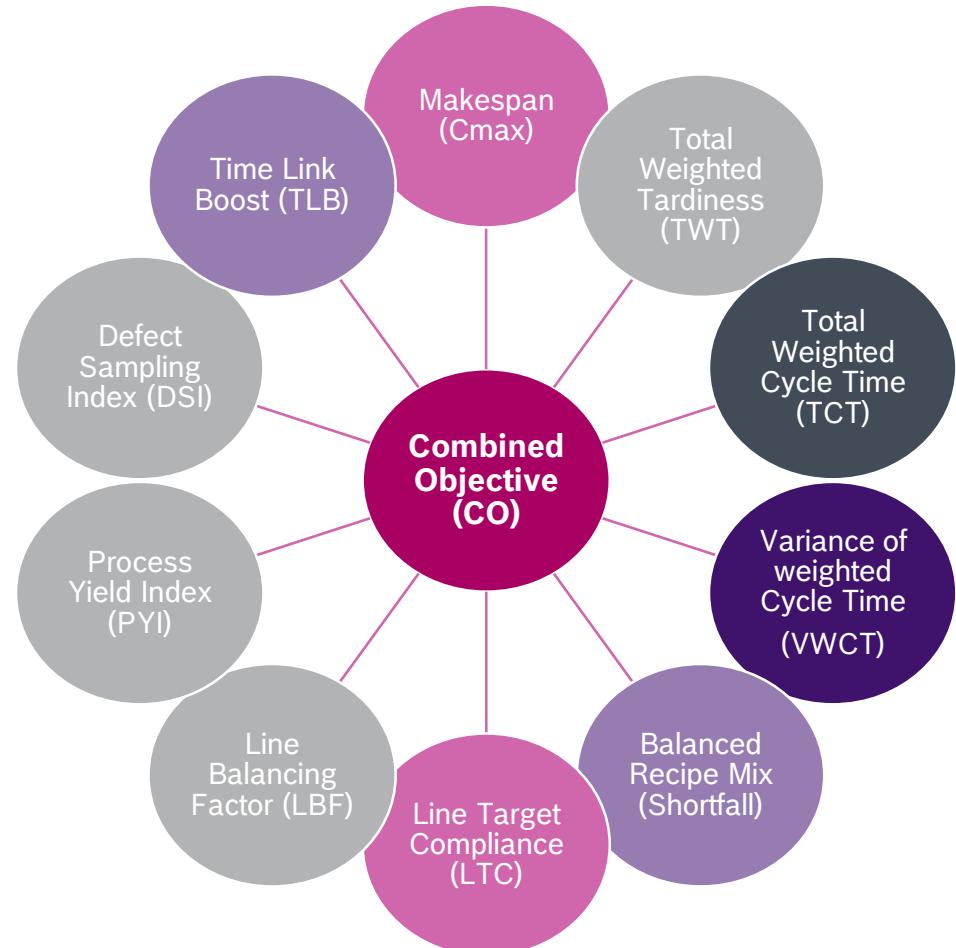
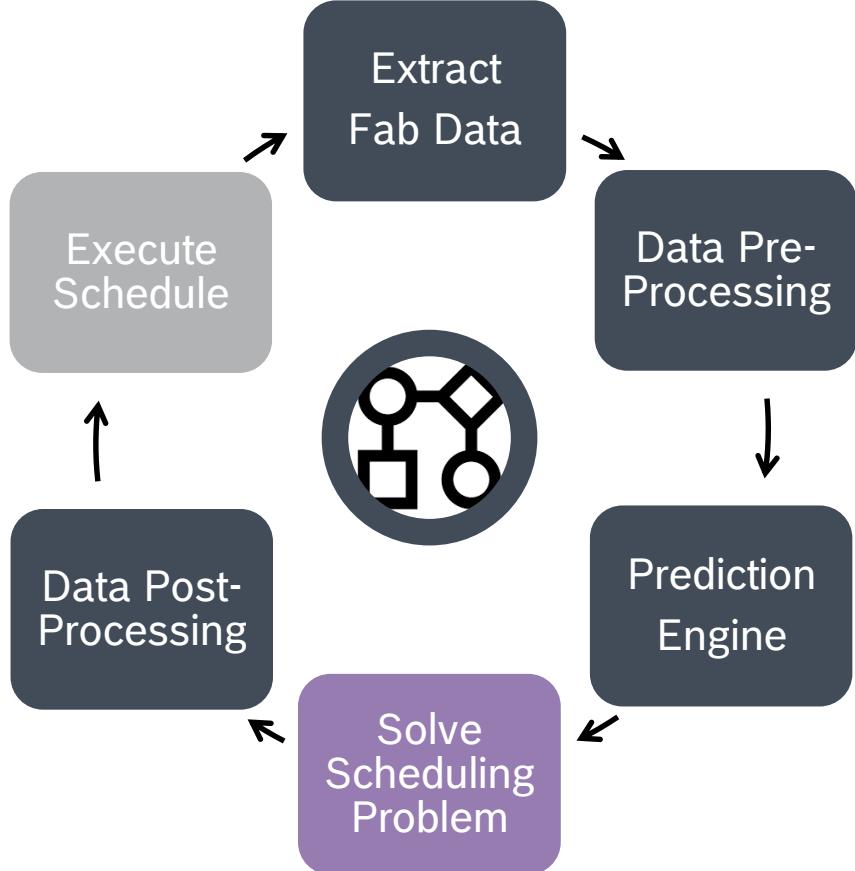
### 200mm Implant Workcenter



8 tools + 2 robots for (un-)loading

# Data Based Value Creation

## Use case: Production Scheduling



# Data Based Value Creation

## Use case: Production Scheduling



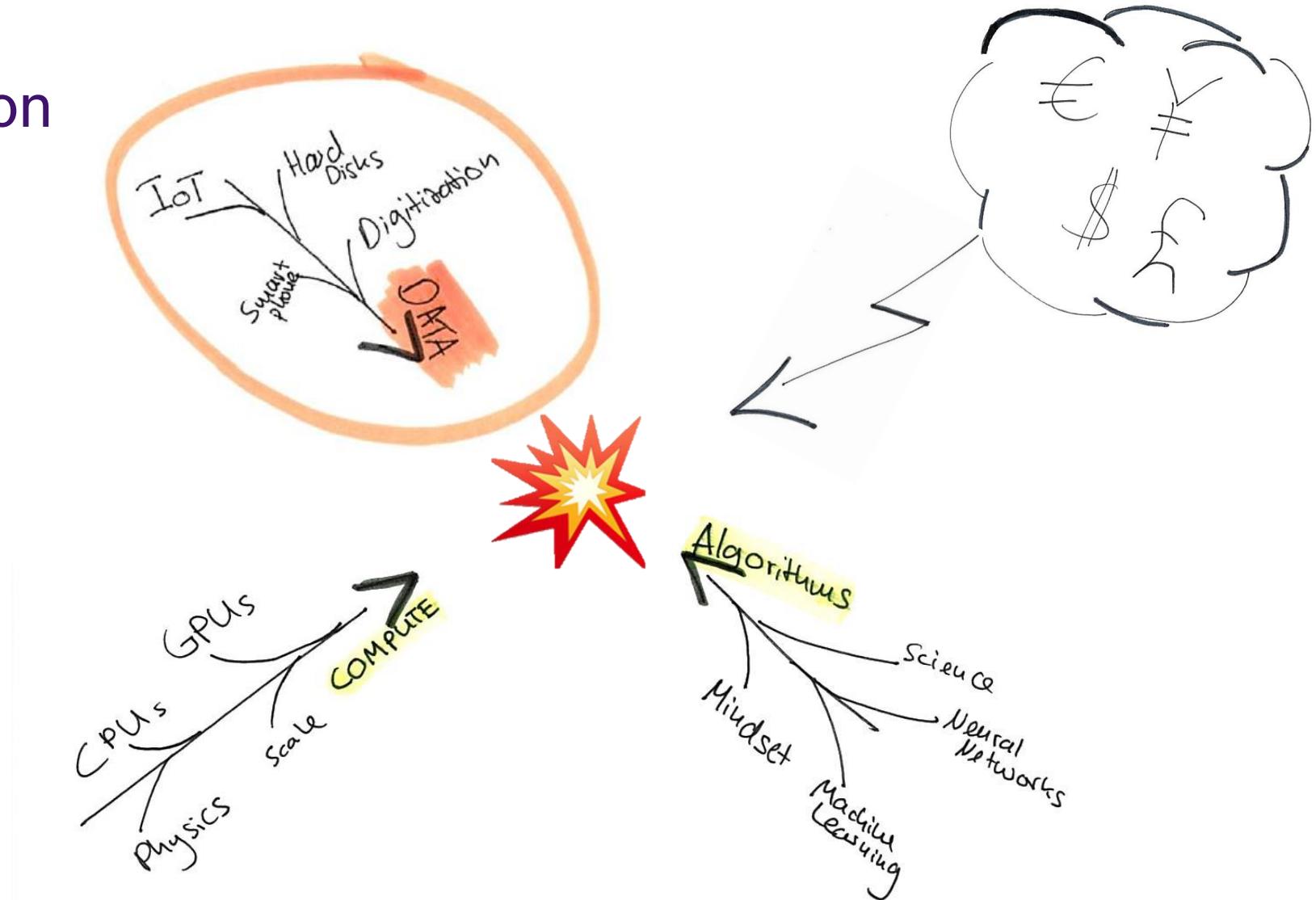
*“Nobody would intuitively do it like that, but it is actually better!”*

Minus ~45%  
StandBy-With-WIP

>5% more  
throughput with all-times high record

# Big Data

## The data dimension



# Big Data

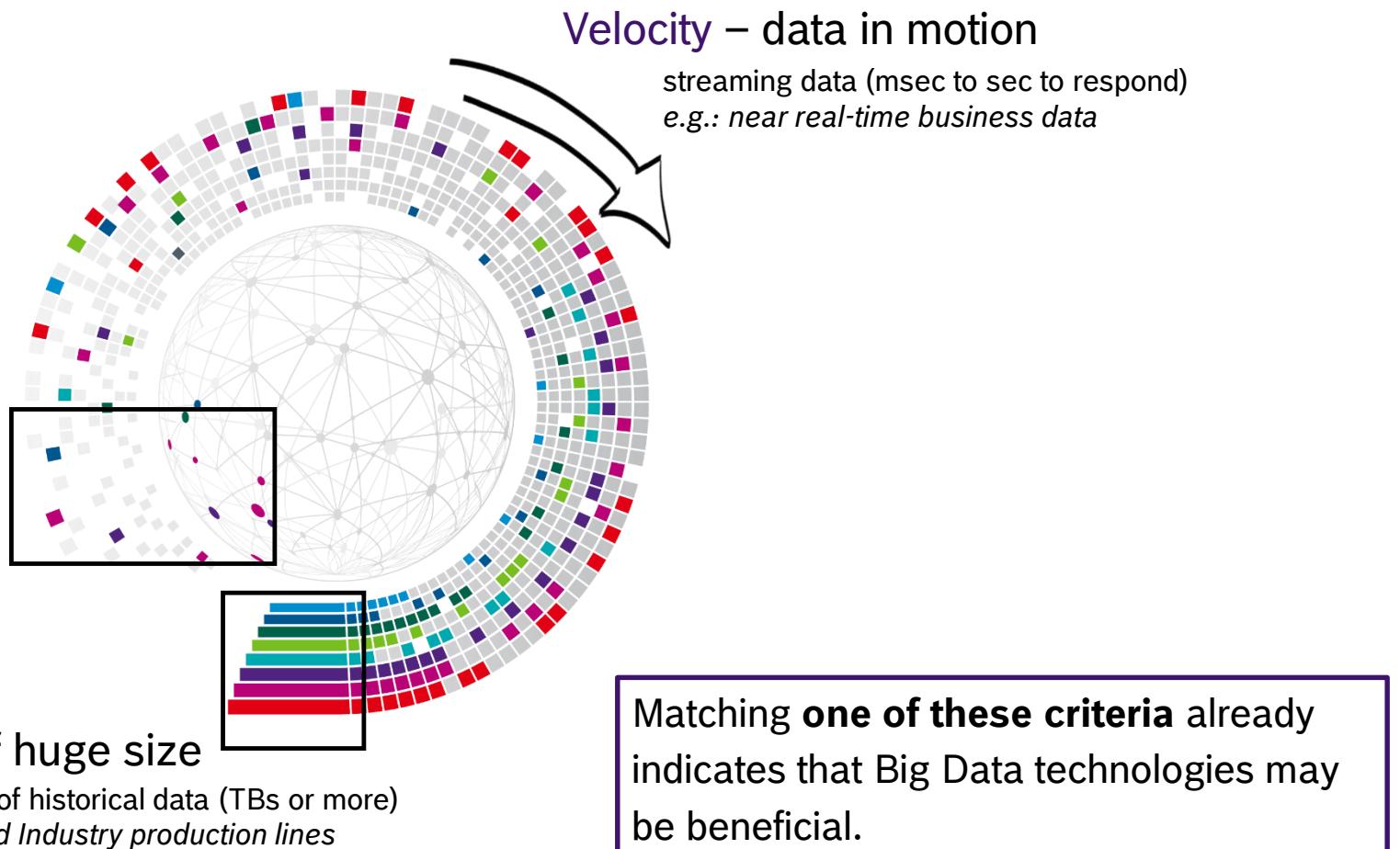
## The 3 V's

**Variety** – data in many forms

e.g. text, video, images;  
structured and unstructured  
*For example: self-driving car's cameras and sensors*

**Volume** – data of huge size

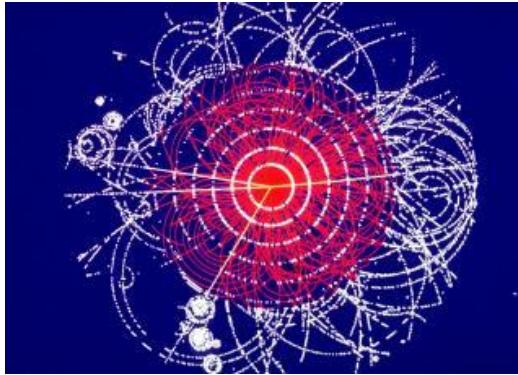
large amounts of historical data (TBs or more)  
*e.g.: Connected Industry production lines*



# Big Data

## What is Big Data? Volume

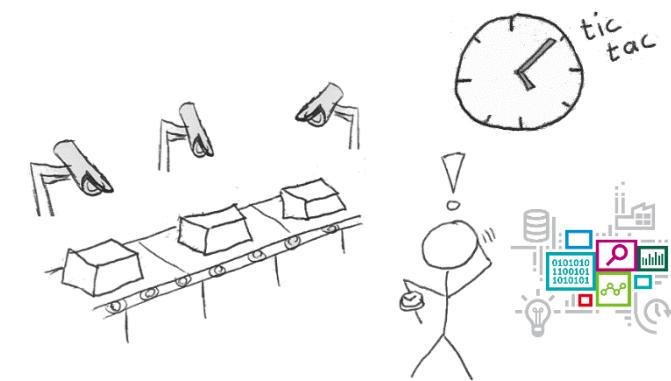
- ▶ Amount of data so large that we need new methods to process



**CERN LHC** data  
totaling 200 PB in 2017



**Each day** 4 PB are  
newly generated on  
Facebook



**Cycle Time Reduction**  
needs a large corpus of  
historical data to reveal  
patterns

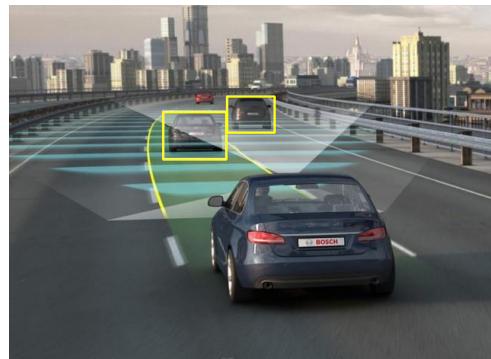
# Big Data

## What is Big Data? Velocity

- Data needs to be processed quickly for fast decision-making



High-frequency trading requires **seconds to milliseconds** reaction times



Autonomous driving needs to process **sensor, image, map data** rapidly to steer the car safely

# Big Data

## What is Big Data? Variety

- Beyond tables: all sorts of data can now be analyzed



**Voice data** is analyzed  
for speech recognition



**Pictures/Videos** can be used  
for image recognition tasks



**Natural language / text data** can be analyzed to  
extract information

# Big Data

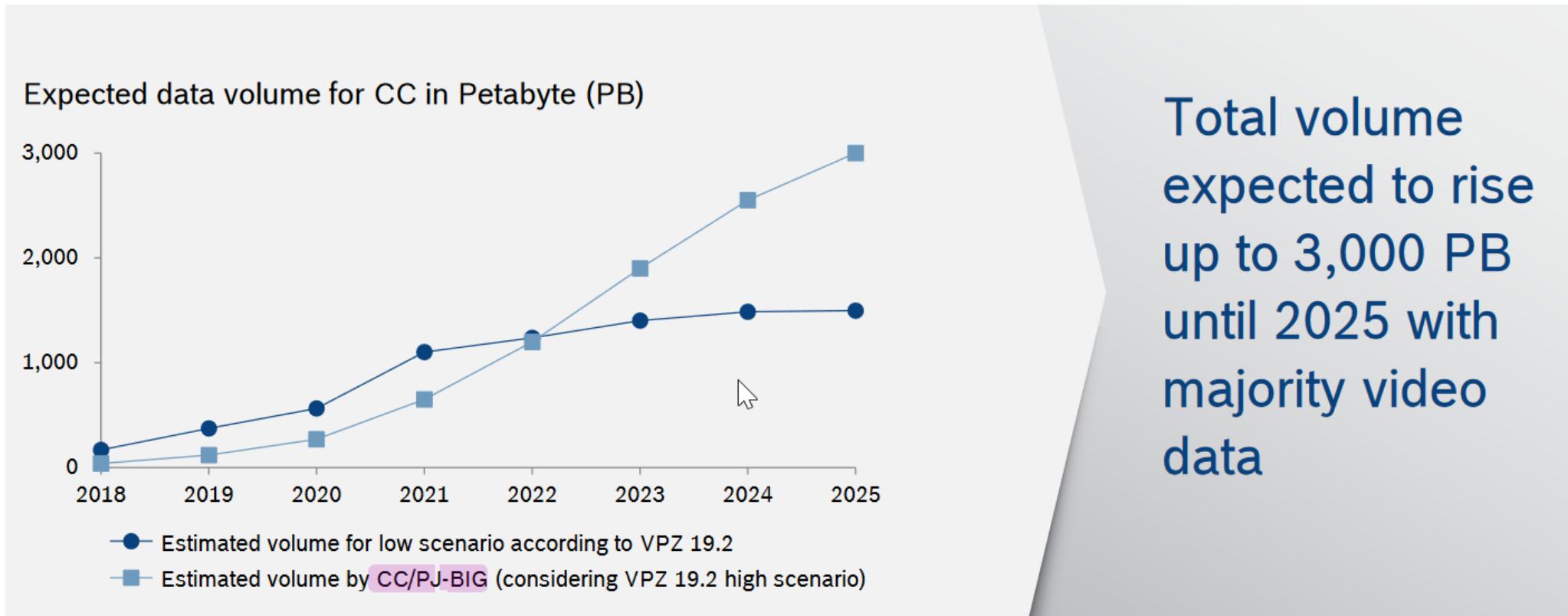
## When do we speak about big volume data?

- When we have > 100 GB of data which need to be processed continuously
- When the working memory of our PC is not sufficient anymore
- When the amount of data is rising in GBs on a monthly basis
- When relational databases, Excel etc. do not work efficiently anymore



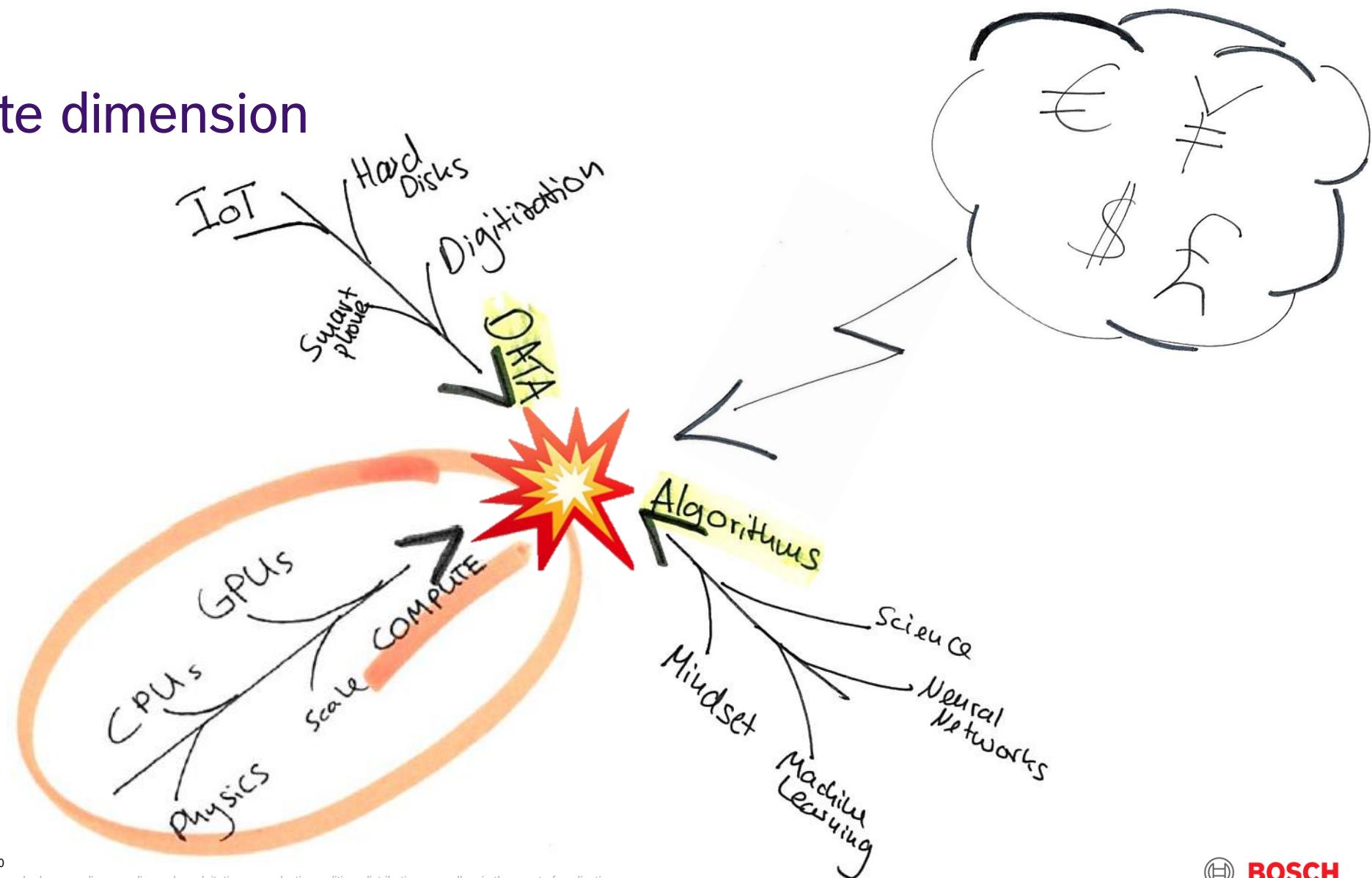
# Big Data @ Bosch

## Example: CC Data Lake



# Big Data

## The compute dimension



# Big Data

## Big Data computation – the idea of batch processing

- ▶ Goal: process very large amounts of (historic) data



- ▶ Idea: Divide and conquer algorithm

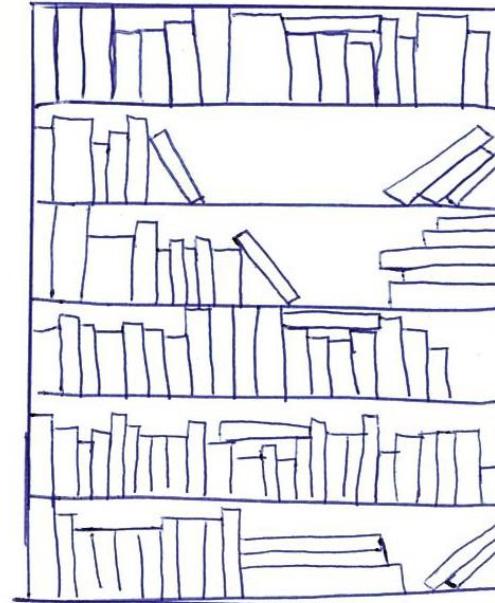


- ▶ How-to: Bring “processing to the data”



# Big Data

## How Big Data computation works – counting words

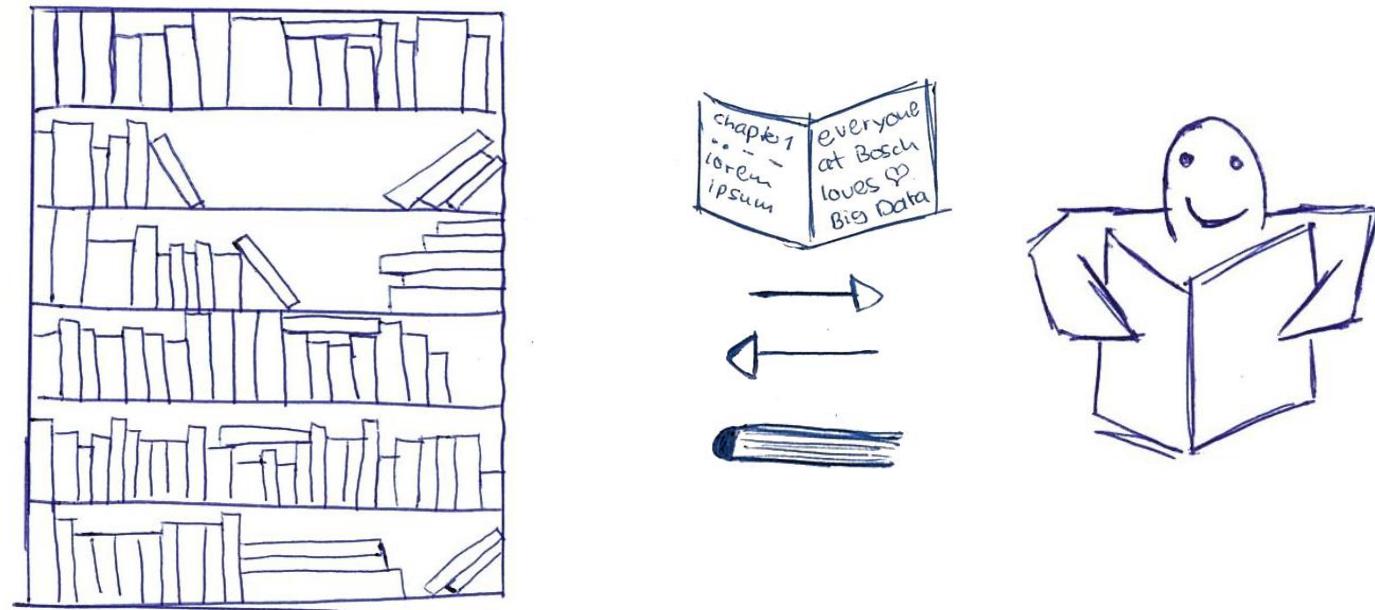


Challenging Task: count number of words in the whole bookshelf.



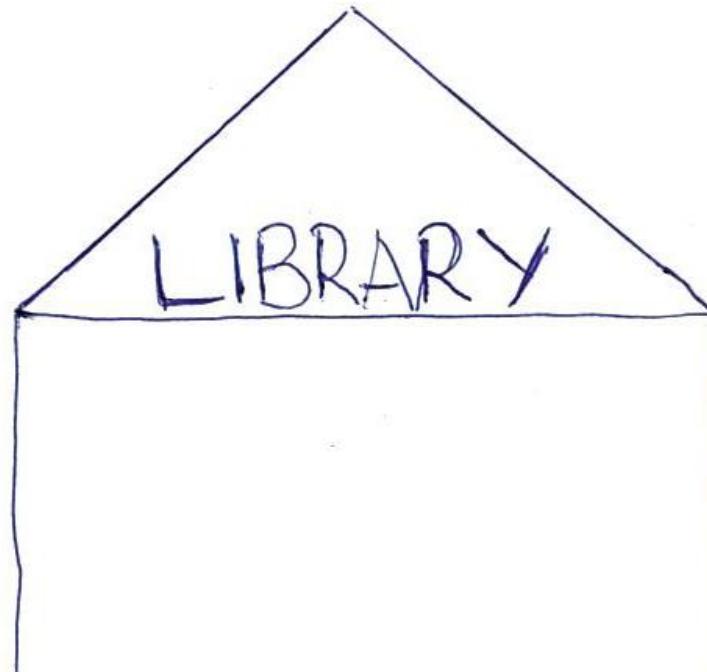
# Big Data

## How Big Data computation works – counting words



# Big Data

## How Big Data computation works – counting words

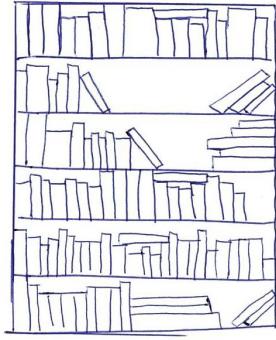


Sometimes you have a  
library to process ...

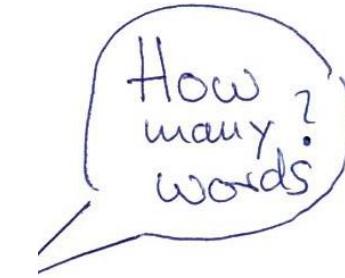
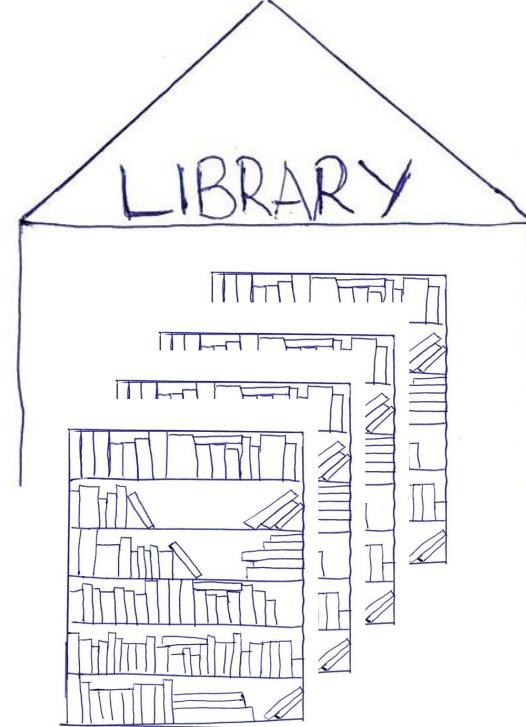


# Big Data

## How Big Data computation works – counting words



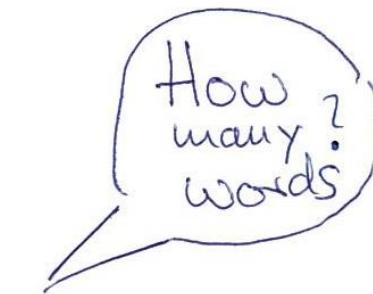
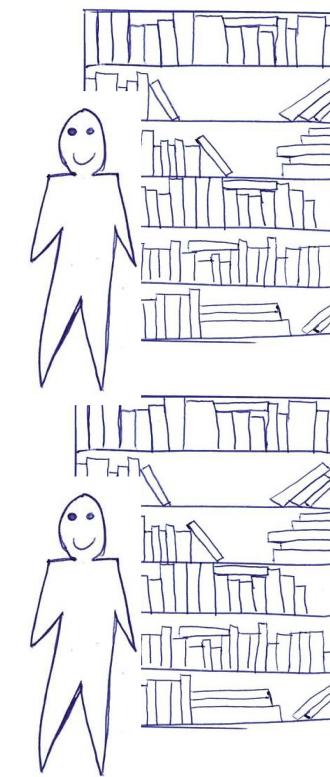
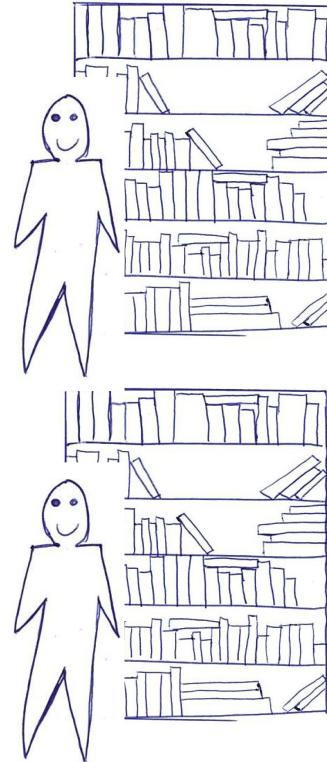
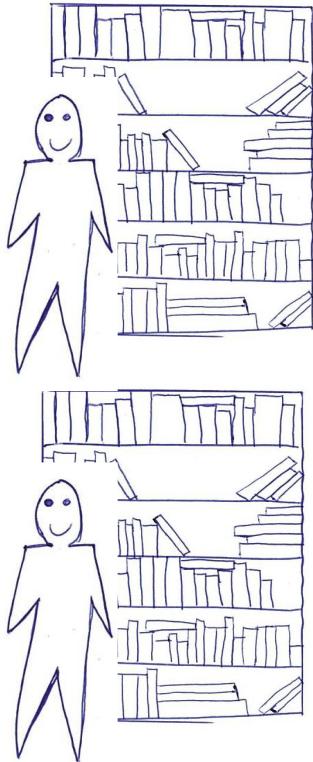
=  
same time



**Limited solution:** in the case of more bookshelves we can only maintain overall execution time by **reading and counting faster!**

# Big Data

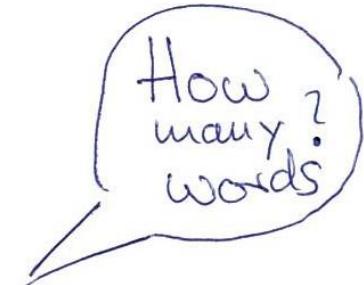
## How Big Data computation works – counting words



We move the workers close to data to minimize overhead: The **computation comes to the data.**

# Big Data

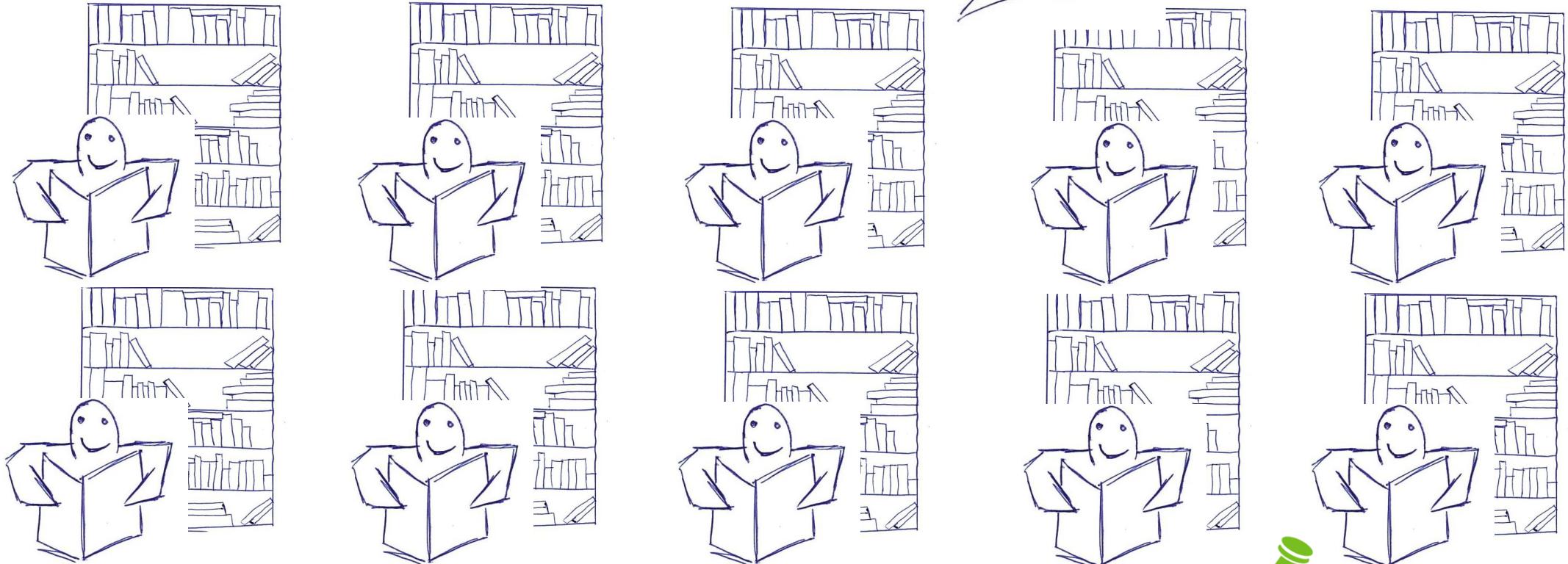
## How Big Data computation works – counting words



The **Big Data** approach is to find a **parallel description** of the task to **process more data in the time**.

# Big Data

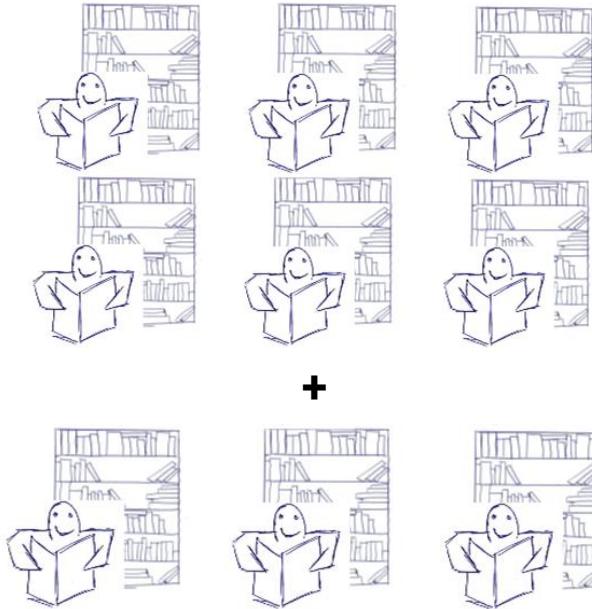
## How Big Data computation works



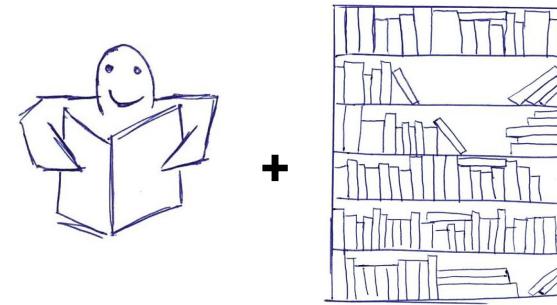
As **data volume grows**, workers can be added simply. The solution is highly **scalable**.

# Big Data

## Big Data computation – key benefits



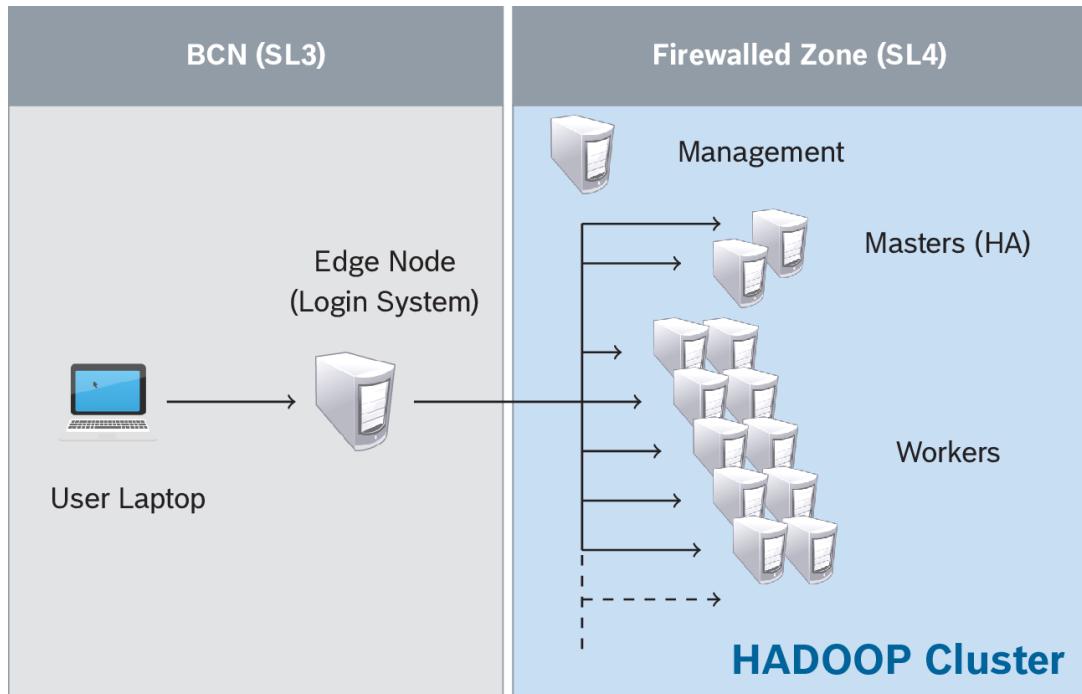
**Scalable solution** that  
can grow dynamically  
with volume



**Computation and data**  
are always **bundled** in  
order make data  
processable

# Big Data

## A typical Hadoop cluster



### Example configuration:

- ▶ Total net storage (10 Worker Nodes): **160 TB**
- ▶ Total working memory: **2560 GB**
- ▶ Total compute: **240 cores (480 with HT)**

# Big Data

## Hadoop ecosystem – tools for many situations



**Search** framework for large amounts of data



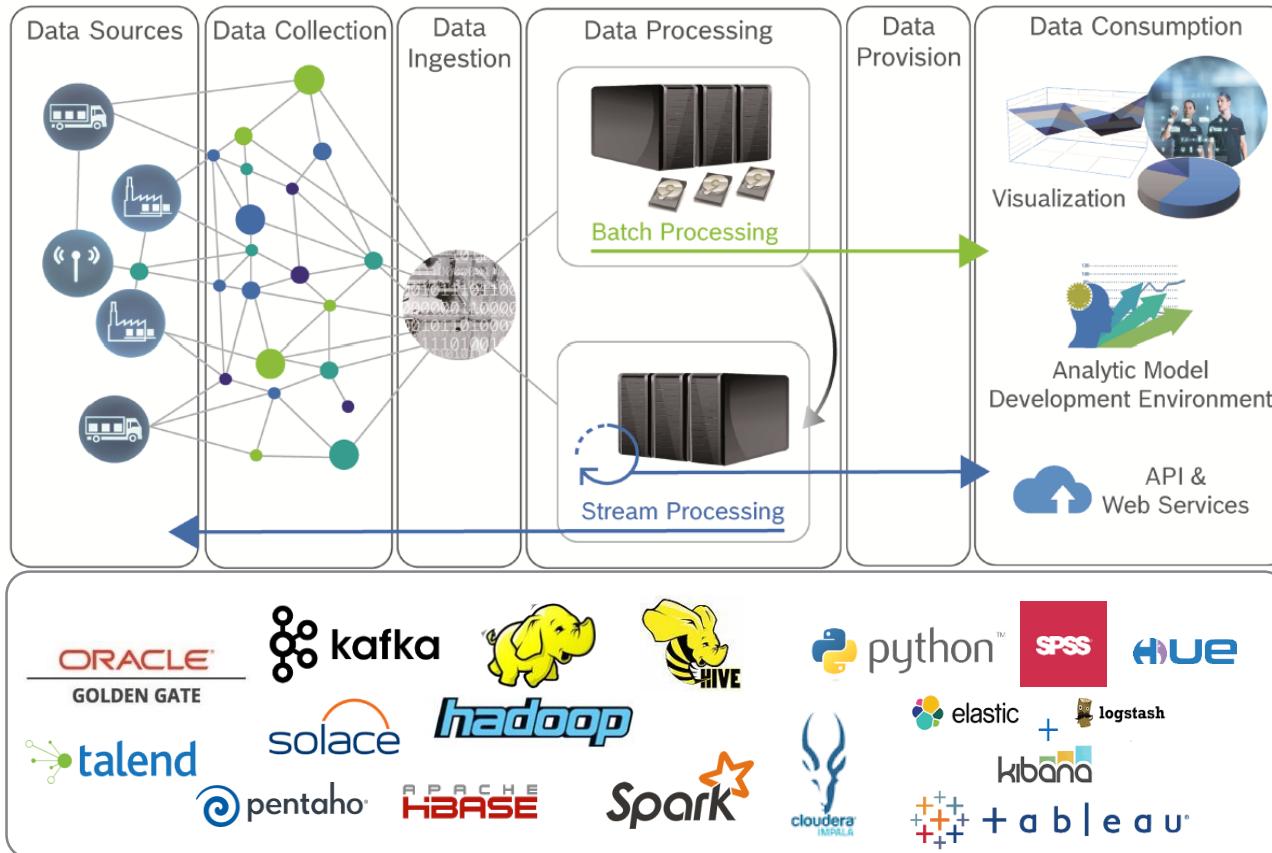
**In-memory** analytics for immediate access



Processing of **quickly incoming data** (velocity)

*Poll:*  
*“What are the essential ideas of  
Hadoop clusters?”*

# Big Data RB Analytics Platform



The RB Analytics Platform is the implementation of Hadoop for Bosch needs.

It is a modular toolstack based on Big Data framework **Hadoop** with many state-of-the-art tools available.

# Big Data

## Use Case: Big Data platform for PS/PJ-DT Xelerator

- ▶ At PS there is a 20-worker-node computer cluster (320 TB net storage) for analytics in production
- ▶ **Collect production data** from production systems of an injector
  - ▶ Access to production data bases without interruption
  - ▶ Unified schemas and datatypes
  - ▶ Data understanding of machine outputs and labels

# Big Data

## Use Case: Big Data platform for PS/PJ-DT Xelerator

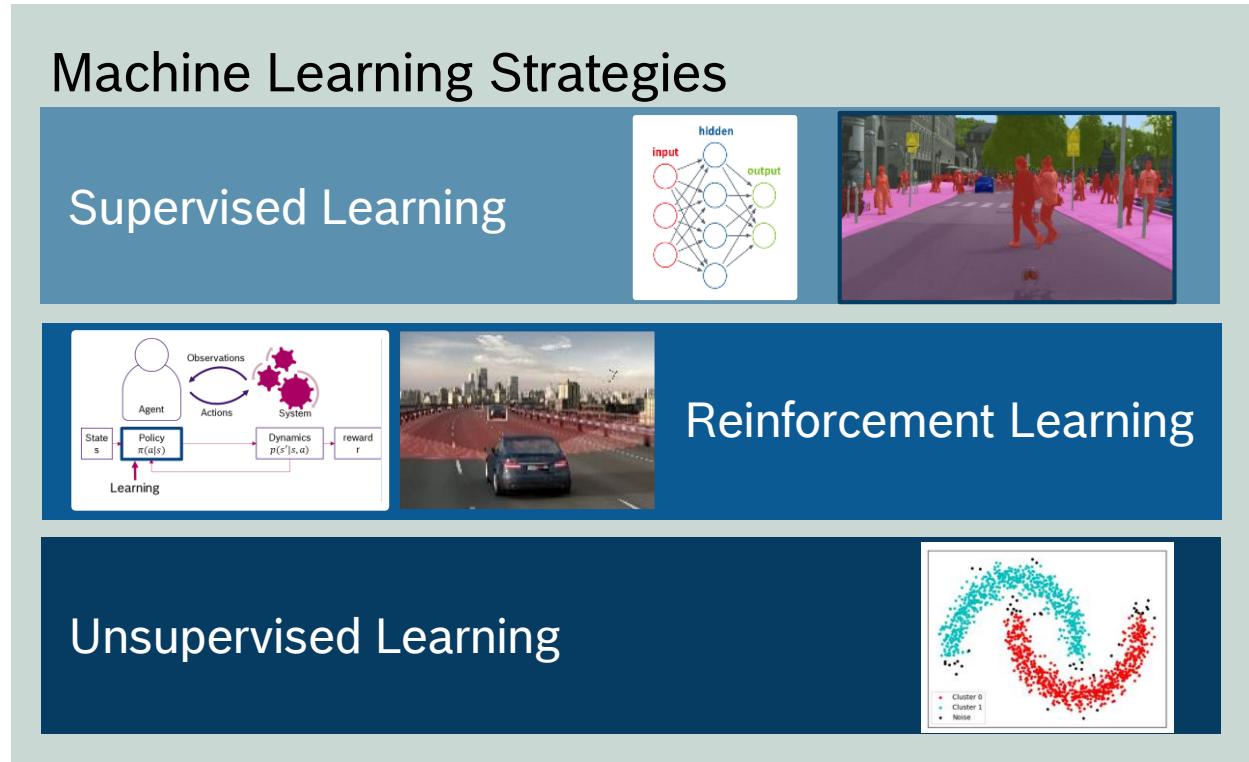
- ▶ Make data accessible to be **analyzed**
  - ▶ Build up of a common truth with production data
  - ▶ Dashboard for visual analytics
  - ▶ “What took weeks before we can now do in minutes”
- ▶ First use case: data-driven **reduction of test points**



# MACHINE LEARNING

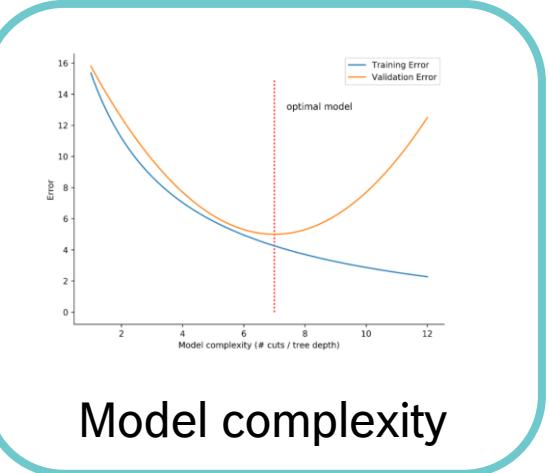
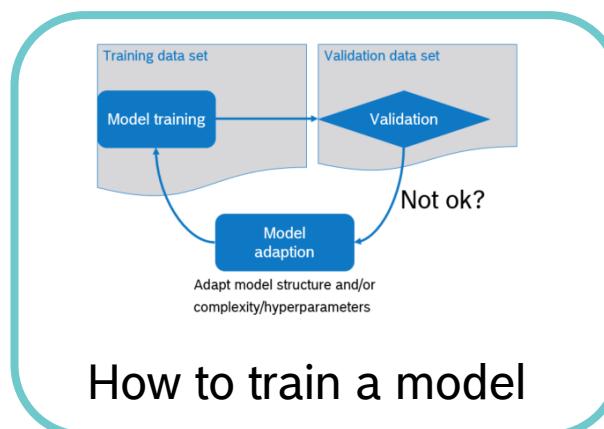
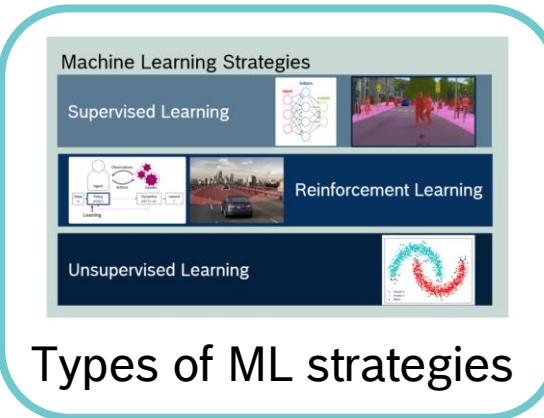
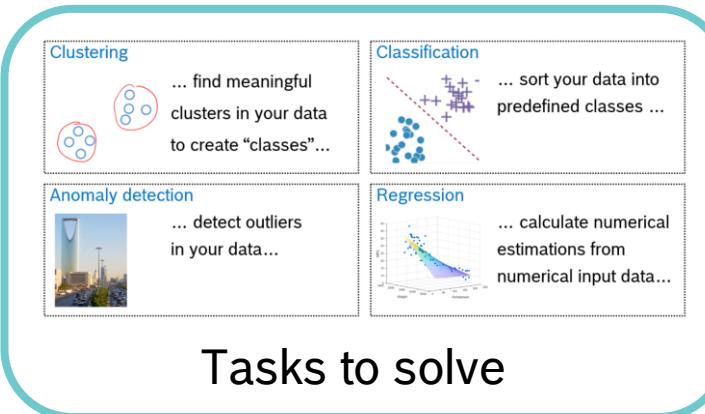
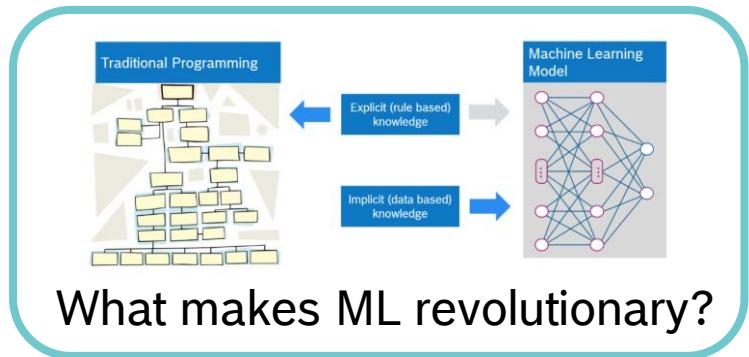
# Machine Learning

## Machine Learning strategies



# Machine Learning

## What will you learn in this section?



# Machine Learning Definition

## Definition by Prof. Tom M. Mitchell:

A computer program is said to **learn** from **experience E**

w.r.t. a **task T** and **measure P**,

if its performance **P** on **T**,

improves with experience **E**.



[http://bzo.bosch.com/bzo/de/article\\_page\\_37325.html](http://bzo.bosch.com/bzo/de/article_page_37325.html) (Bosch Zündler Online)

## Example

Your e-mail program improves its spam filter mechanism by watching you marking e-mails as spam or not.

# Machine Learning

## Learning from experience



Depositphotos, Bosch License

Learning...

- ❖ To say “car”
- ❖ To distinguish cars from trucks
- ❖ To drive a car ...

all requires **experience!**

# Machine Learning

## Example: a daisy vs tulip model (supervised learning)

In your garden, there are daisies and tulips. Your mom tells you to pick daisies for her.



We want to solve your daisy picking task  
by building a **model**,  
i.e. a system that helps you to  
distinguish daisies and tulips!

# Machine Learning Features as a basis for the model

Now choose **features**,

i.e. criteria that help you and the model  
to decide if a flower is a daisy or a tulip.

Examples features:

- ❖ Number of leaves
- ❖ Height
- ❖ Color



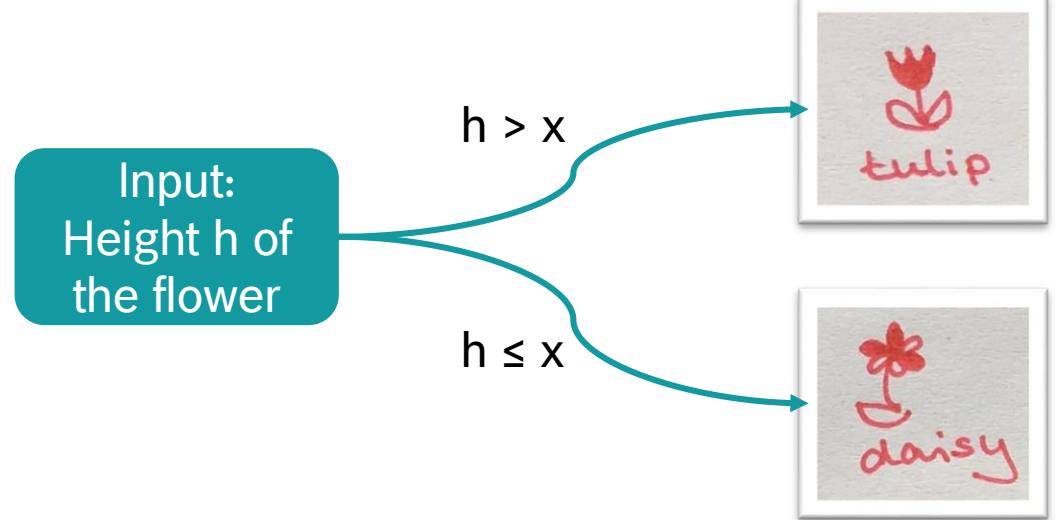
# Machine Learning Model building

1. Choose a feature (height)
2. Take measurements

Type	Height (cm)
Daisy	8
Tulip	16
Tulip	20
Daisy	4
Tulip	9
Daisy	5
Daisy	10

## 3. Build a model

Output:  
Type of  
the flower

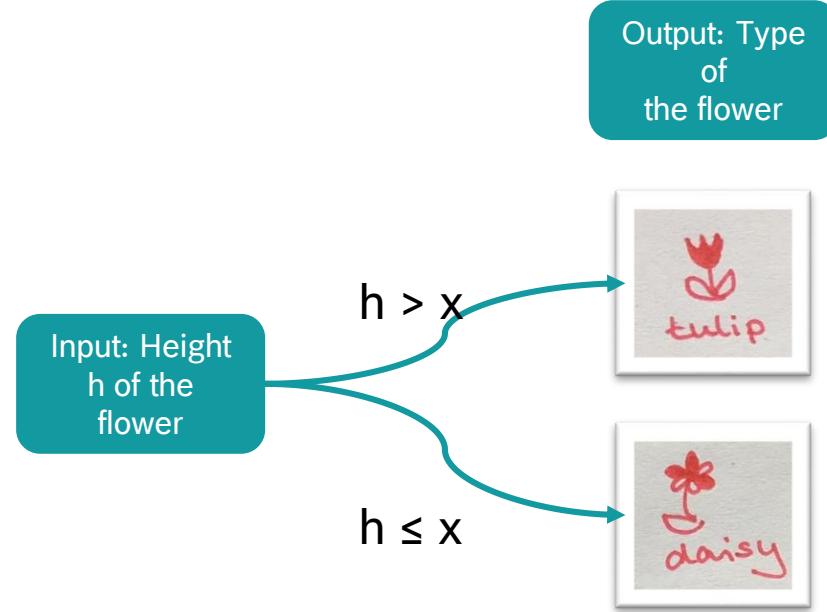


This model has one parameter:  $x$ .

# Machine Learning

## Model training

Type	Height (cm)
Daisy	8
Tulip	16
Tulip	20
Daisy	4
Tulip	9
Daisy	5
Daisy	10



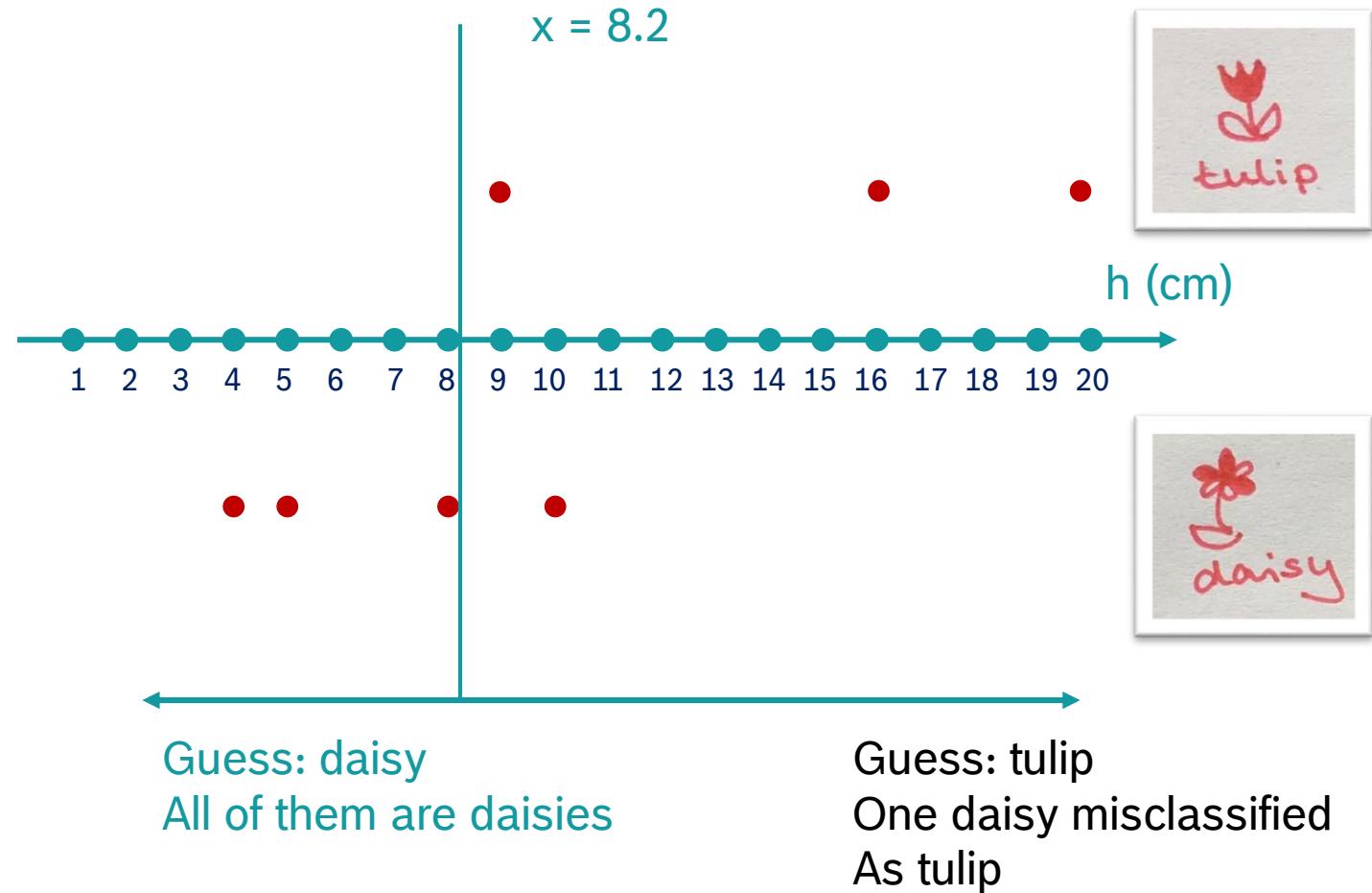
Model training means to optimize the parameter  $x$  such that it makes the least errors.

We learn the parameter of the model from data!

Exercise: Optimize  $x$ !

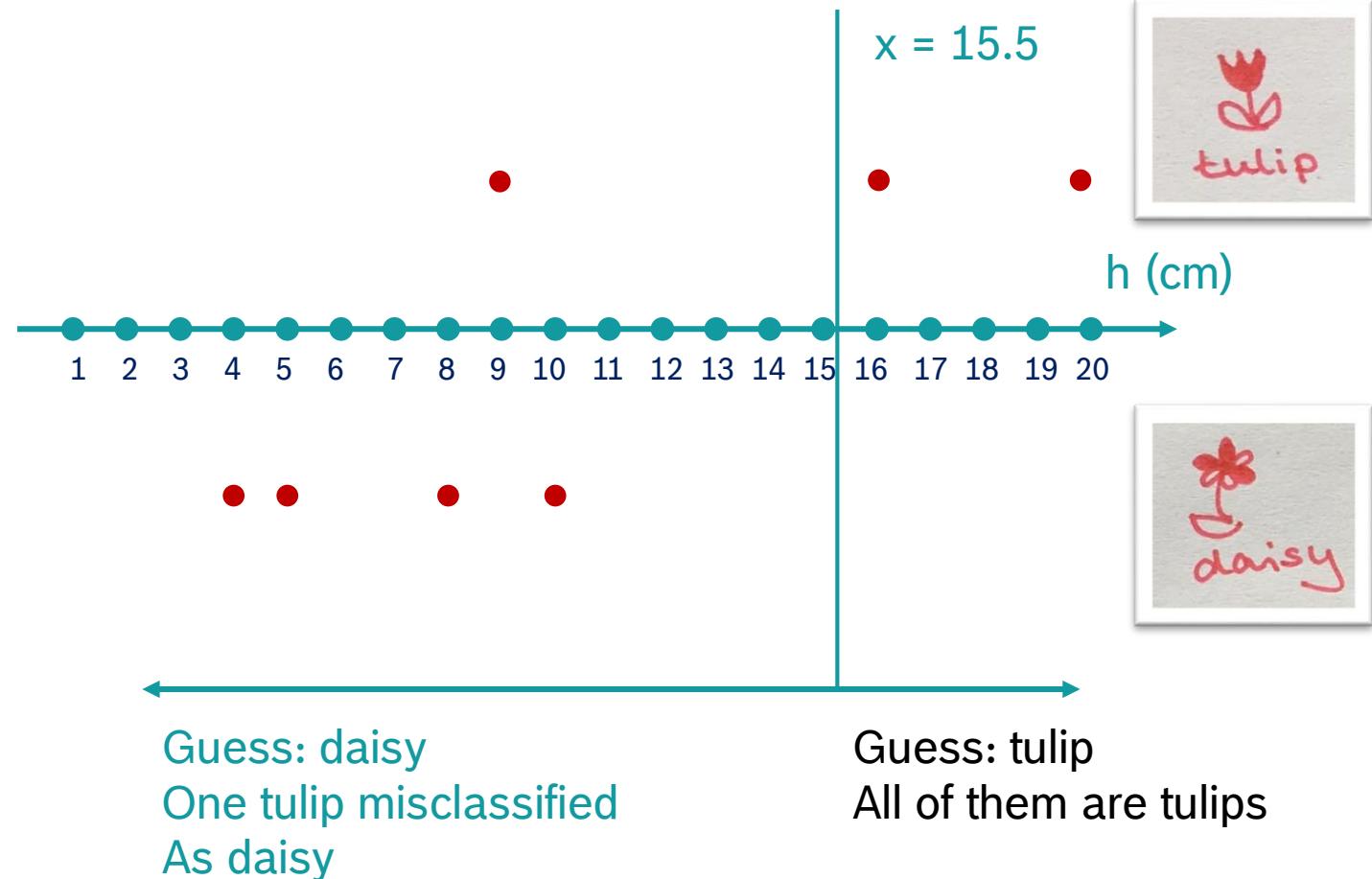
# Machine Learning Optimized model 1

Type	Height (cm)
Daisy	8
Tulip	16
Tulip	20
Daisy	4
Tulip	9
Daisy	5
Daisy	10



# Machine Learning Optimized model 2

Type	Height (cm)
Daisy	8
Tulip	16
Tulip	20
Daisy	4
Tulip	9
Daisy	5
Daisy	10



# Machine Learning Model performance

How good is our model and our parameter choice?

Different ways to measure model performance

Accuracy:

$$\frac{\# \text{ correct predictions}}{\# \text{ total predictions}}$$

Confusion matrix:

Prediction Reality	 tulip	 daisy
 tulip	OK	Error 1
 daisy	Error 2	OK

# Machine Learning

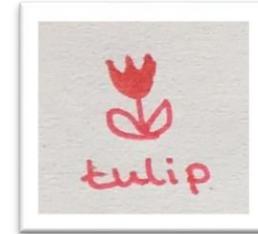
## Training strategy: supervised learning

Model training  
in 3 steps:

**modify x**

Update model  
parameters to  
minimize error

Predict



Learn

Estimate output of your model  
based on new input



Error  
check

Evaluate the error  
between prediction  
and target output

# Machine Learning

## Do machines learn from experience?

### Traditional software development

- ❖ Task described by formal specification
- ❖ Implemented with an unambiguous set of instructions

```
def bar(n):  
    if n < 0:  
        n = 0  
  
    result = 0  
    for i in range(n+1):  
        result += i  
    return result  
  
def foo(m):  
    l = lambda x: (x+1)*x / 2  
    return l(m)  
  
if __name__ == "__main__":  
    main(sys.argv)
```

### Job of the programmer:

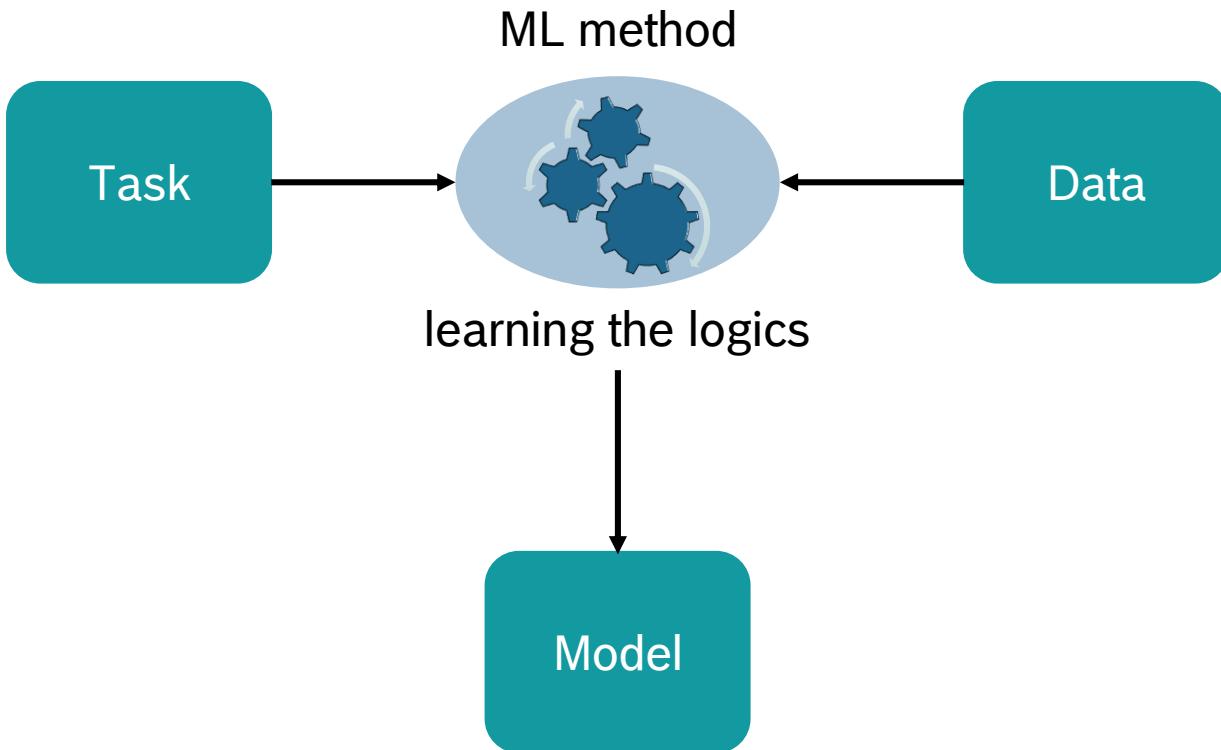
- ❖ Find out the logics to solve the task
- ❖ Implement path to solution step by step

### Job of the program:

- ❖ Execute step by step what the programmer implemented
- ❖ No changes from experience
- ❖ Explicit process steps implemented

# Machine Learning

## Machine Learning (ML) as a new software development paradigm



**Job of the ML engineer:**

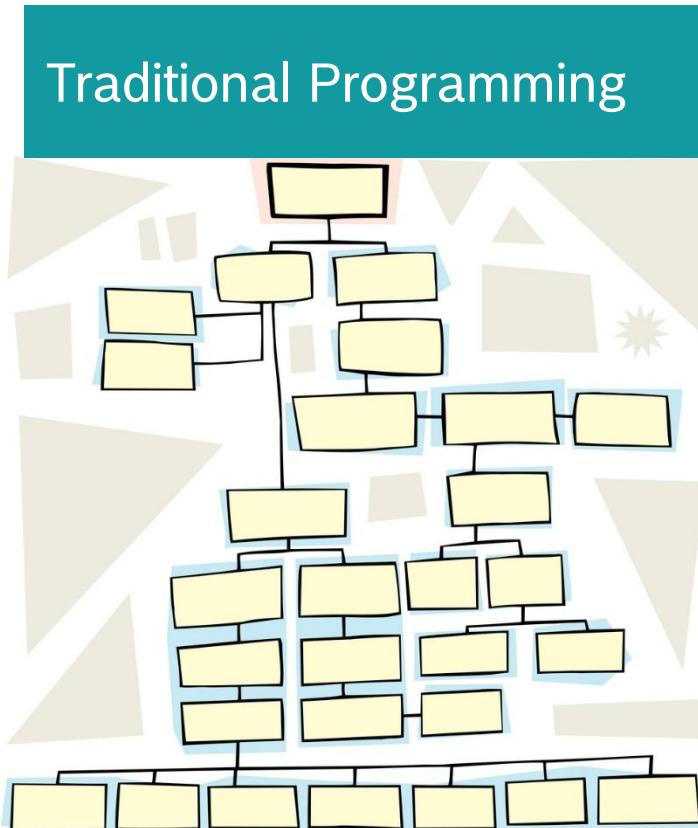
- ❖ Find the right ML method
- ❖ Feed it with the right data according to the task to solve

**Job of the ML method:**

- ❖ Learn the logic to solve the task
- ❖ Optimize iteratively by learning from data describing the right behavior

# Machine Learning

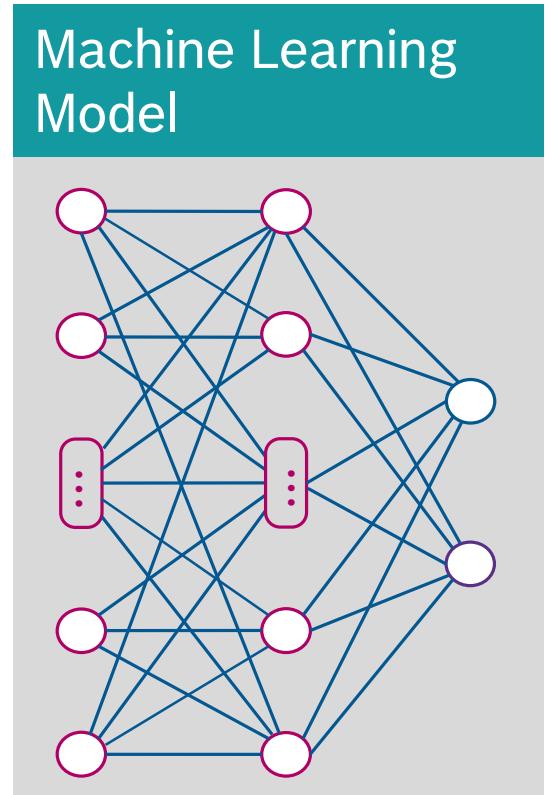
## Explicit vs. implicit knowledge



Explicit (rule based)  
knowledge



Implicit (data based)  
knowledge



# Machine Learning

## Second example: pool data set

Which house has a pool?

Price	Pool (0=no, 1=yes)
200k	0
405k	1
230k	0
357k	1
189k	0
171k	1
...	...



Flickr designmilk, CC BY-SA 2.0

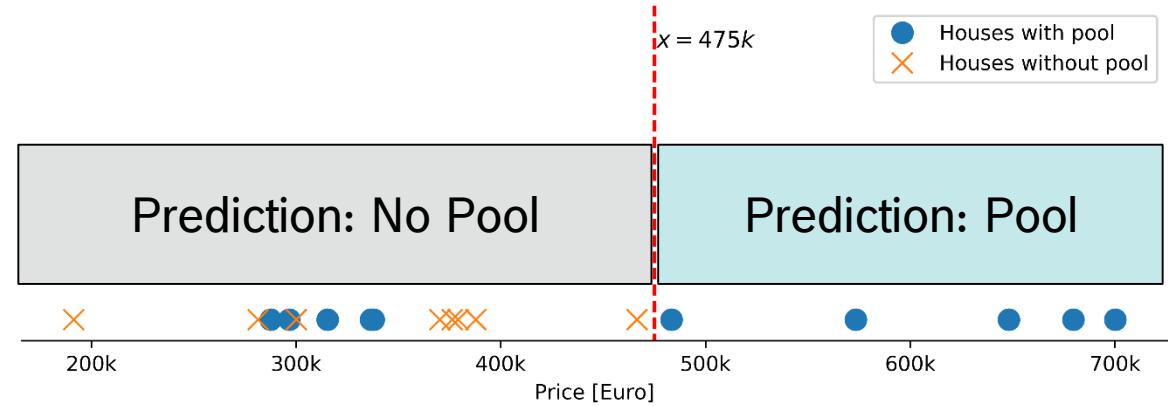
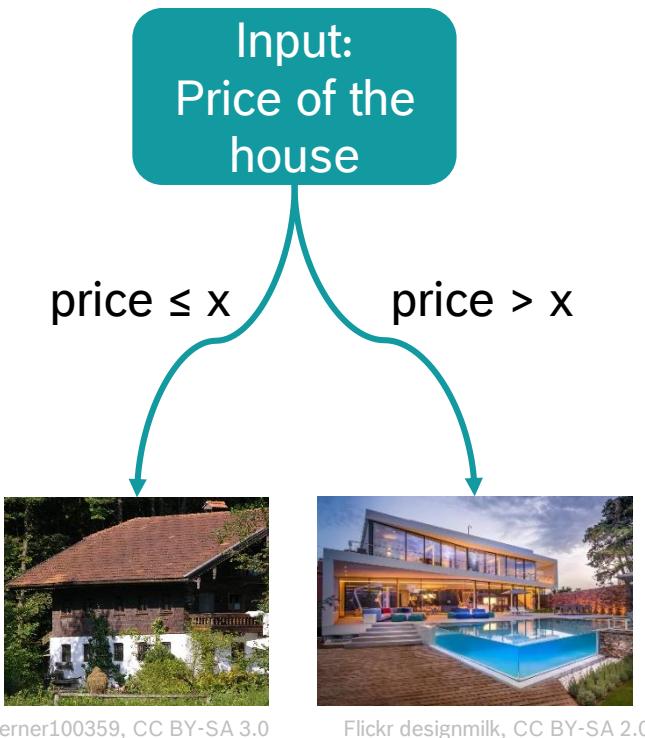
- Houses with pool
- ✖ Houses without pool

# Machine Learning

## Simple cut-based model

### Definition:

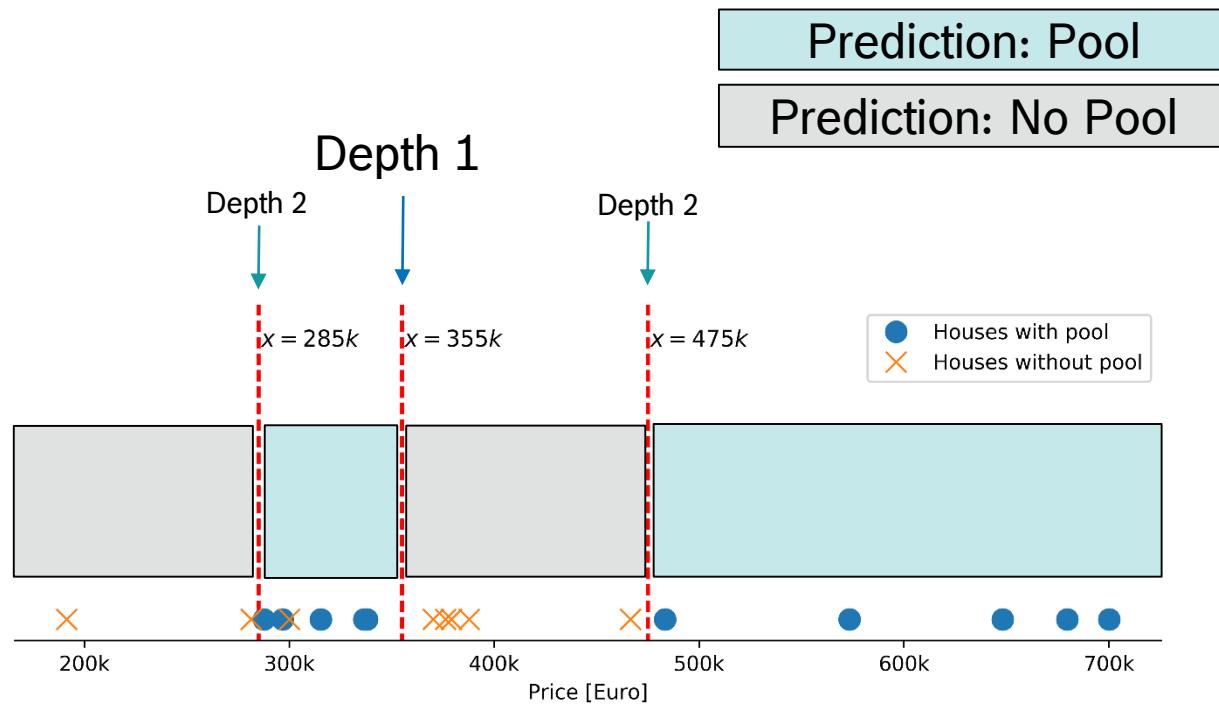
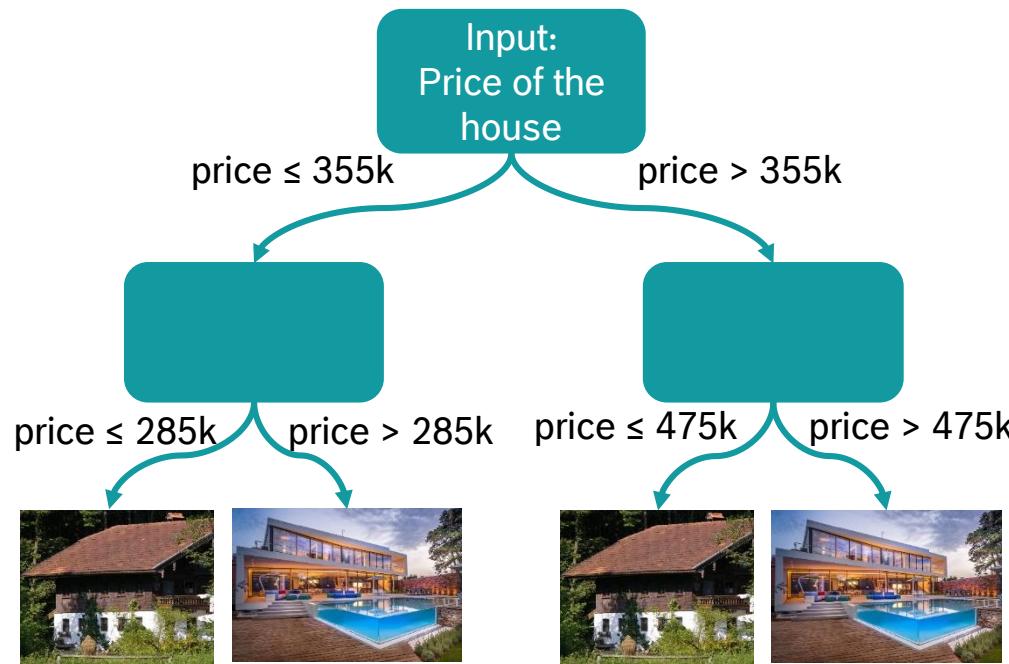
$$\text{Accuracy} = \frac{\# \text{ correctly classified data samples}}{\# \text{ total data samples}}$$



### Performance on training data

4 misclassifications: Accuracy =  $\frac{14}{18} = 77.8\%$

# Machine Learning Model with depth 2



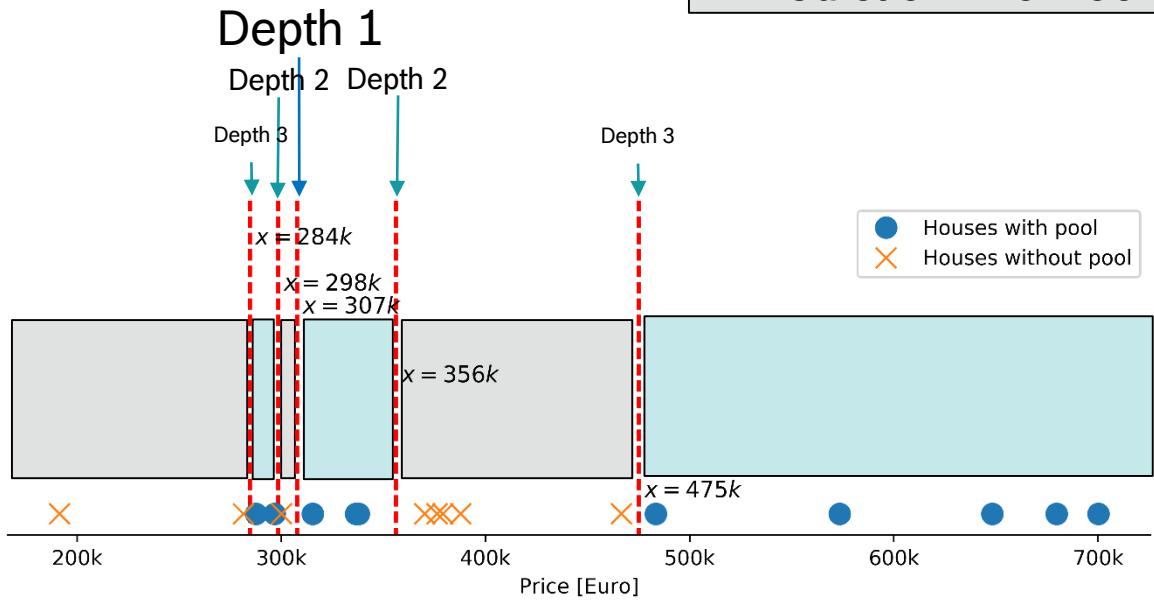
Performance on training data

1 misclassification: Accuracy =  $\frac{17}{18} = 94.4\%$

# Machine Learning Model with depth 3



Prediction: Pool  
Prediction: No Pool



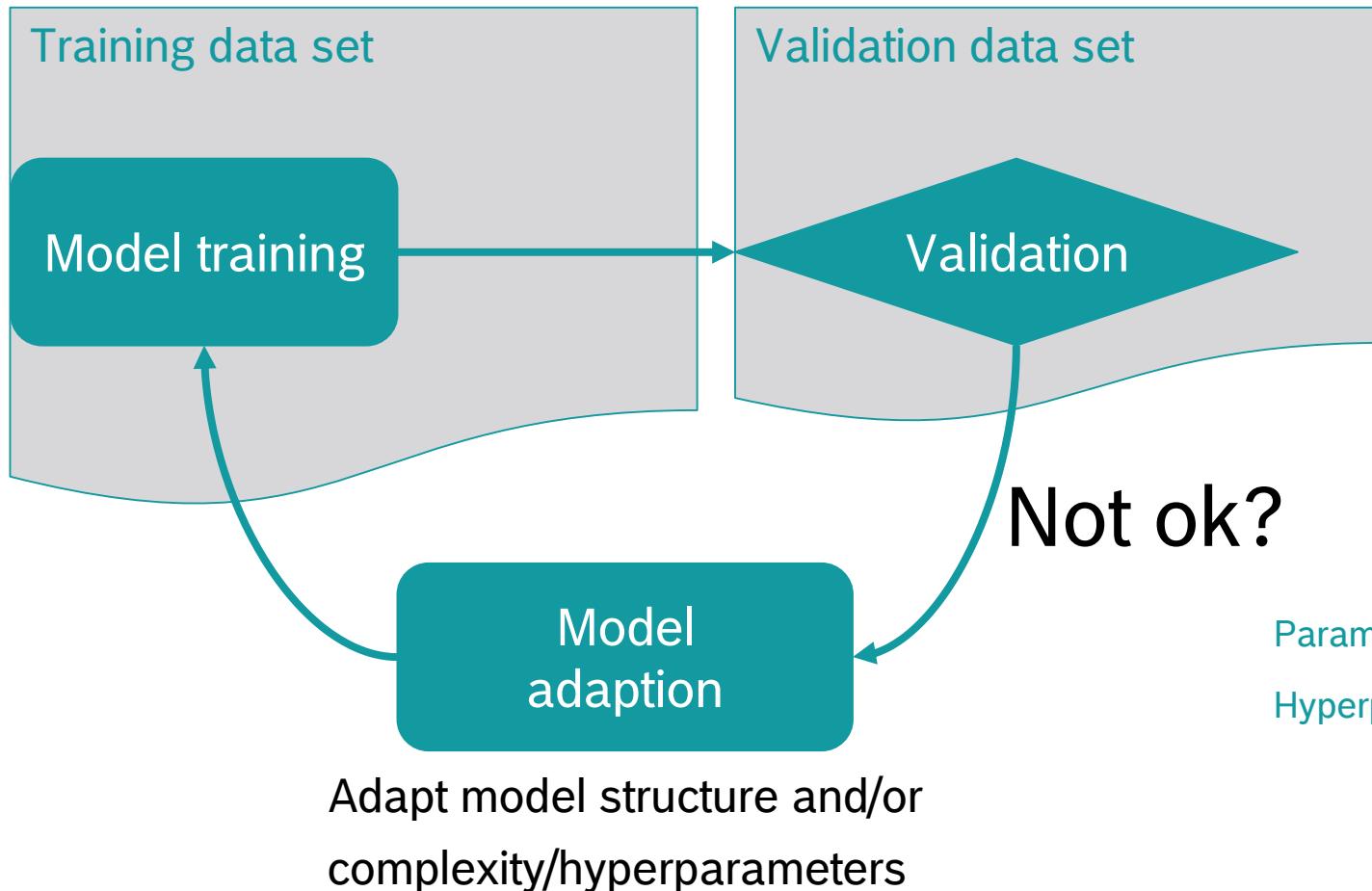
## Performance on training data

0 misclassifications: Accuracy =  $\frac{18}{18} = 100\%$

**Poll:**  
„Would you use this model for new data?”

# Machine Learning

## Model validation & adaption



Accuracy:

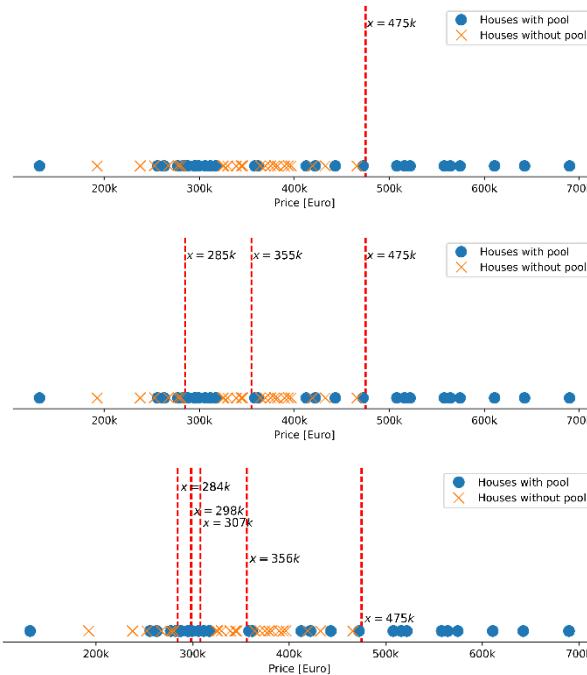
$$\frac{\text{\# correct predictions}}{\text{\# predictions}}$$

Parameters: learned by the training of the model

Hyperparameters: have to be set by the Data scientist,  
will not be trained by the model  
(examples: tree depth)

# Machine Learning Model validation

Apply trained model to houses not used for training (validation data)



Training accuracy: 77.8%  
Validation accuracy: 61.1%



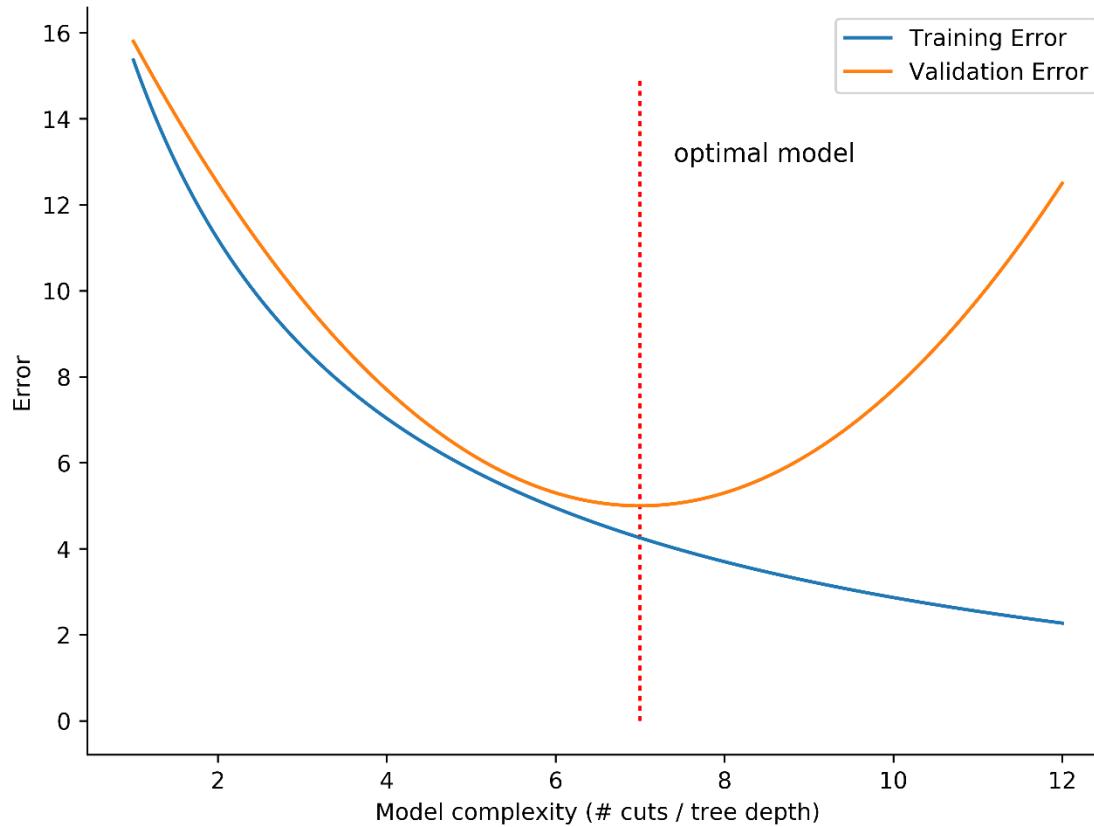
Training accuracy: 94.4%  
Validation accuracy: 66.7%



Training accuracy: 100%  
Validation accuracy: 62.9%

# Machine Learning

## Training vs validation error



# Machine Learning Poll

*Poll:*  
*“Why do we need a validation data set?”*

# Machine Learning Task: classification

The task in the examples is called **classification**.

**Target:** sort data into predefined classes

**Examples:** scrap (yes/no)

driver types (sporty, economic, ...)

image recognition (car, tree, pedestrian)

choosing the right type of “gummy bear”



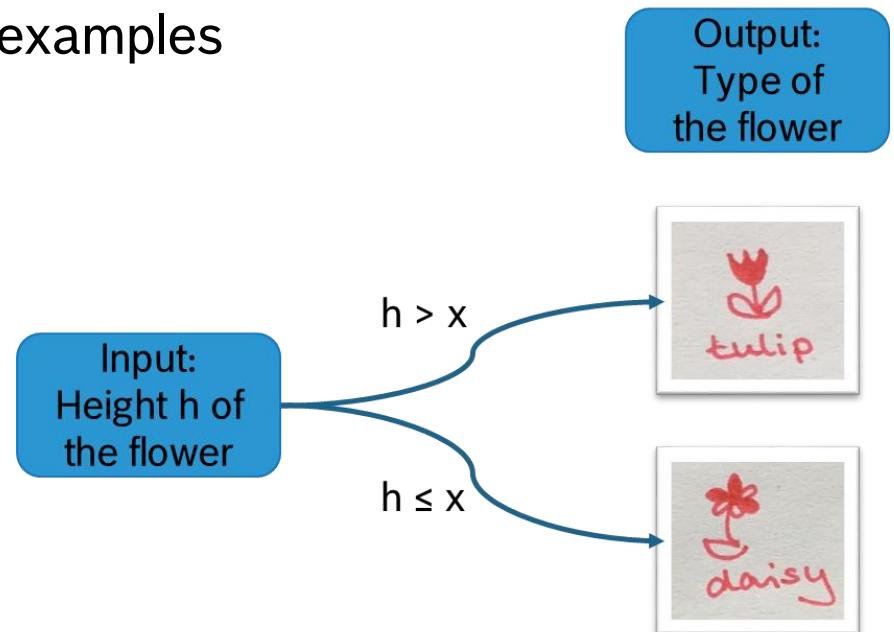
Swedish Fish, gummi bears and gummi worms by ChildofMidnight, CC BY-SA 3.0

# Machine Learning

## Classification methods

The task of classification is often solved by

- ❖ Decision trees as in the daisy/tulip, pool/no pool examples



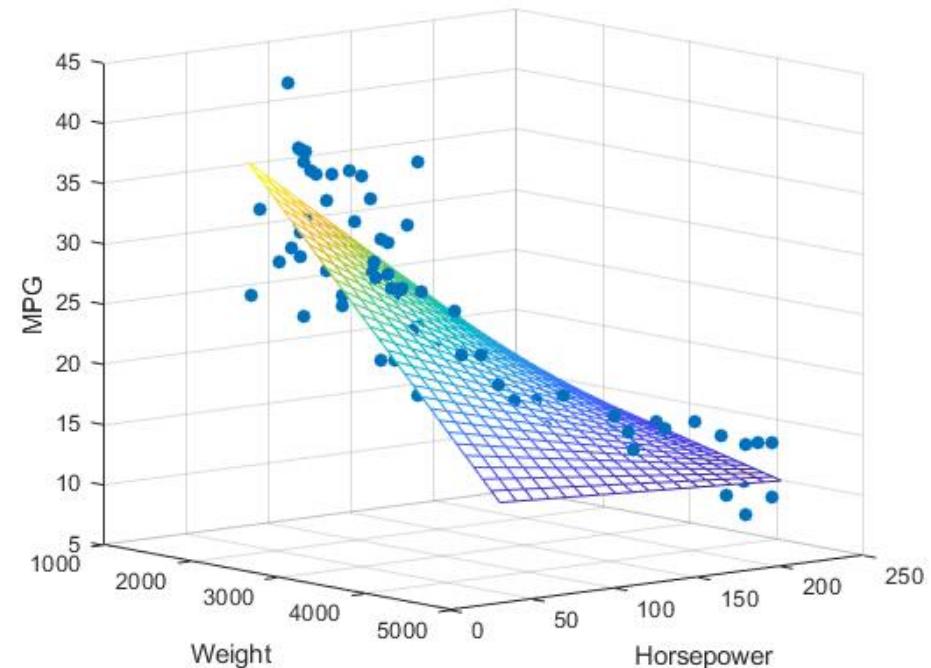
- ❖ Deep learning (later)

# Machine Learning

## Task: regression

Target: numerical estimation of a variable due to certain input variables

Example: vehicle range (MPG)  
depending on vehicle  
weight and horsepower

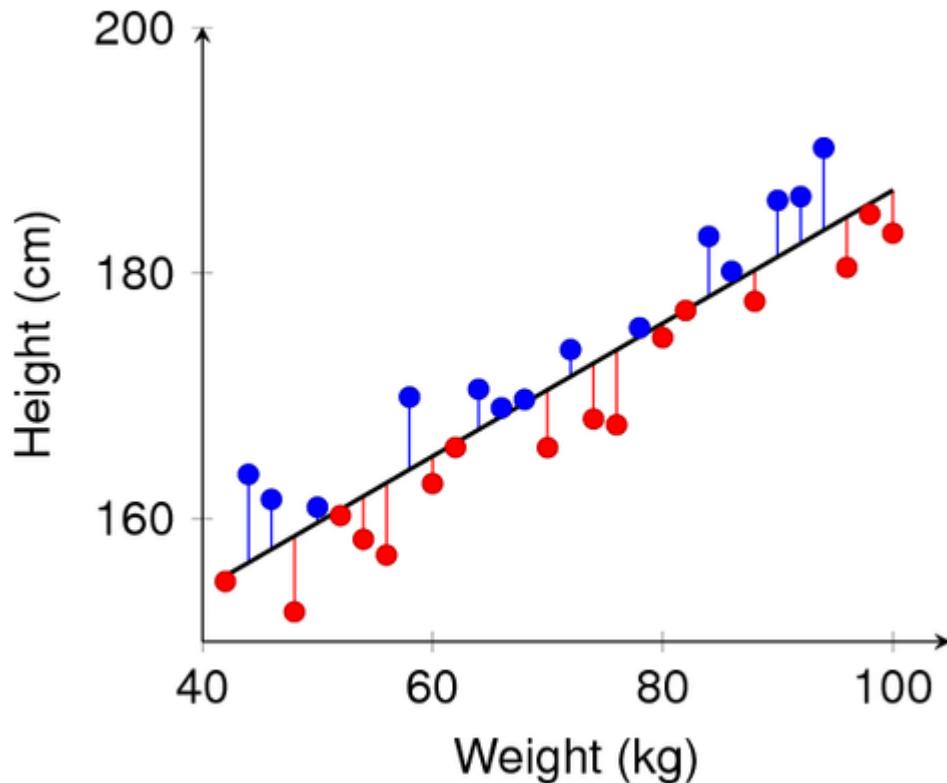


Multiple linear regression graphic by MathWorks

# Machine Learning

## Regression methods

- ❖ Polynomial regression
- ❖ Deep learning (later)



Regression with Residuals by Jake, CC BY 2.5

# Machine Learning

## Training vs validation error for polynomial regression

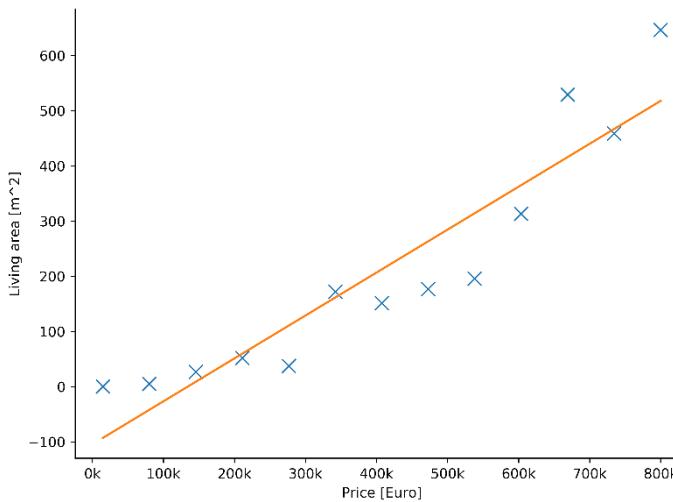
- Here we see an example for model complexity in regression tasks.

Poll:

„What can we learn from these plots?“

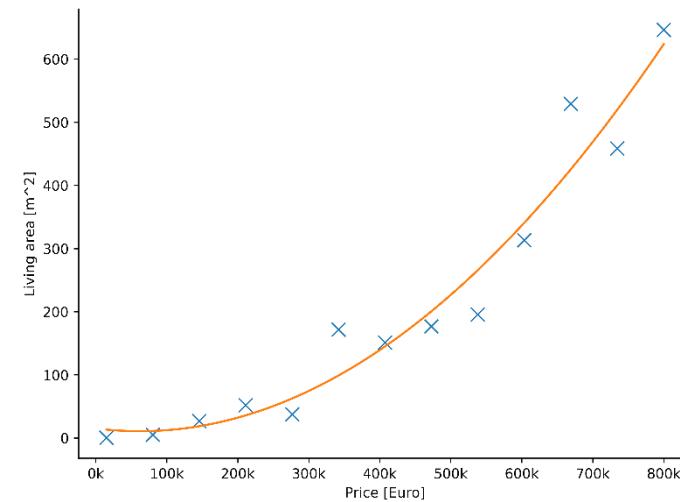
### Linear regression

- High training error
- High validation error



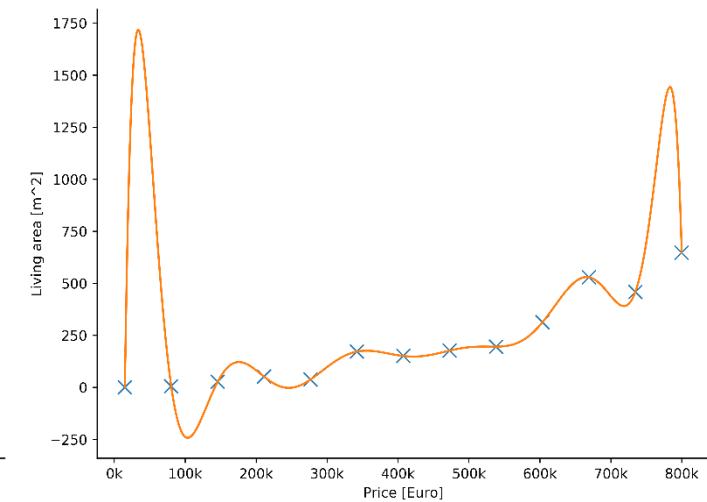
### Quadratic regression

- Lower training error
- Low validation error



### Polynomial regression ^10

- Low training error
- High validation error



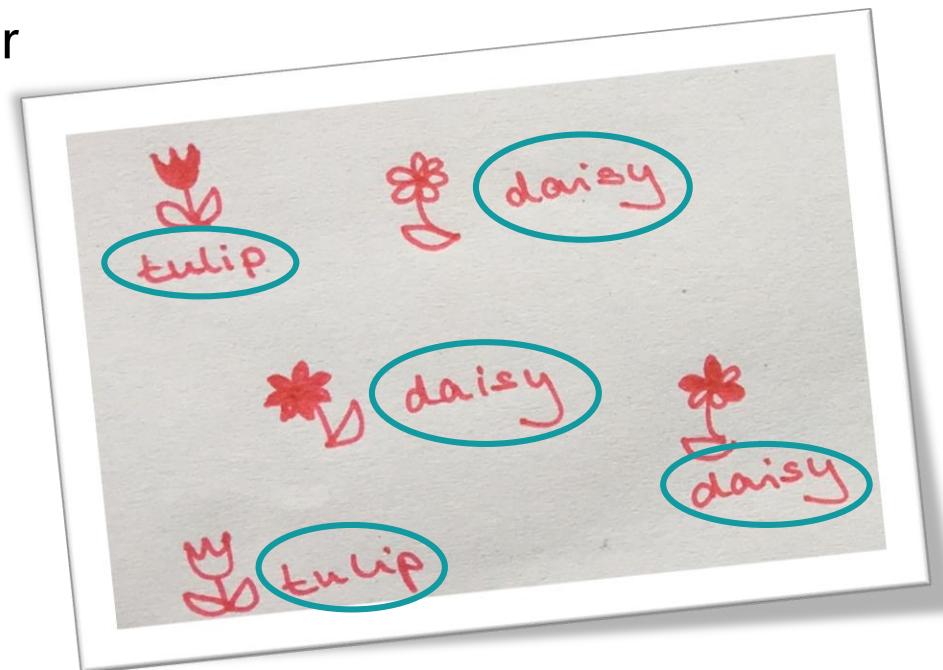
# Machine Learning

## Labeled data

Supervised learning need **labeled** or **tagged** data which provide the piece of information you are searching for and the model shall provide.

The problem with supervised learning is:

- ▶ Often there is not enough labelled data available
- ▶ Labelling of data sets can be very time and cost intensive
- ▶ Bosch has hundreds of people working on data labelling – located in India



# Machine Learning Labeled data – a billion \$ business

The Future of AI Depends on a Huge Workforce of Human Teachers

By Matthew Hutson

For an autonomous car to recognize pedestrians and stop signs, it's typically fed thousands or millions of photos, all hand-labeled. To nail a conversation, a digital assistant needs to be told over and over when it's failed. And so Rubin spends 10 to 30 hours a week on her phone or computer evaluating search results and chat records through a site called Clickworker. Her income, generally \$10 to \$14 an hour, pays for part of her commute from New Jersey and some of her child-rearing expenses. "It adds up," she says. "It really adds up."

As automation and AI evolves, a range of relatively rote jobs, the need to train software is also creating other opportunities. People must label massive amounts of data so machines can learn to perform more complex tasks, such as reading medical records or translating conversations. Clickworker GmbH is one company that's capitalizing on this trend.

**Bloomberg**

Jacques Bughin, a director of the McKinsey Global Institute, speculates that the nine-figure market could hit \$5 billion in five years... A radiologist tagging a medical image can cost up to \$2000.

Providers of data labelling service



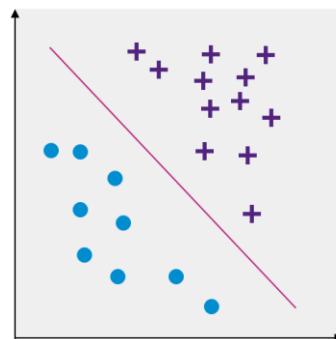
Reducing labelling efforts significantly is an ongoing research topic.

# Machine Learning

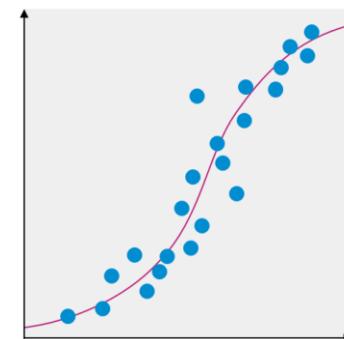
## Supervised vs. unsupervised learning

### Supervised Learning

Build a predictive model using training data with known output (labels)



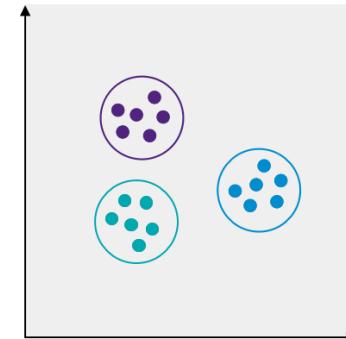
Classification



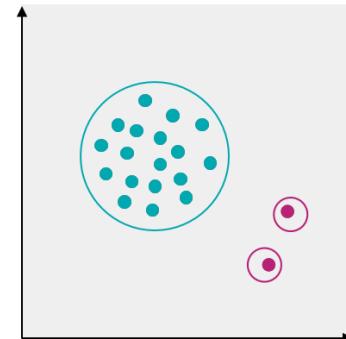
Regression

### Unsupervised Learning

Describe “hidden” structure in unlabeled data



Clustering



Anomaly Detection

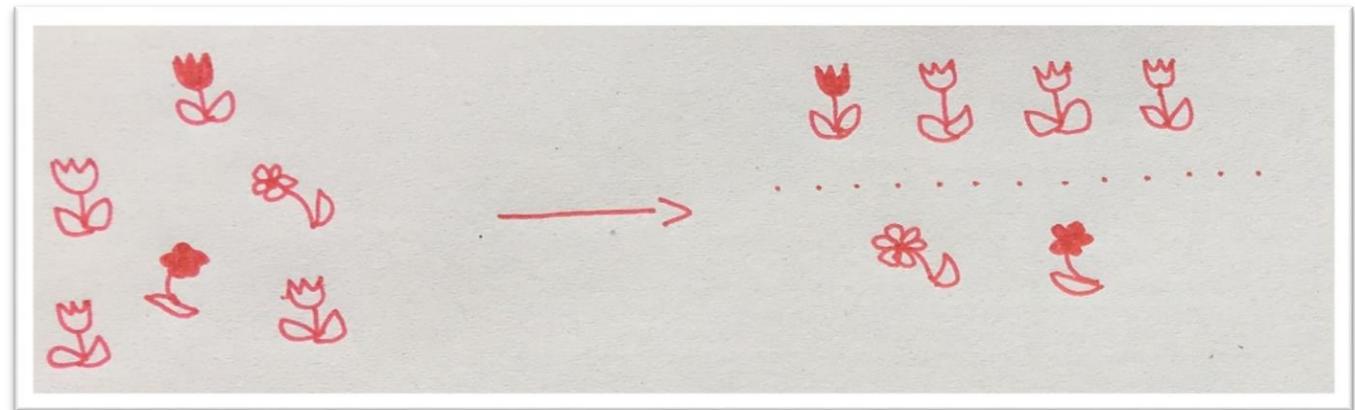
# Machine Learning

## Unsupervised learning task: clustering

Target: find meaningful groups in your data and create “classes”

- Discover patterns in data
- Replace high-dimensional data by representatives
- Data labelling
- Outlier detection

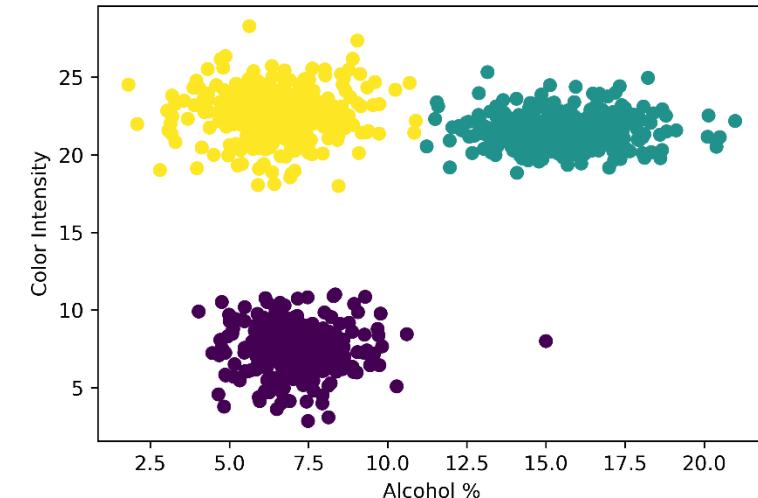
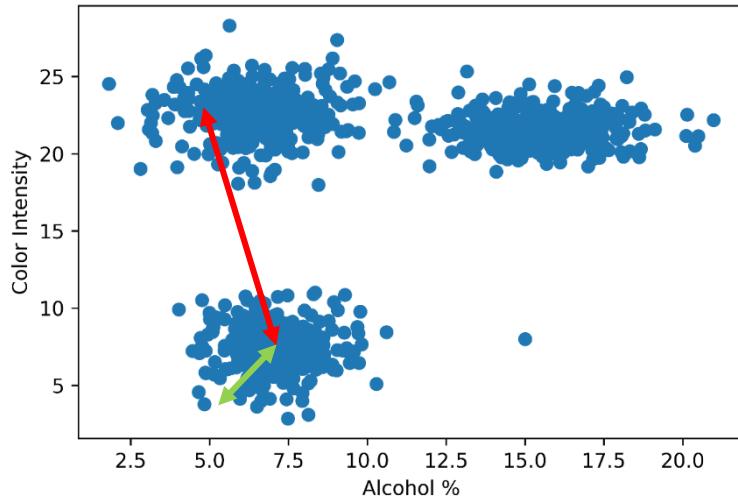
Height (cm)
8
16
20
4
9
5
10



# Machine Learning

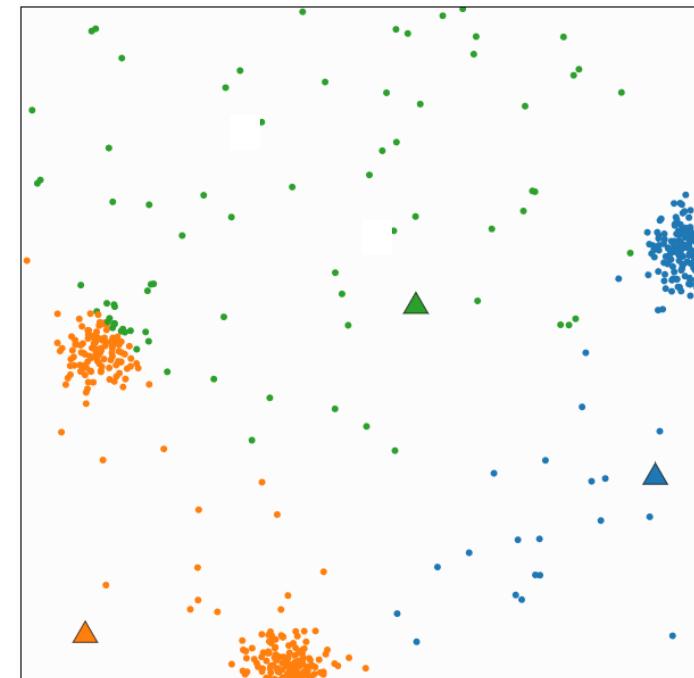
## Distance based clustering

Strategy: data in the same group are “closer” to each other than to data in other groups

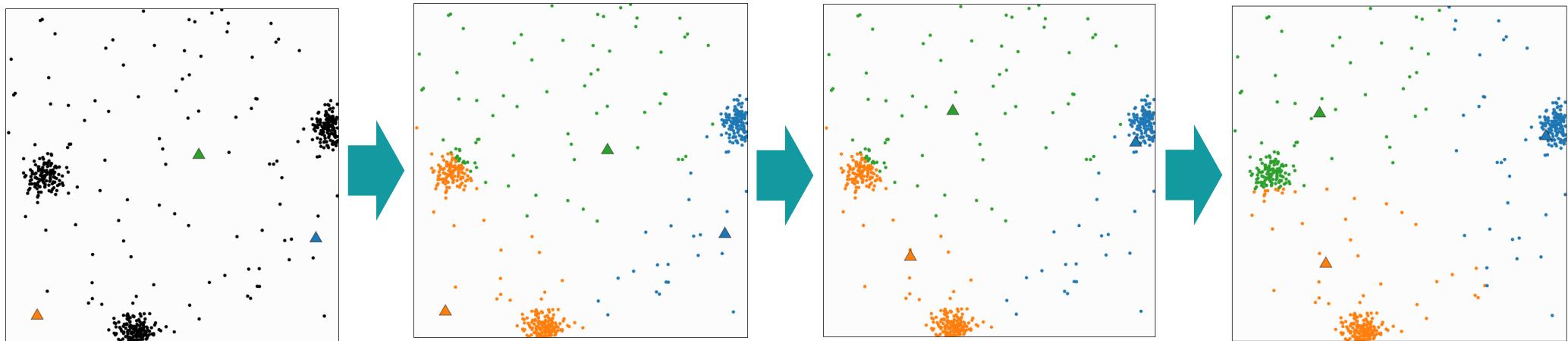


# Machine Learning K-means algorithm

- 1. Input:**  $N$  data points
- 2. Initialize k centroids randomly**
- 3. Repeat until converged:**
  - **Assign** each data point to the closest centroid:
  - **Recompute** new centroids as the mean of the newly assigned cluster members



# Machine Learning K-means algorithm

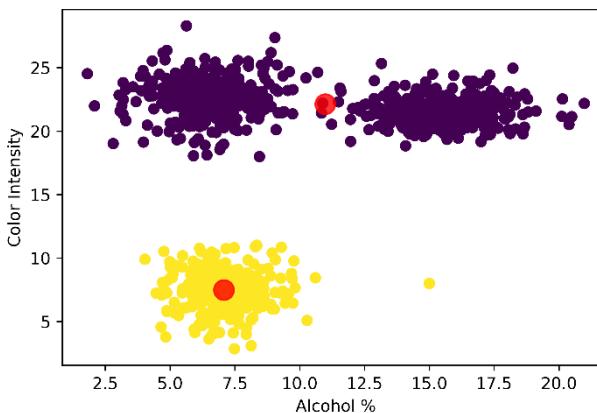


Karanveer Mohan, MIT License

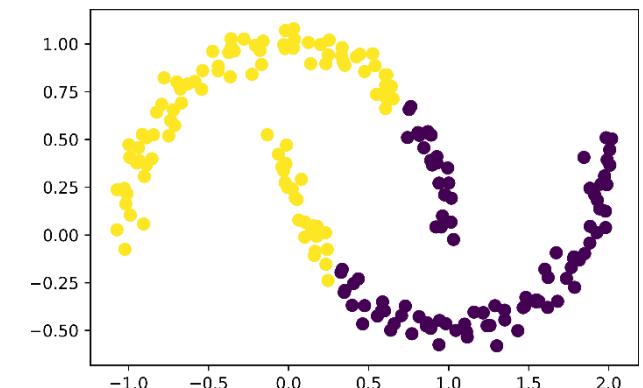
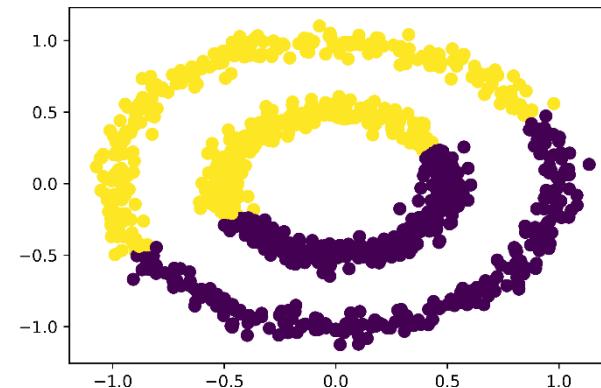
<http://stanford.edu/class/ee103/visualizations/kmeans/kmeans.html>

# Machine Learning Problems with K-means

1. Wrong number of clusters



2. Non-spherical distribution

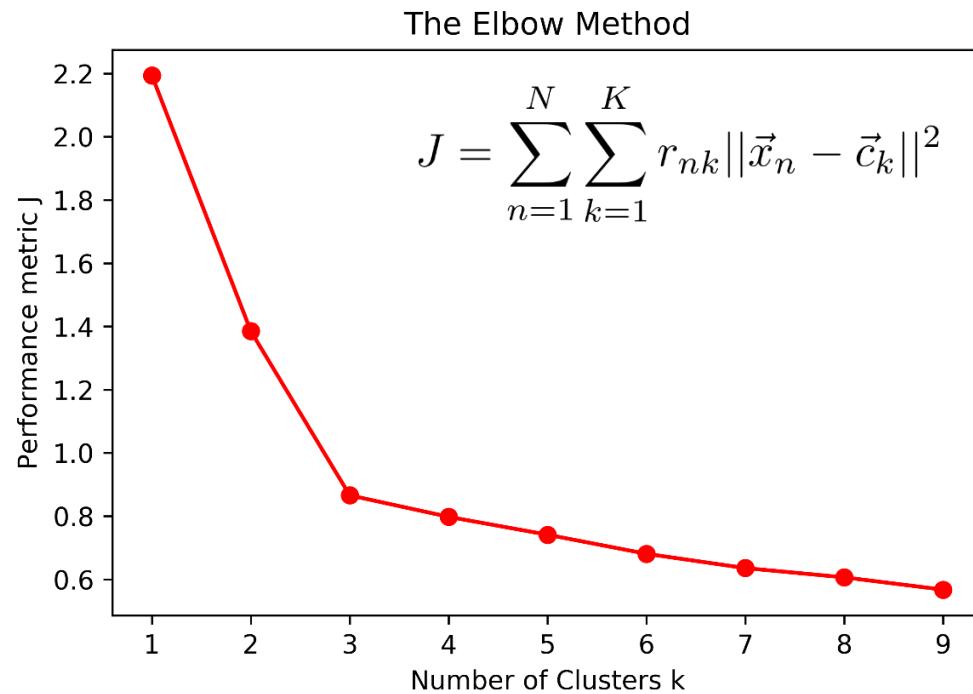


3. k-means is very sensitive to outliers

# Machine Learning

## Elbow method

How many clusters to choose?



$\vec{x}_n$ : data points

$\vec{c}_k$ : cluster centers (centroids)

$$r_{nk} = \begin{cases} 1 & \text{if point } n \text{ belongs to centroid } k \\ 0 & \text{otherwise} \end{cases}$$

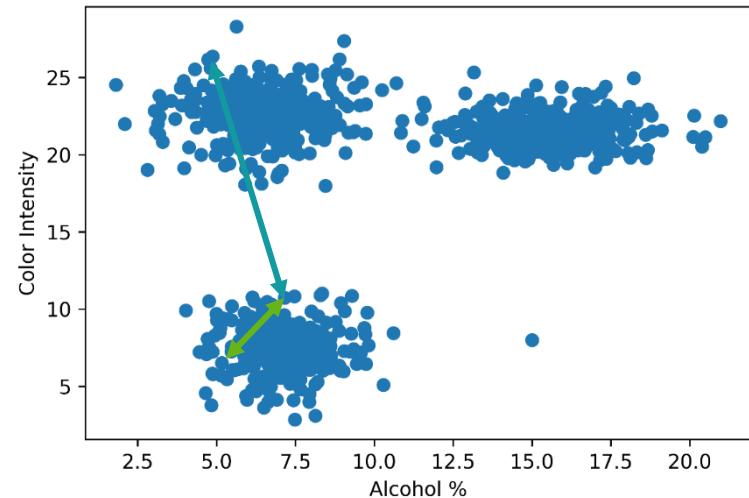
*Poll:*

*“How do you use the elbow criterium to determine the number of clusters in K-means?”*

# Machine Learning Clustering

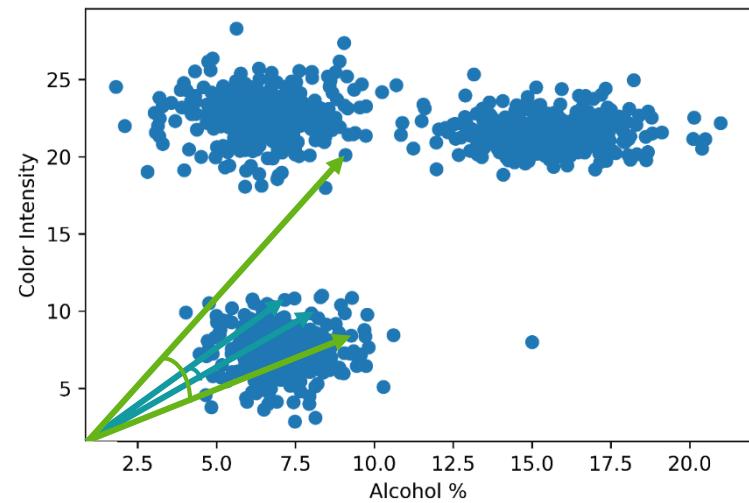
Euclidean distance as a similarity measure:

$$\text{dist}(\vec{x}, \vec{y}) = \sqrt{\|\vec{x} - \vec{y}\|^2}$$



Cosine similarity works better in higher dimensions:

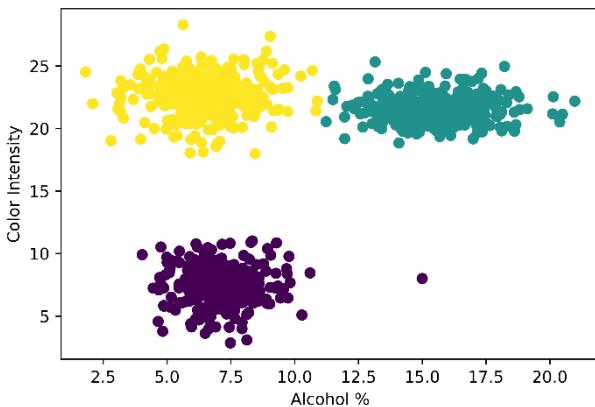
$$\text{dist}(\vec{x}, \vec{y}) = \cos \theta = \frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\| \|\vec{y}\|}$$



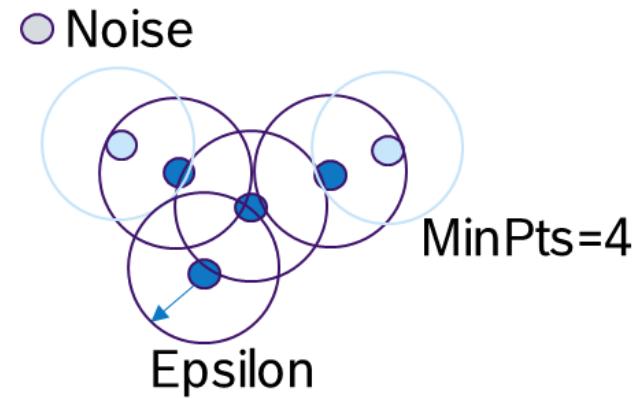
# Clustering

## Overview of methods

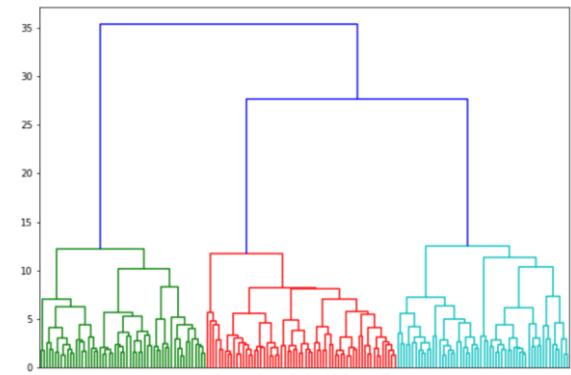
### Partitioning Methods



### Density-Based Methods



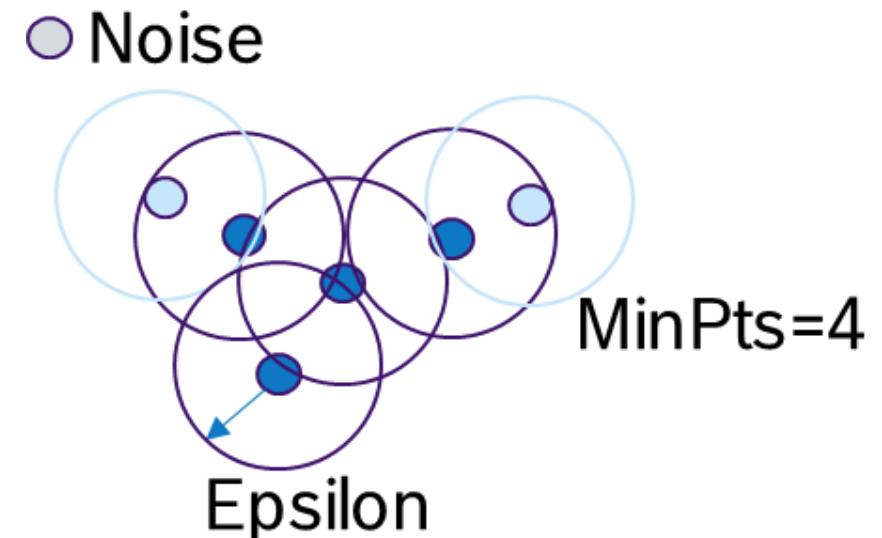
### Hierarchical Methods



# Machine Learning

## Density-based clustering

- $p$  is a **core point** if  
 $\geq \text{minPts}$  points are within distance  $\varepsilon$
- $q$  is **directly reachable** from a core point  $p$  if  
point  $q$  is within distance  $\varepsilon$  from  $p$
- $q$  is **reachable** from  $p$  if there is a “chain” of  
directly reachable points connecting  $p$  and  $q$
- Reachable points form a **cluster**
- All other points are **outliers**



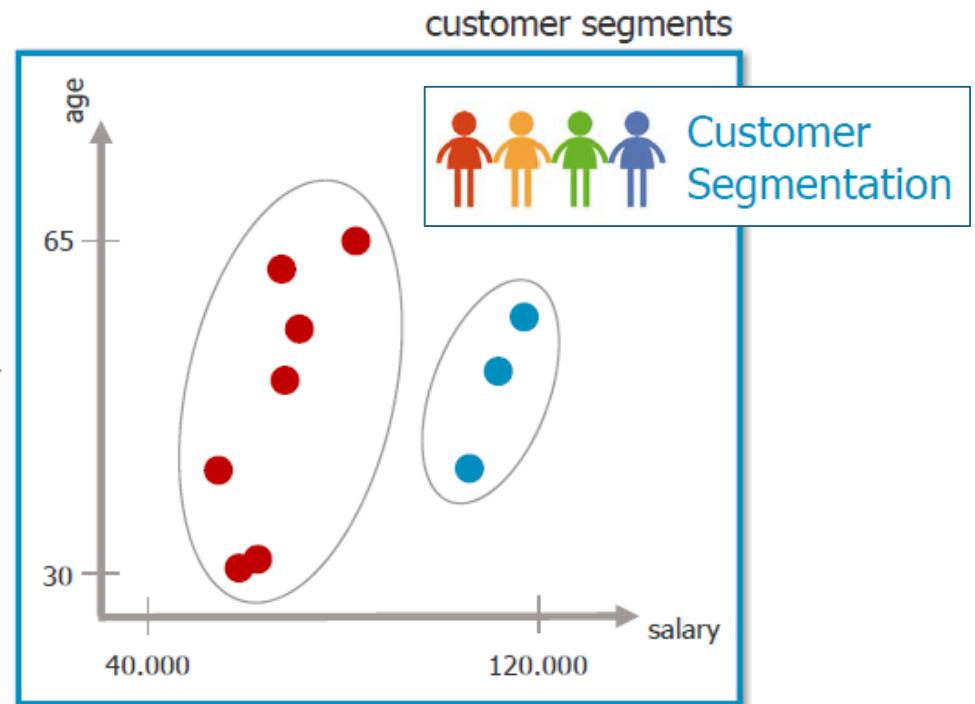
# Machine Learning Clustering application

Example: customer segmentation

customer data

ID	Age	Salary	Address (Town)	
1	30	55.000	Stuttgart	...
2	31	57.000	Frankfurt	...
3	56	120.000	Munich	...
4	55	65.000	Stuttgart	...
5	47	66.000	Hamburg	...
6	65	76.000	Hamburg	...
7	48	105.000	Berlin	...
8	42	49.000	Köln	...
9	42	99.000	Munich	...
10	63	62.000	Berlin	...
...	...	...	...	...

cluster algorithm



Customer Segmentation by Prof. Mitschnang, Universität Stuttgart, IVPS

# Machine Learning

## Unsupervised learning task: anomaly detection

Depositphotos, Bosch License

Target: detect outliers in your data

Examples:

- unrealistic sensor data
- technical problems in production
- fraud detection
- cyber security

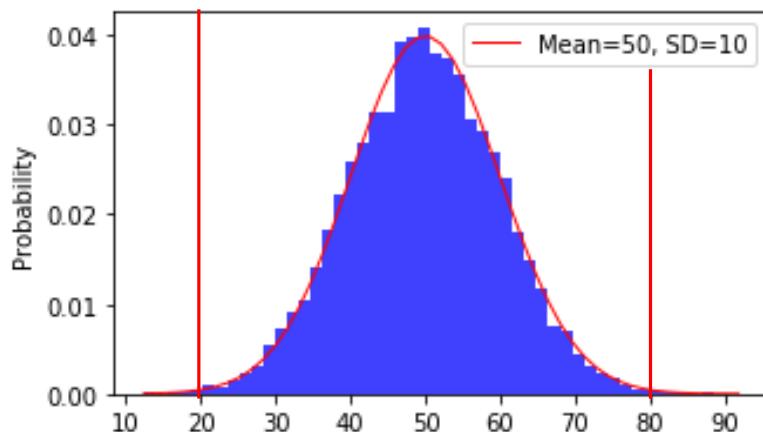


# Machine Learning

## Anomaly detection methods

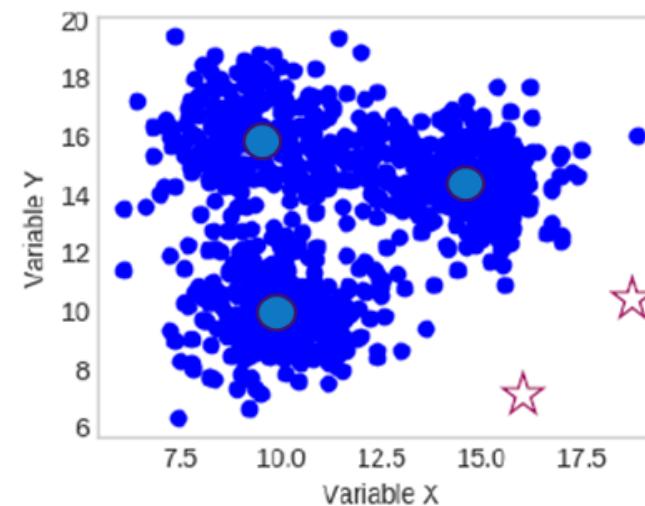
### Statistical Methods

Outliers are points with a certain deviation from the mean value, often  $3\sigma$  (standard deviation)



### K-Means

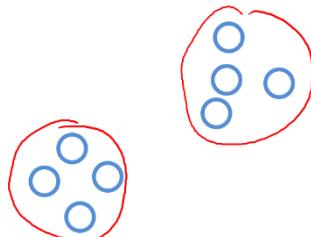
Outliers are clusters with very few points and points far away from the cluster centers



# Machine Learning

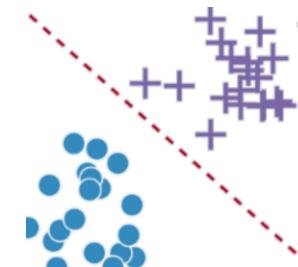
## Overview of 4 important ML tasks

### Clustering



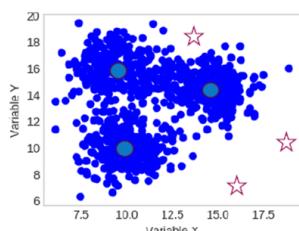
... find meaningful clusters in your data to create “classes”...

### Classification



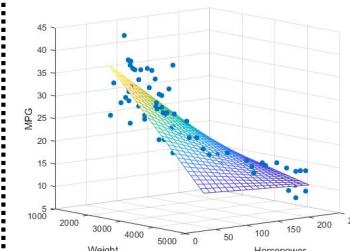
... sort your data into predefined classes ...

### Anomaly detection



... detect outliers in your data...

### Regression



... calculate numerical estimations from numerical input data...

# Machine Learning

## ML tasks: exercise 1



Bosch Media Space

*Poll: „Which task will he solve?“*

Robert is a line manager.

In order to detect scrap earlier, he wants to predict whether a part will pass or fail at the end of line test based on measurements in previous parts of the production cycle.

Classification, Clustering, Regression, or Anomaly detection?

# Machine Learning

## ML tasks: exercise 2



Bosch Media Space

*Poll: „Which task will he solve?”*

Classification, Clustering, Regression, or Anomaly detection?

Andrew is a logistics manager.

His plant uses 500 different packaging materials.

He would like to reduce it to 20 standardized boxes based on product type, form and dimensions.

# Machine Learning

## Sweet spot of Machine Learning

Work on data based machine learning  
if you have ...

- ❖ A clear business case
- ❖ Sufficient amounts of data carrying the relevant information
- ❖ Sufficient computational resources
- ❖ Knowledge, experience, and/or partners that help you get started
- ❖ Patience to go through trial and error process



Depositphotos, Bosch License

# Machine Learning

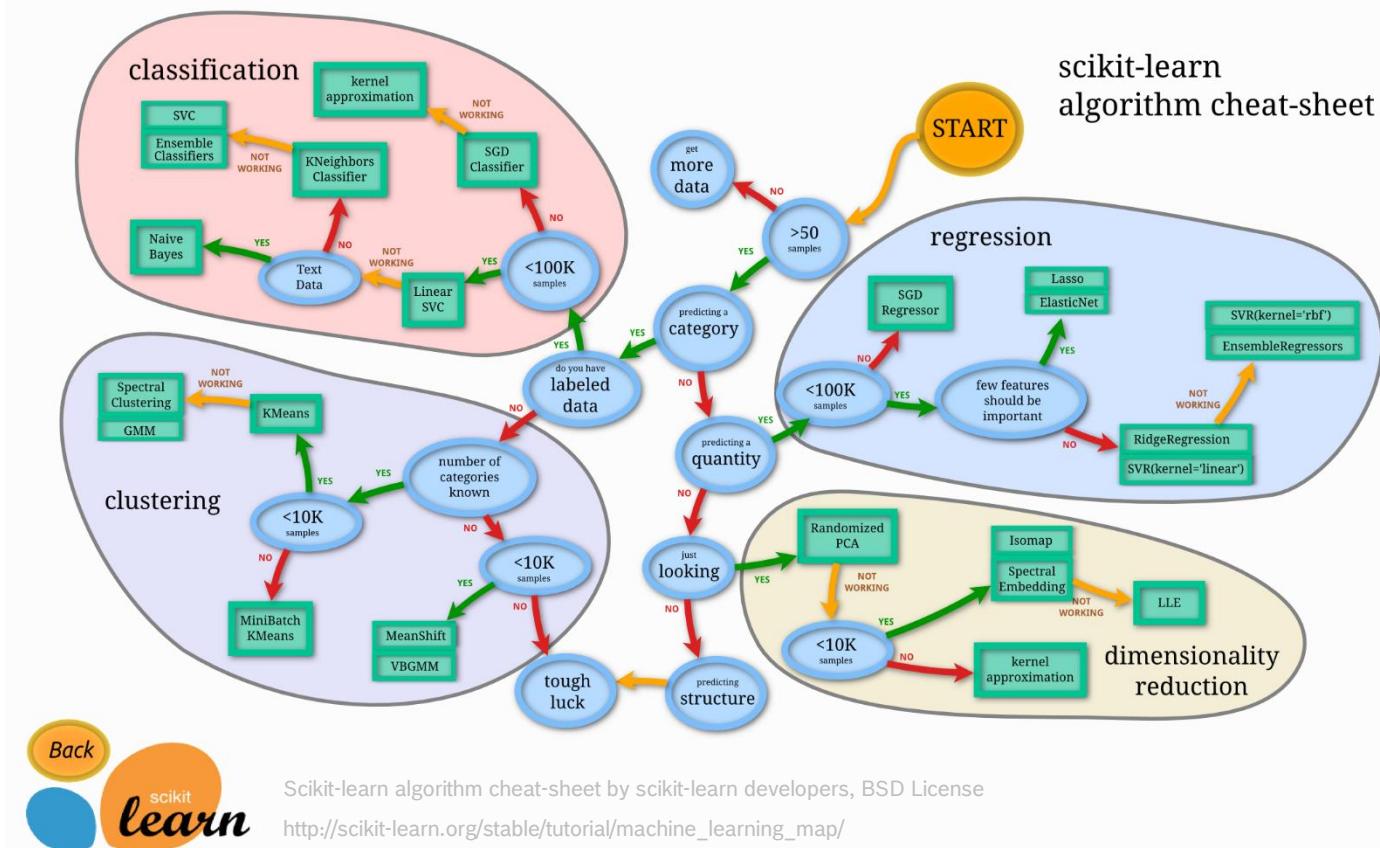
## Helpful resources for Machine Learning

### ❖ Frameworks, libraries & tutorials

- [Scikit-learn](#)
- [H2O](#)
- [TensorFlow](#)
- [Microsoft CNTK](#)

### ❖ Guidelines:

- [ML decision tree \(Scikit-learn\)](#)
- [Method pros & cons \(recast.ai\)](#)



# Machine Learning Poll

*Poll:*  
*“Which of these are unsupervised learning methods?”*

# Machine Learning

## What is reinforcement learning?

- Reinforcement learning is the field of sequential decision making under uncertainty
- Goal: maximize the long-term cumulative reward



Atari video games



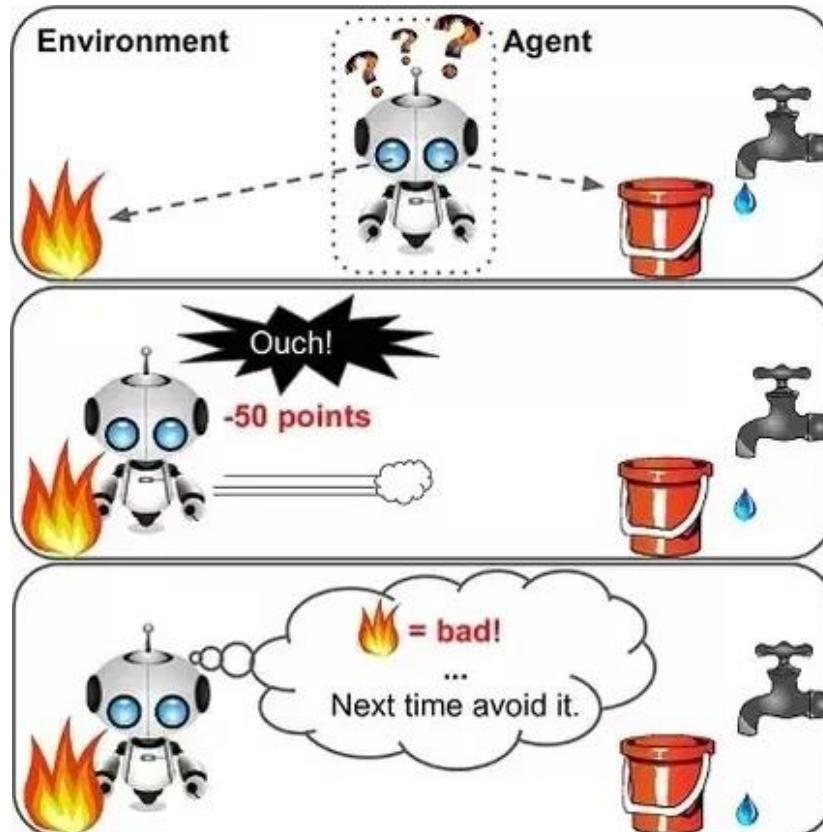
Robotics



Learning to walk

# Machine Learning

## ML strategy: reinforcement learning



- ❖ System **perceives** environment
- ❖ Decides what to do according to its **policy**
- ❖ System **interacts** with environment
- ❖ Gets a **penalty or reward**
- ❖ System **learns** = changes its policy

# Machine Learning

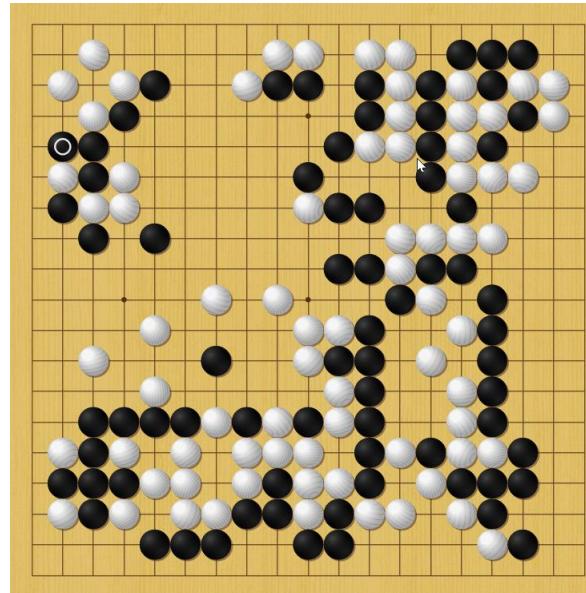
## ML strategy: reinforcement learning

Solved in classical way:



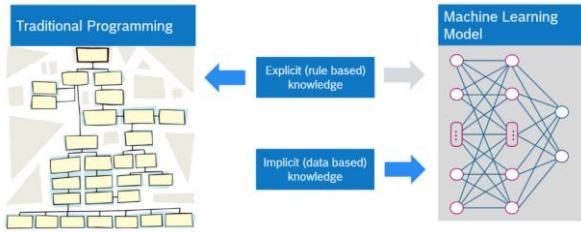
Depositphotos, Bosch License

Only solved with RL:

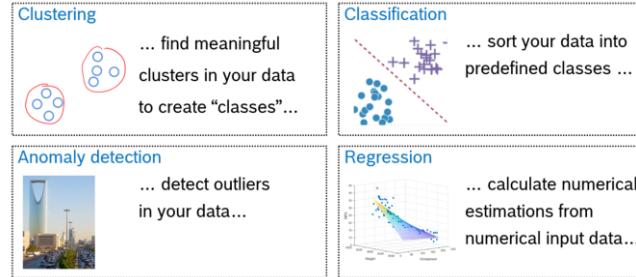


- ❖ Not every action provokes reactions in the environment that provide information about how successful the policy is!
- ❖ Example: Games like chess, Go
- ❖ Reinforcement learning always needs **interaction** with the environment and/or simulation!

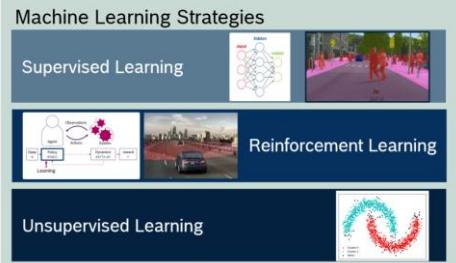
# Machine Learning Summary



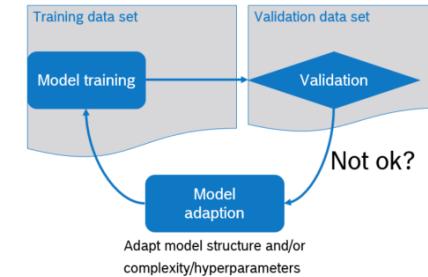
What makes ML revolutionary?



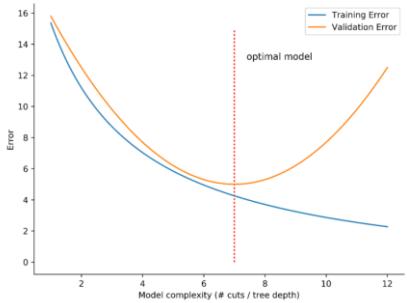
Tasks to solve



Types of ML strategies



How to train a model

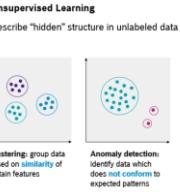
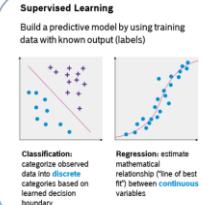


Model complexity

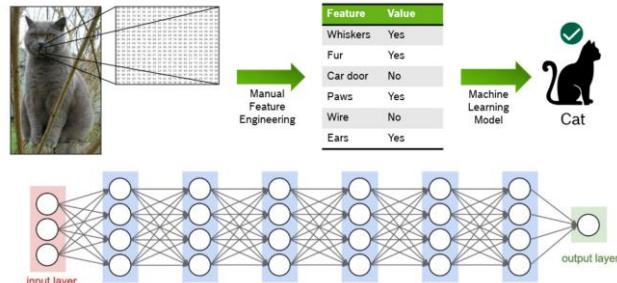
# DEEP LEARNING

# Deep Learning

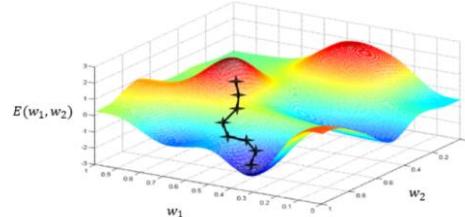
## What will you learn in this section?



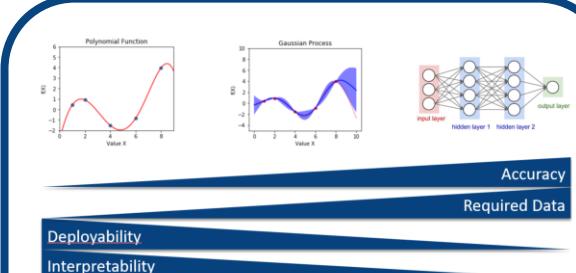
What tasks can DL solve?



Classical ML vs DL



Training of DL Models



When to use DL

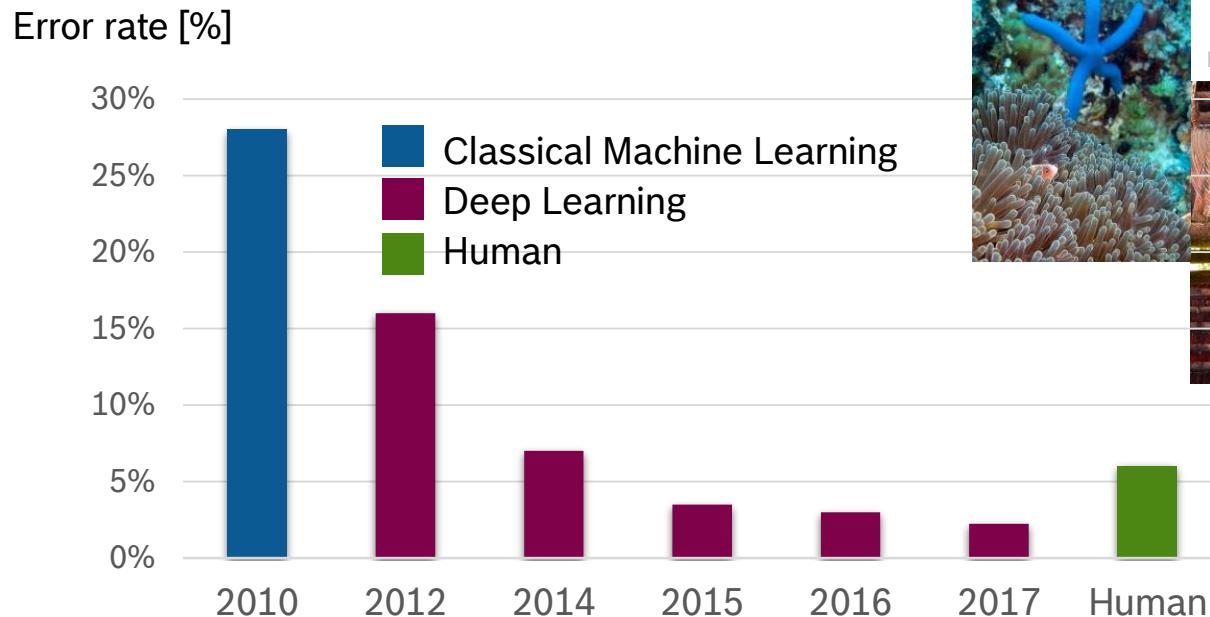


Why CNNs?

# Deep Learning

## The Deep Learning revolution

Algorithmic advances, especially in the area of deep learning



Depositphotos, Bosch License



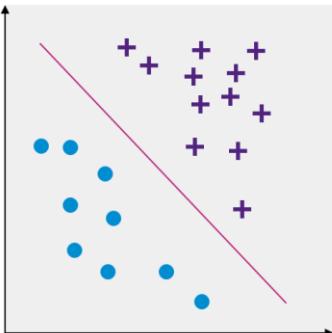
Error rate of image recognition “Imagenet” challenge. In 2015, algorithms surpassed human image recognition error rate.

# Deep Learning

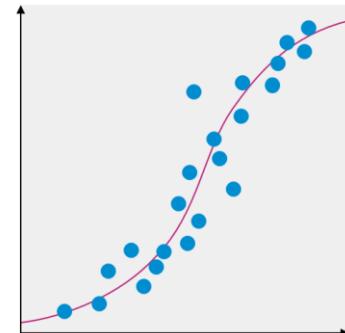
## Supervised Learning vs. Unsupervised Learning

### Supervised Learning

Build a predictive model by using training data with known output (labels)



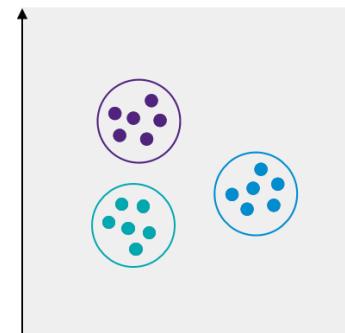
**Classification:** categorize observed data into **discrete** categories based on learned decision boundary



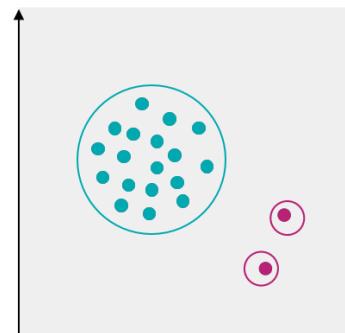
**Regression:** estimate mathematical relationship ("line of best fit") between **continuous** variables

### Unsupervised Learning

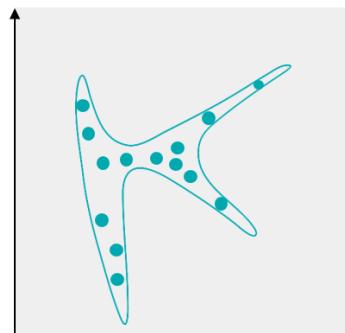
Describe "hidden" structure in unlabeled data



**Clustering:** group data based on **similarity** of certain features



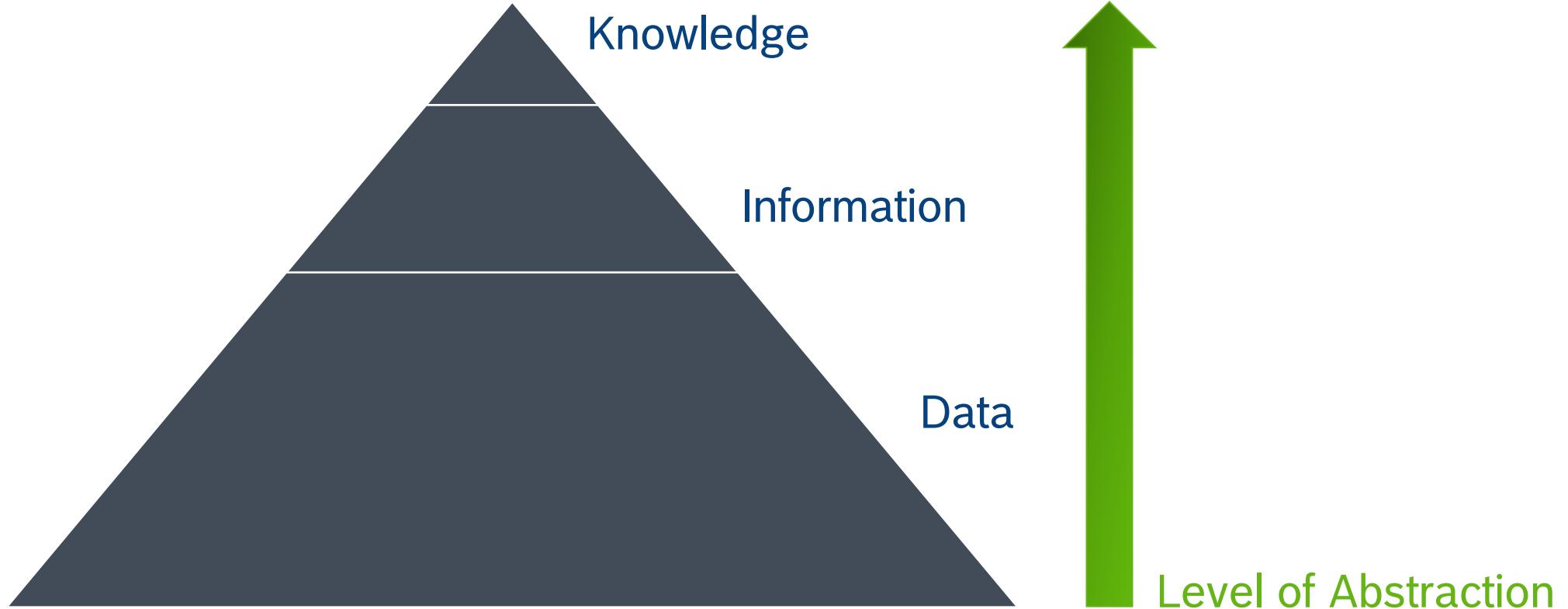
**Anomaly detection:** identify data which does **not conform** to expected patterns



**Density estimation:** **approximate distribution** from observed data

# Deep Learning

## Learning more levels of abstraction



# Deep Learning

## Distilling knowledge from data



08 02 22 97 38 15 00 40 00 75 04 05 07 78 52 12 50 77 91 41 49 49 99 40 17 83 18 57 60 87 17 40 98 43 69 40 94 56 62 00 81 49 31 73 55 79 14 29 93 71 40 67 51 85 30 03 49 13 36 65 52 70 95 23 04 60 11 42 69 51 85 56 01 32 56 71 37 02 36 91 22 31 16 71 51 62 43 59 41 92 36 54 22 40 40 28 66 33 13 80 24 47 33 60 99 03 45 02 44 75 33 53 78 36 84 20 35 17 12 50 32 98 81 28 64 23 67 10 26 38 40 67 59 54 70 66 18 38 64 70 67 26 20 68 02 62 12 20 95 63 94 39 63 08 40 91 66 49 94 21 24 55 58 05 66 73 99 26 97 17 78 78 96 83 14 88 34 69 63 72 21 36 23 09 75 00 76 44 20 45 35 14 00 61 33 97 34 31 33 95 78 17 53 28 22 75 31 67 15 94 03 80 04 62 16 14 09 53 56 92 16 39 05 42 96 35 31 47 55 58 88 24 00 17 54 24 36 29 85 57 86 56 00 48 35 71 89 07 05 44 44 37 44 60 21 58 51 54 17 58 19 80 81 68 05 94 47 69 28 73 92 13 86 52 17 77 04 89 55 40 04 52 08 63 97 35 99 16 07 97 57 32 16 26 26 79 33 27 98 66 68 84 68 87 57 62 20 72 03 46 33 67 46 55 12 32 63 93 53 69 04 42 16 73 55 01 39 11 24 94 72 18 08 46 29 32 40 62 76 36 20 69 36 41 72 30 23 88 34 07 99 69 82 67 59 85 74 04 36 16 20 73 35 29 78 31 90 01 74 31 49 71 46 83 81 16 23 57 05 54 01 70 54 71 83 51 54 69 16 92 33 48 61 43 52 01 89 13 62 48
--



Feature	Value
Whiskers	Yes
Fur	Yes
Car door	No
Paws	Yes
Wire	No
Ears	Yes

Image: Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT)

# Deep Learning

## Classical Machine Learning



09 02 22 97 38 15 00 40 00 75 04 03 07 78 52 12 50 14	49 49 99 40 17 81 18 57 60 87 17 40 98 43 69 41 05 36 62 00
81 49 31 73 55 79 14 29 93 71 40 57 51 05 30 03 49 13 36 65	52 70 95 23 04 60 11 42 69 31 49 56 01 32 56 71 37 02 36 91
22 31 16 71 51 67 43 59 41 92 36 54 22 40 40 28 66 33 13 80	24 43 10 60 93 03 45 02 44 75 33 53 70 36 84 20 35 17 12 50
32 98 81 28 64 23 67 10 26 38 40 67 53 54 70 66 18 38 64 70	67 26 20 68 08 62 12 20 95 63 94 39 63 08 40 91 66 49 98 21
24 55 58 05 63 73 99 26 97 17 78 78 98 63 14 88 34 09 63 72	21 36 23 09 75 00 76 44 20 45 35 14 00 61 33 97 34 31 33 95
78 17 53 28 22 75 31 67 15 94 03 80 01 62 16 14 09 53 56 92	16 39 05 42 96 35 31 47 55 58 88 24 00 17 54 24 36 29 85 57
86 56 00 48 35 71 89 07 05 44 44 37 44 60 21 58 51 54 17 58	19 80 81 68 05 94 47 69 28 73 92 18 86 52 17 77 09 89 55 40
04 52 08 83 97 35 99 16 07 97 57 32 16 26 26 79 33 27 98 66	05 16 68 87 57 62 20 72 03 46 35 67 46 55 12 32 63 93 55 69
04 42 16 73 35 43 11 24 94 72 18 08 46 29 32 40 62 76 36	20 69 36 41 72 30 23 88 37 04 69 62 82 67 59 85 74 04 36 16
20 73 35 29 78 31 90 01 74 33 49 71 45 14 16 23 57 05 54	01 70 54 71 63 51 54 69 16 92 33 48 61 43 52 01 37 54 48

Manual Feature Engineering



Feature	Value
Whiskers	Yes
Fur	Yes
Car door	No
Paws	Yes
Wire	No
Ears	Yes

Machine Learning Model

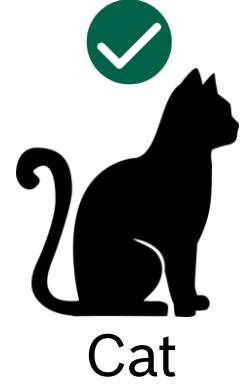
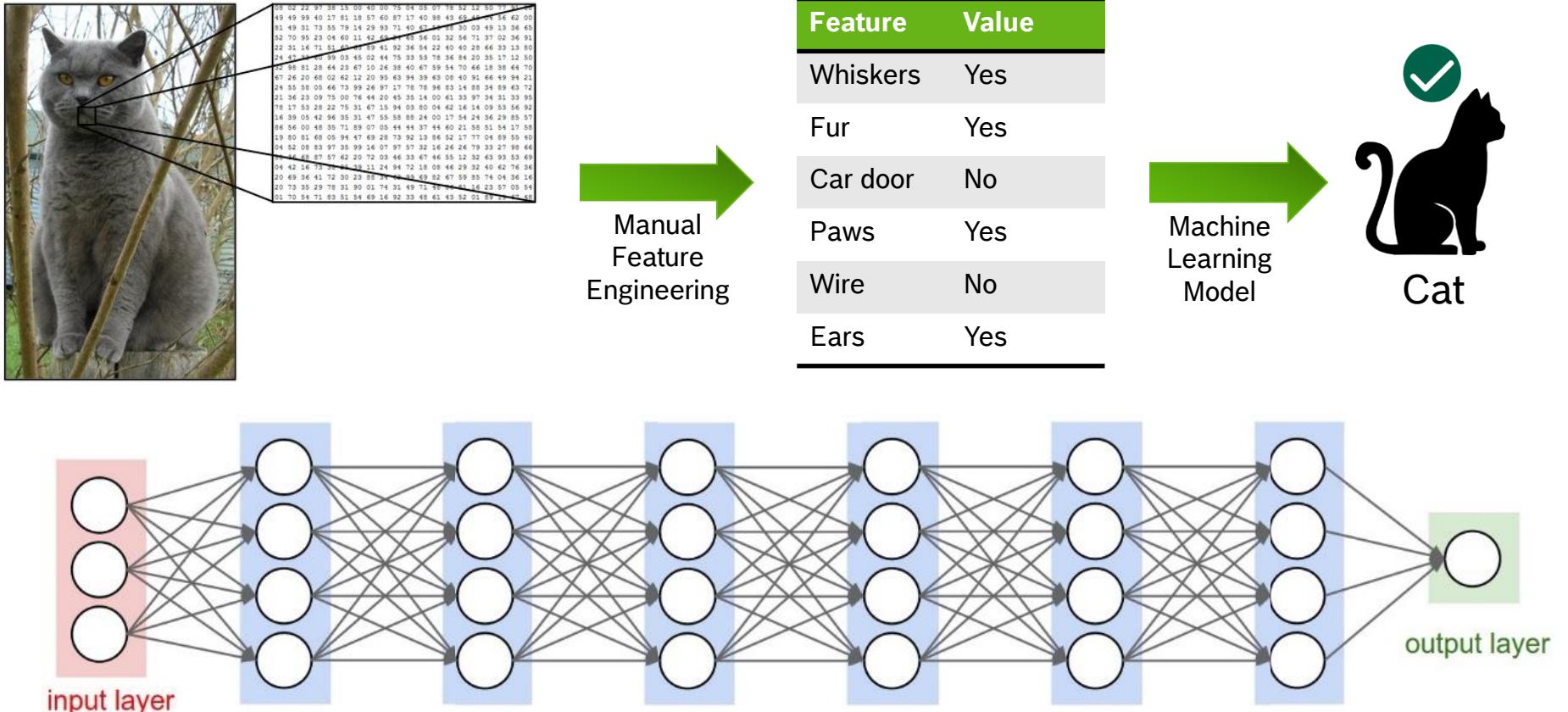


Image: Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT)

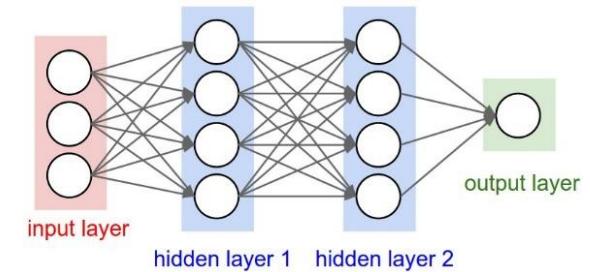
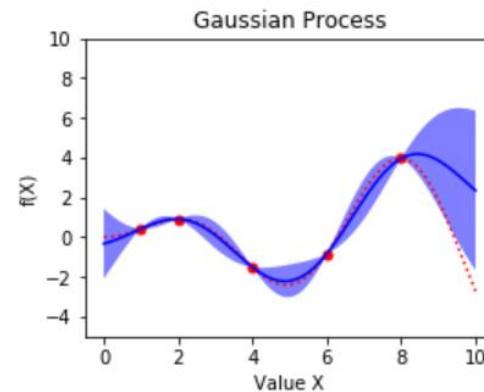
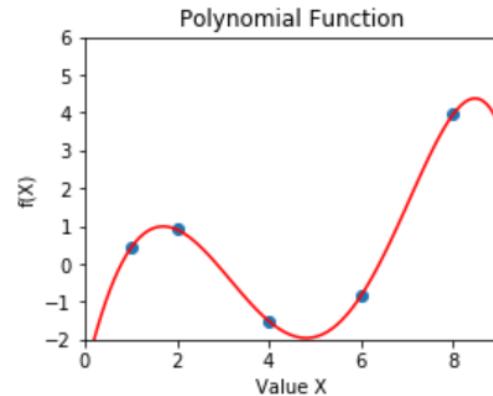
# Deep Learning

## Deep Learning



# Deep Learning

## When should I use Deep Learning?



Accuracy

Required Data

Deployability

Interpretability

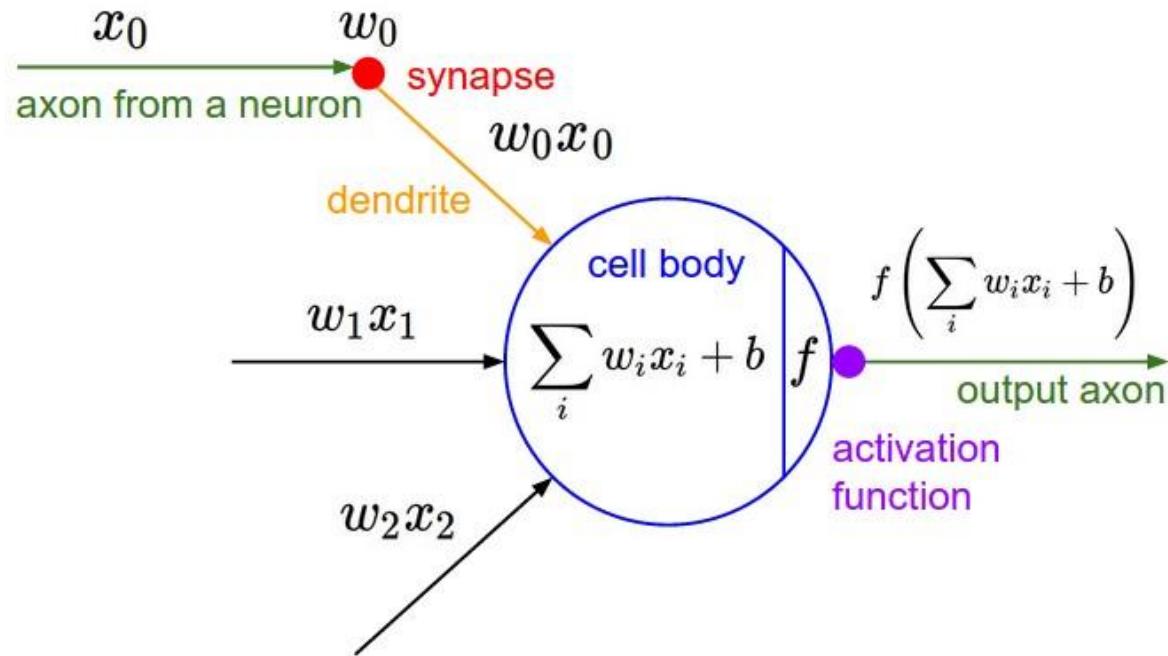
*Poll:*

*“What is the relationship between  
Deep Learning and Machine  
Learning?”*

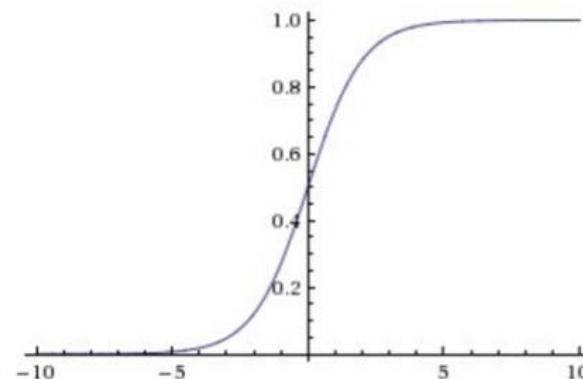
# How does it work?

# Deep Learning

## Artificial neurons



Non-linear activation function  $f(x)$ :

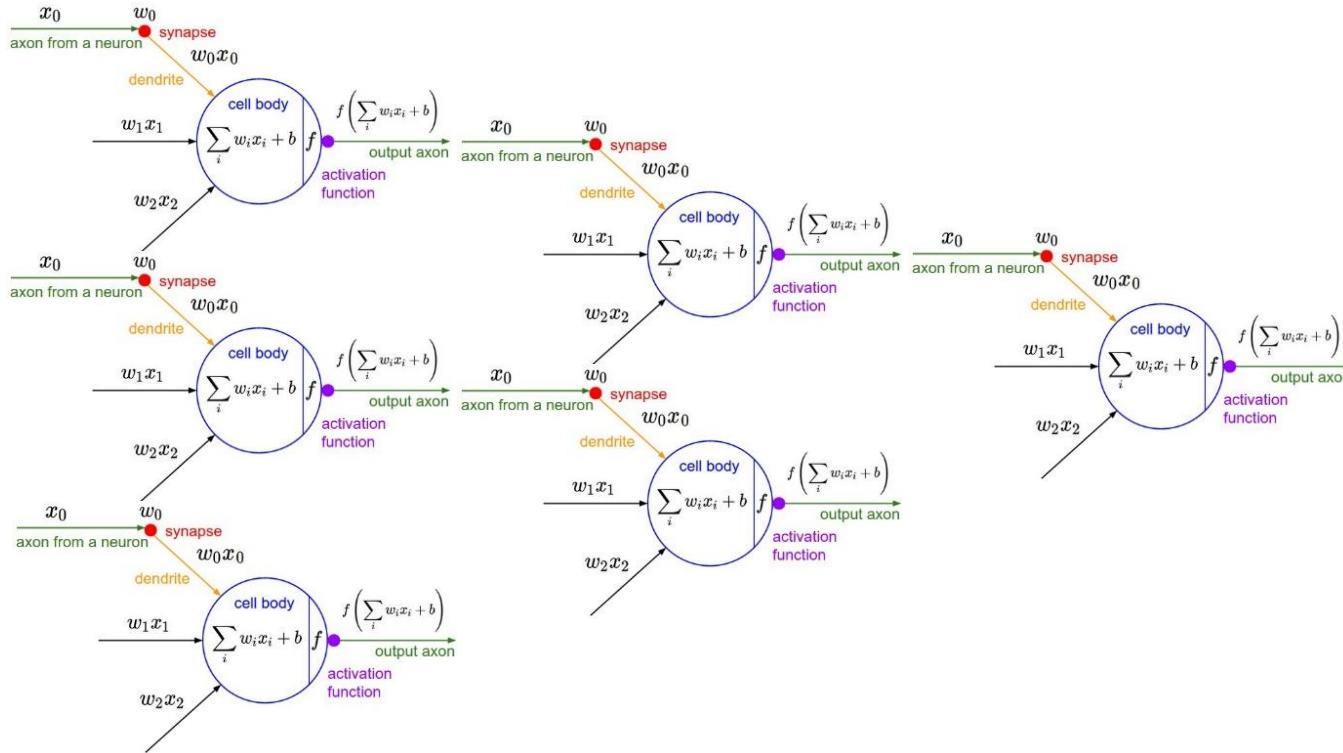


e.g. Sigmoid

Image: Single neuron in neural network using c++ by Stackoverflow,, CC BY-SA 3.0

# Deep Learning

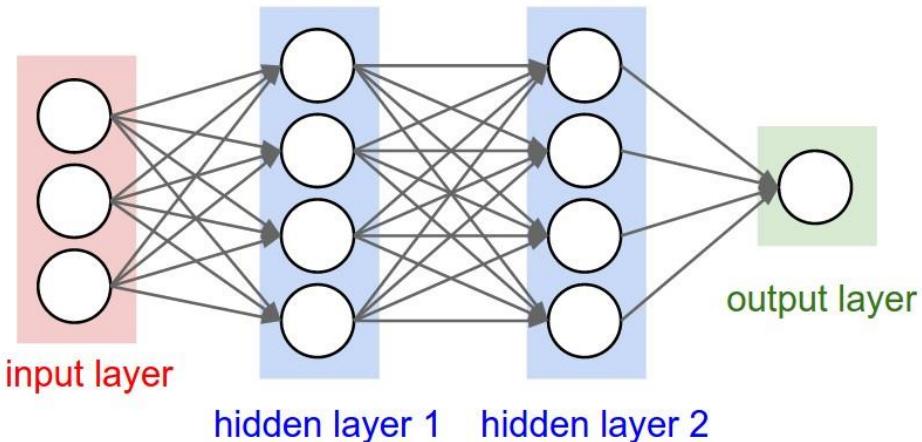
## Artificial neurons



The number of neurons and their connections are defined by the Network Architecture

# Deep Learning

## Layered structure



Modern artificial neural networks  
combine artificial neurons in layers

with:

- No connections between neurons of the same layer
- Typically no connections skipping a layer

→ Why is this structure of layers so powerful?

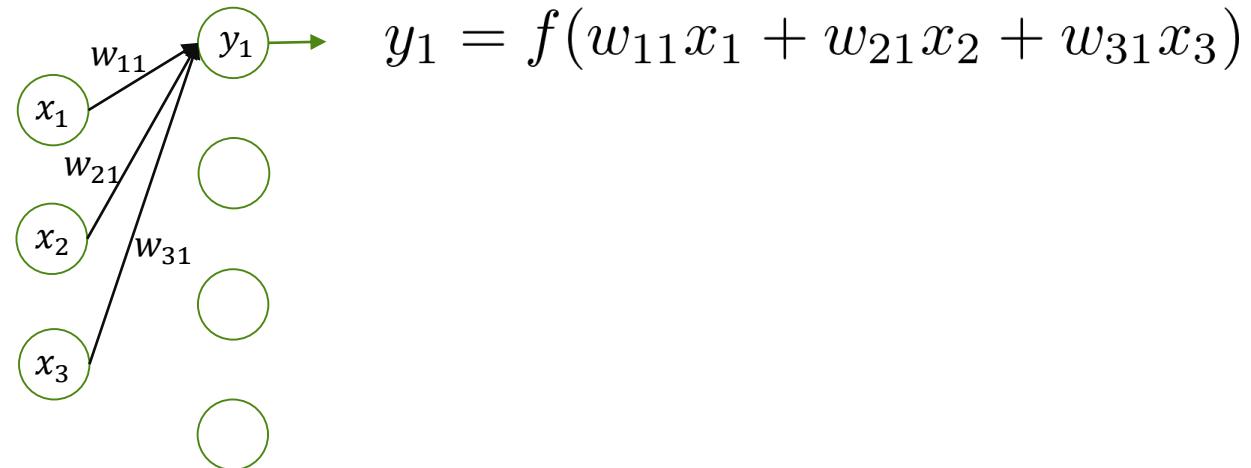
Image: Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT)

# Deep Learning

## Layered structure

1.

It's computationally efficient

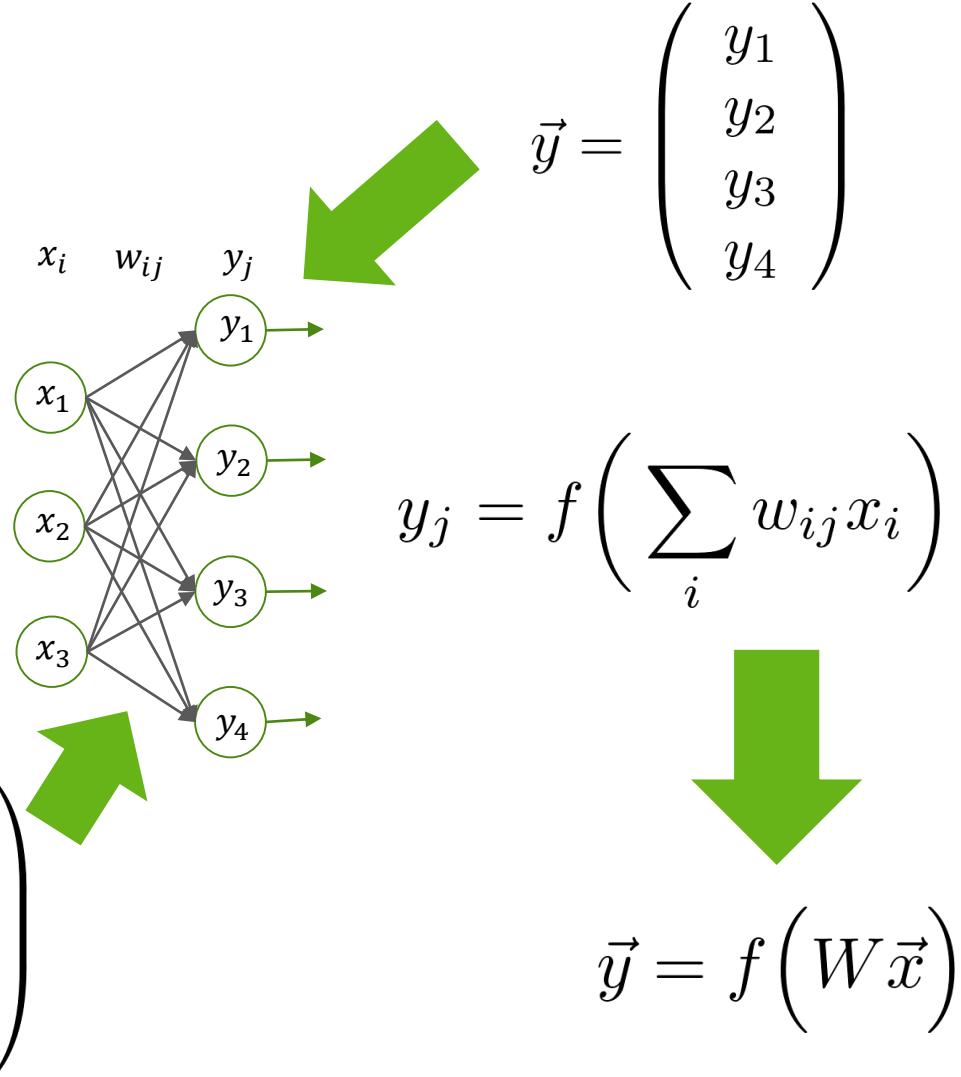


# Deep Learning

## Layered structure

$$\vec{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

$$W = \begin{pmatrix} w_{11} & w_{21} & w_{31} \\ w_{12} & w_{22} & w_{32} \\ w_{13} & w_{23} & w_{33} \\ w_{14} & w_{24} & w_{34} \end{pmatrix}$$



# Deep Learning

## Layered structure



GPUs are designed precisely for the task of fast, parallelized matrix multiplication.

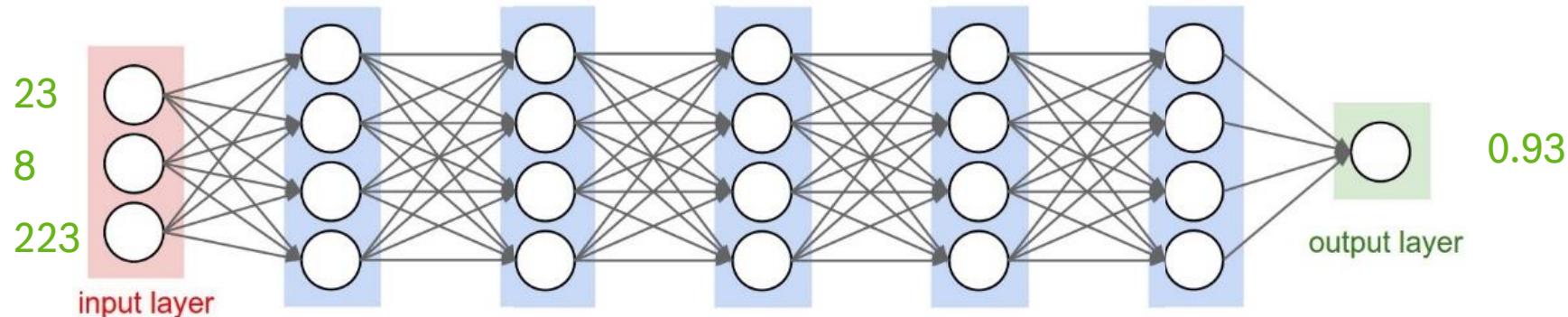
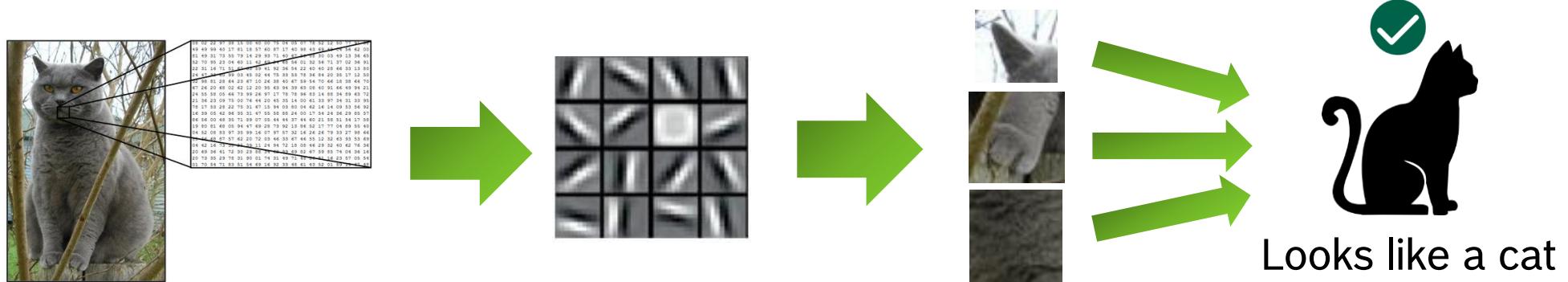
Image: Evan Amos, Public domain

# Deep Learning

## The power of representation learning

2.

A layered structure encapsulates the hierarchical structure of the world

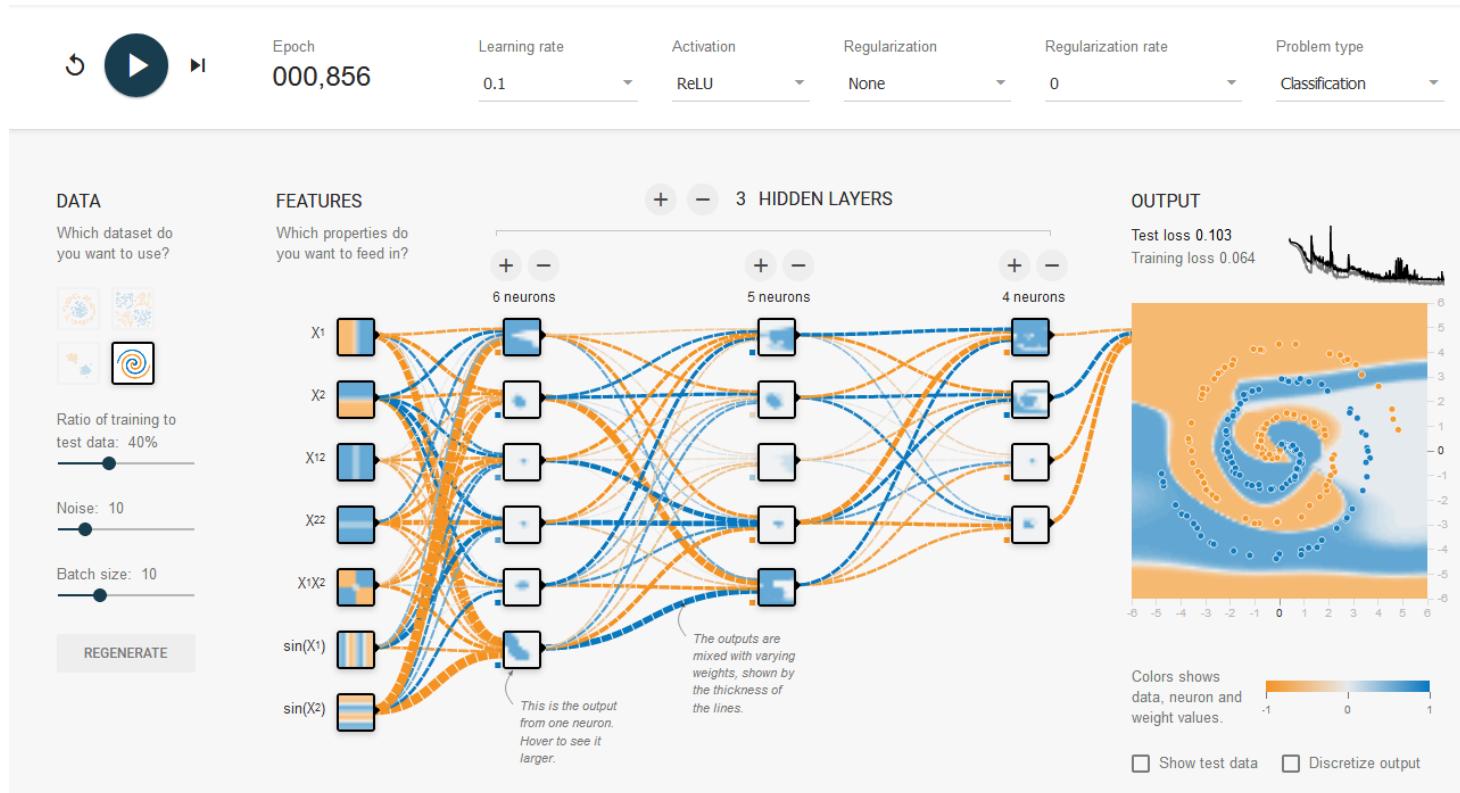


Images: Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT), CC-A-3.0 Wikipedia, CC-BY-2.0 Mic V.

# Deep Learning

## Tensorflow Playground

Nice website to get an intuitive feeling for neural networks. Click picture for link.



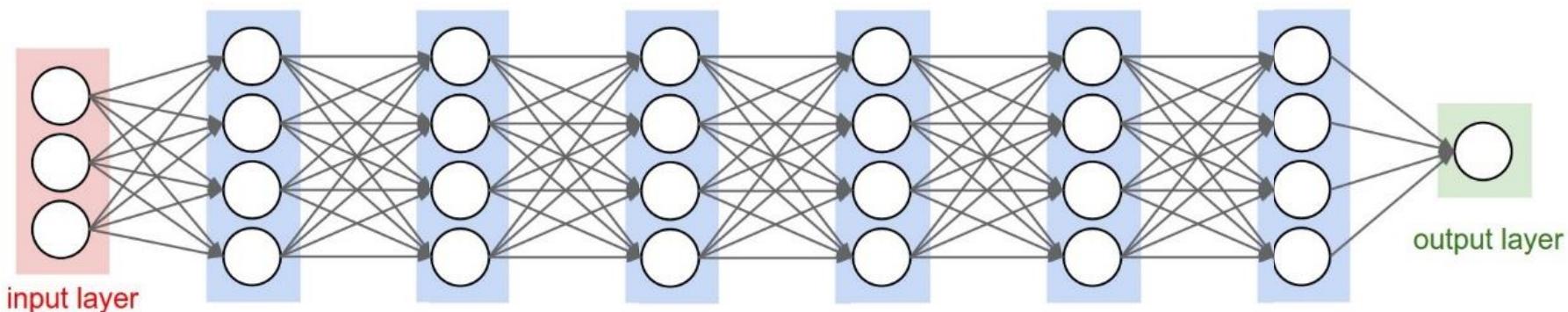
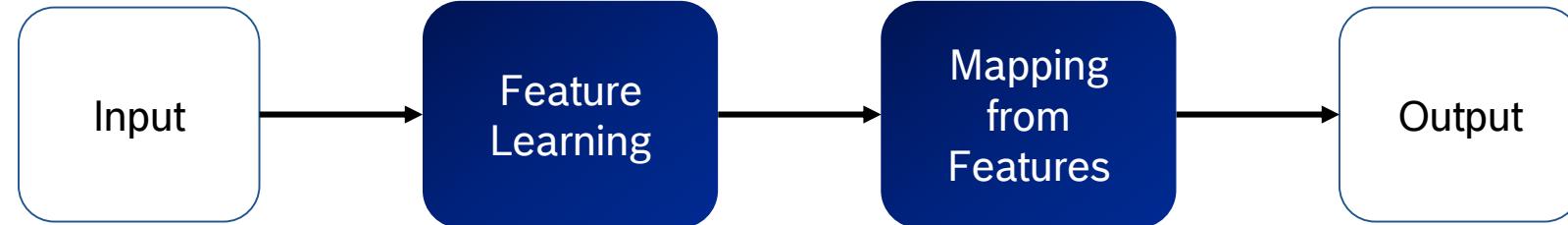
[playground.tensorflow.org](http://playground.tensorflow.org)

*Poll:*

*“What is the purpose of the activation function?”*

# Deep Learning

## The power of representation learning



# The actual learning

# Deep Learning

## Network training

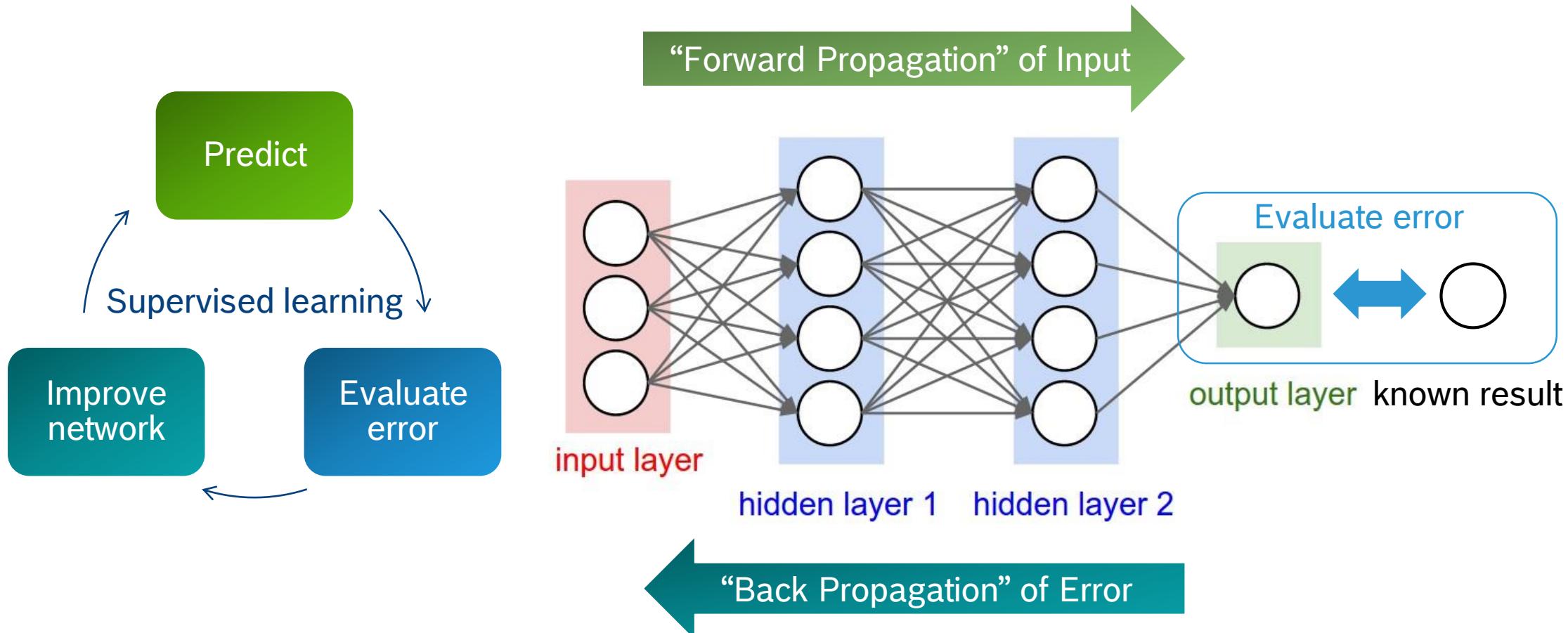
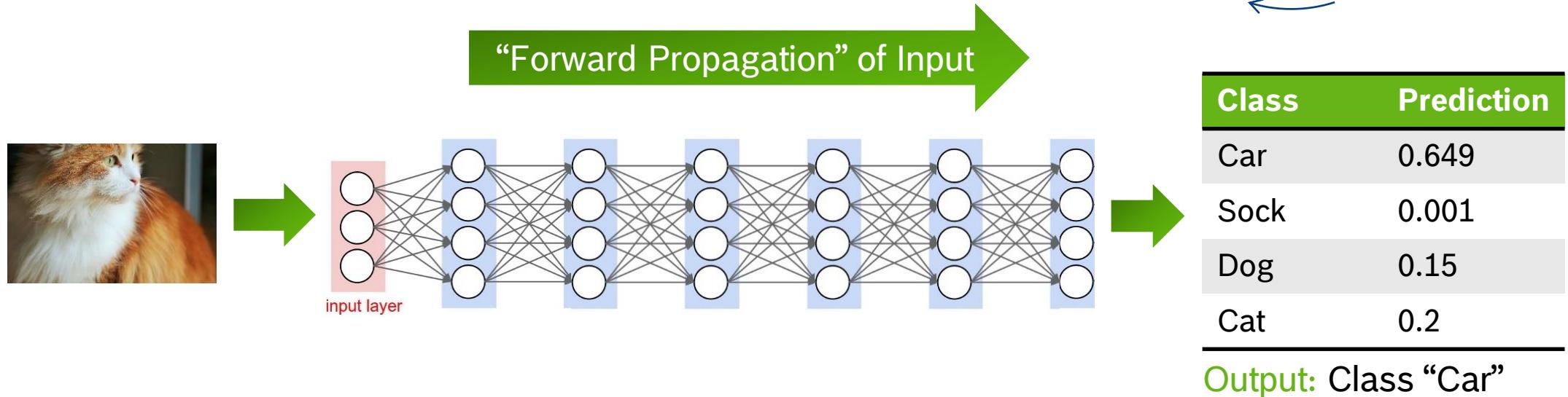


Image: Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT)

# Deep Learning

## 1<sup>st</sup> Step: Forward propagation



# Deep Learning

## 2<sup>nd</sup> Step: Error evaluation



Prediction

Class	Prediction	Label
Car	0.649	0
Sock	0.001	0
Dog	0.15	0
Cat	0.2	1

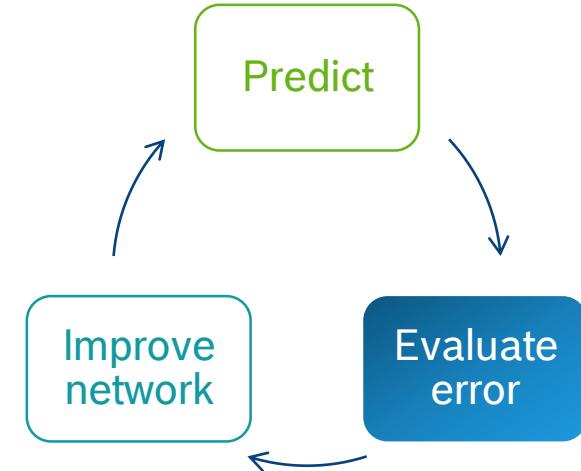
$$Error = \sqrt{(0 - 0.649)^2 + (0 - 0.001)^2 + (0 - 0.15)^2 + (1 - 0.2)^2} = 1.041$$



Prediction

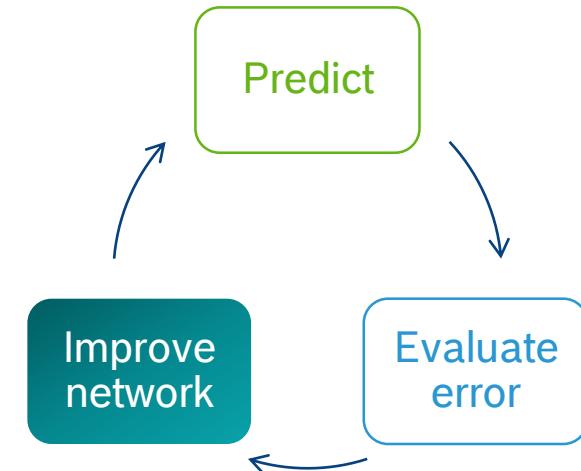
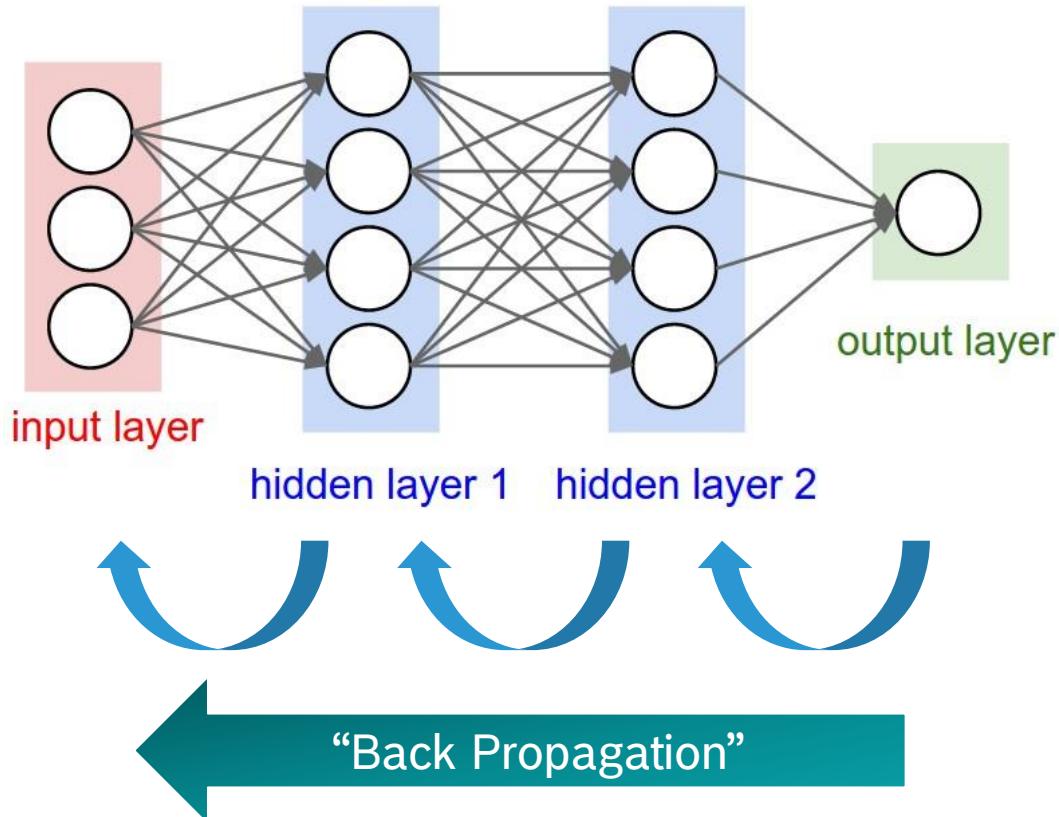
Class	Prediction	Label
Car	0.05	0
Sock	0.6	1
Dog	0.01	0
Cat	0.34	0

$$Error = \sqrt{(0 - 0.05)^2 + (1 - 0.6)^2 + (0 - 0.01)^2 + (0 - 0.34)^2} = 0.536$$

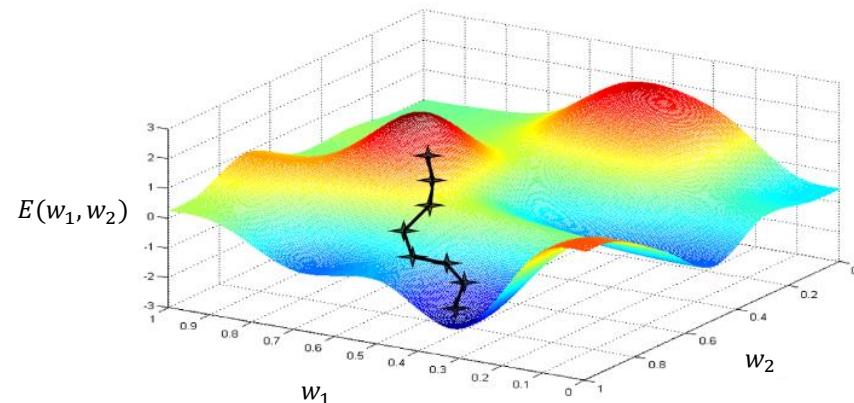


# Deep Learning

## 3<sup>rd</sup> Step: Back propagation



The error is a function of the network's weights



Minimize error using Gradient Descent

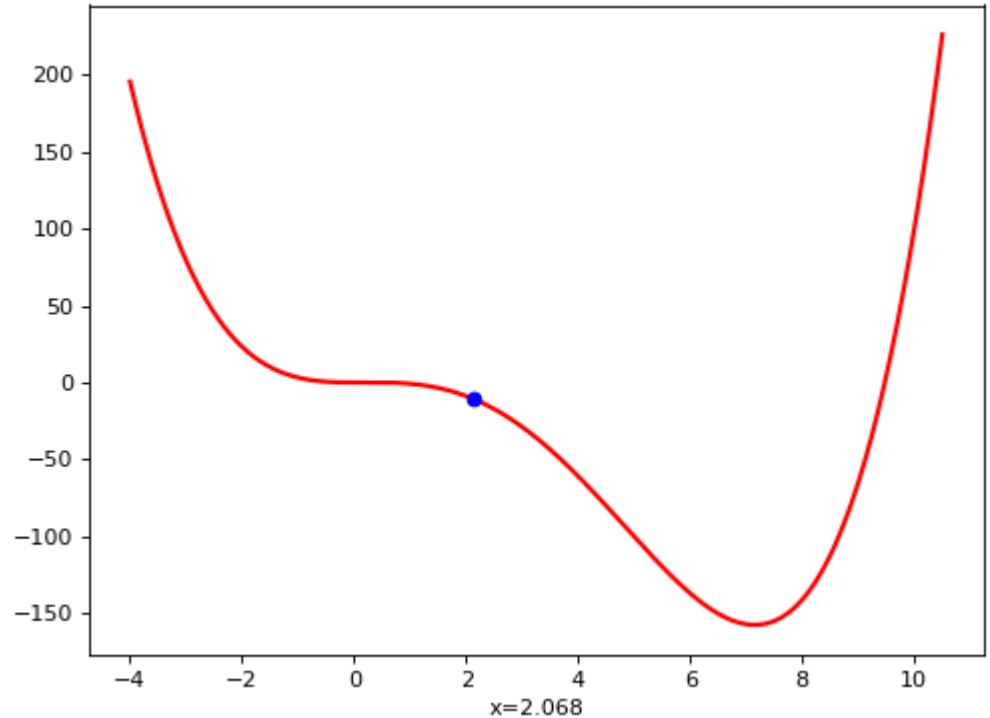
Images: Gradient Descent by StackOverflow, CC-BY 3.0, Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT)

# Deep Learning

## Gradient descent

Weight update:

$$w^{(k+1)} = w^{(k)} - \eta \frac{\partial E}{\partial w}$$

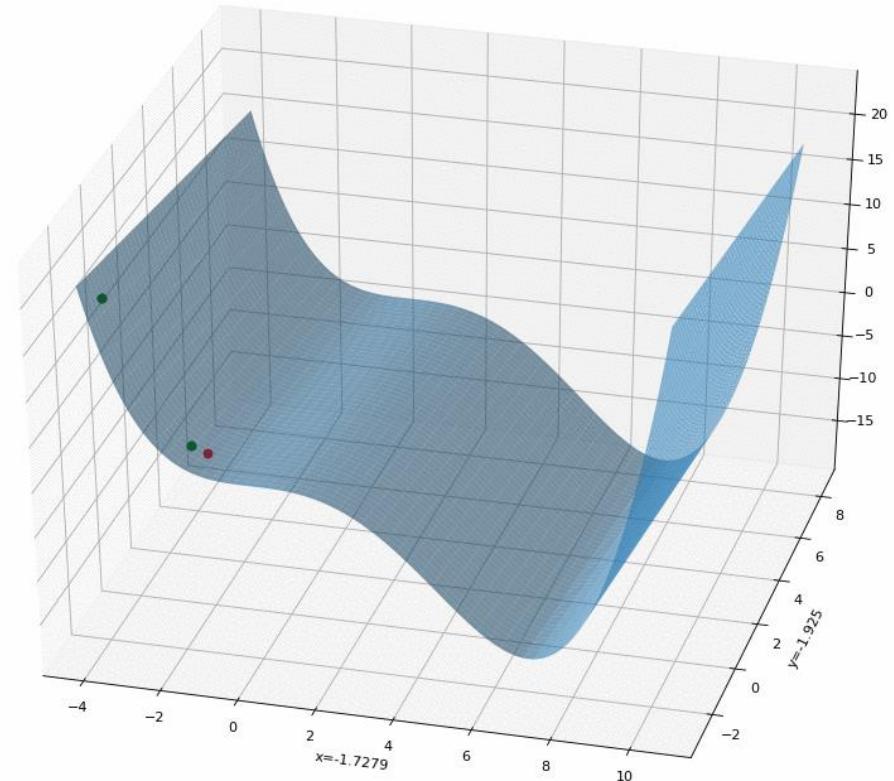


# Deep Learning

## Gradient descent

Weight update in 2D:

$$\vec{w}^{(k+1)} = \vec{w}^{(k)} - \eta \nabla E$$



*Poll:*  
*“What is the idea of gradient descent?”*

# Advanced Architectures

# Deep Learning

## Convolutional Neural Networks (CNNs)

### Challenge:

- Vision involves a large number of input neurons  
(e.g. 1000x1000 pixel values)

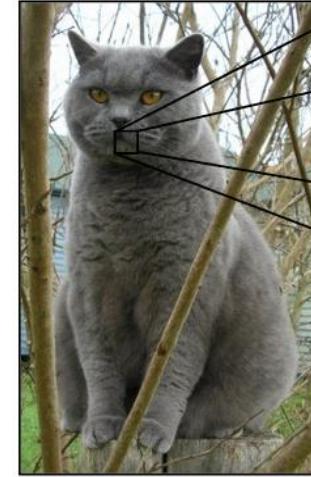


$10^6 \times 10^6$  neurons =  $10^{12}$  weights!

Connecting all neurons entirely unfeasible

### Solution:

- Take advantage of **symmetries** and **locality**



95.02	22	97	38	15	50	40	60	75	84	55	67	78	52	12	50	17	2
49	49	99	40	17	81	18	57	60	87	17	40	98	43	64	56	62	00
81	49	99	73	46	14	50	93	71	40	50	50	50	43	13	45	45	45
85	95	95	04	40	41	42	43	44	01	22	36	71	36	36	36	36	91
37	21	14	71	52	60	35	42	92	36	54	23	40	40	28	66	33	35
24	47	33	33	03	45	02	44	75	33	53	78	36	84	20	35	17	12
67	26	20	68	02	62	12	20	95	63	94	39	63	08	40	91	66	49
21	36	23	09	75	03	76	44	20	45	14	00	61	30	97	34	31	33
23	55	58	05	64	73	99	26	97	17	78	78	96	03	18	88	34	69
72	21	36	23	09	75	03	76	44	20	45	14	00	61	30	97	34	69
75	17	53	28	22	75	31	67	15	94	80	04	62	14	14	09	53	56
92	16	89	89	89	89	89	89	89	89	89	89	89	00	17	42	42	29
87	86	00	48	35	71	89	07	47	94	44	24	24	38	51	54	68	68
19	80	81	68	05	94	47	69	38	73	92	13	86	82	21	77	09	35
49	52	08	83	97	35	99	16	07	97	57	32	16	26	79	33	27	98
64	68	87	57	62	20	72	03	46	33	67	46	55	12	32	63	93	53
69	42	16	73	31	31	39	11	24	94	72	18	08	46	29	32	40	62
20	69	36	41	72	30	23	88	31	31	69	82	67	59	85	74	04	36
20	73	35	29	78	31	90	01	74	31	49	71	49	74	81	16	23	57
01	70	54	71	83	51	54	69	16	92	33	48	61	43	52	01	39	46

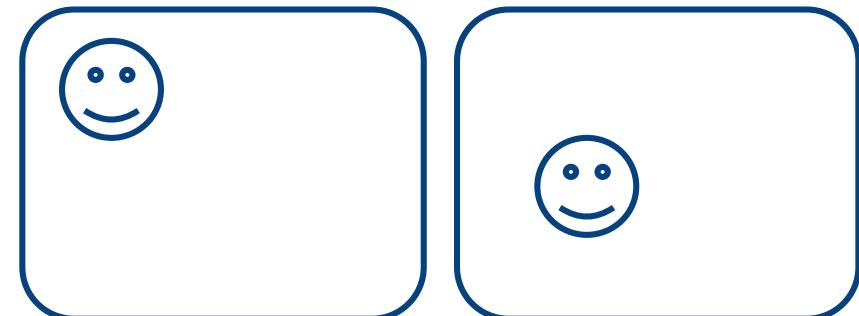
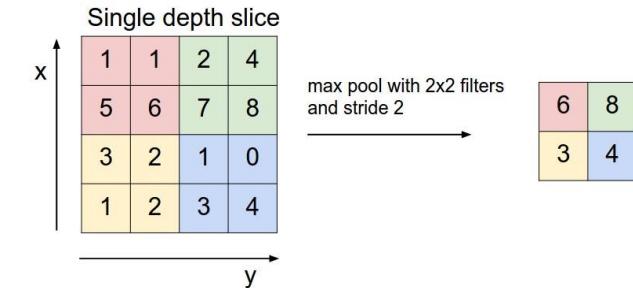
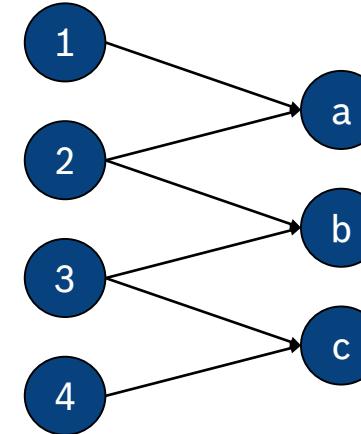
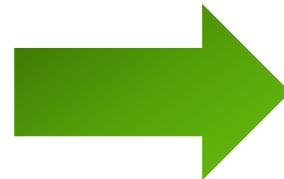
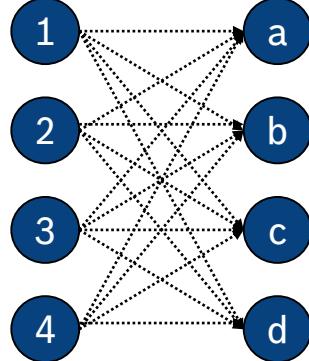


Image: Copyright (c) 2015 Andrej Karpathy, The MIT License (MIT)



# Deep Learning

## Convolutional Neural Networks (CNNs)



*Poll:*

*“Why would you use a convolutional neural network over a standard fully connected network?”*

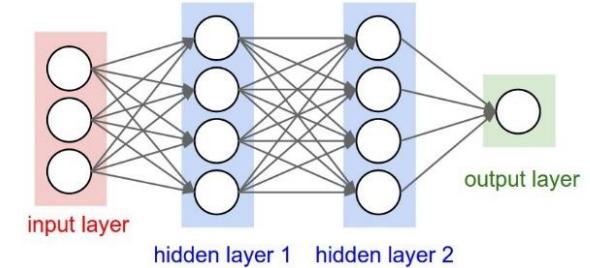
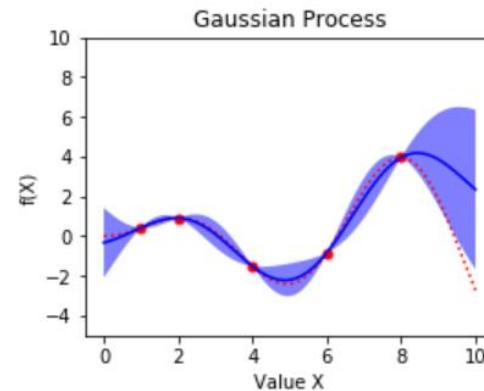
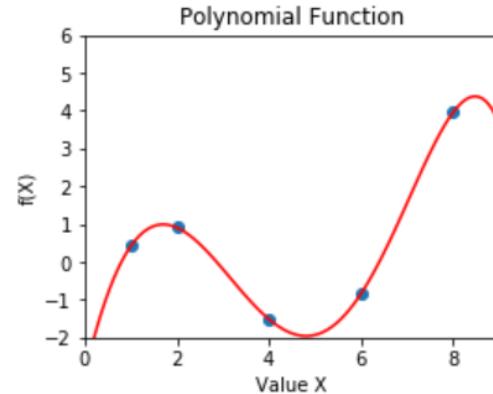
# When to use deep learning (and when not to)

*Poll:*

*“Which of these increase as we move from classical methods to neural networks?”*

# Deep Learning

## When should I use Deep Learning?



Accuracy

Required Data

Deployability

Interpretability

# Deep Learning

# Deep Learning model complexity



Depositphotos,  
Bosch License

0  
1  
2  
3  
4 4 8 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4  
5  
6  
7  
8  
9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9

CC0

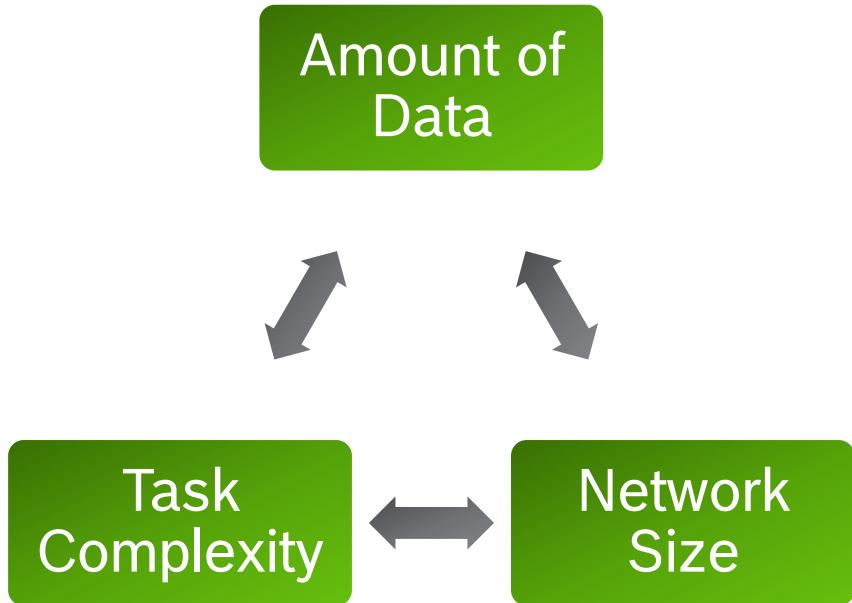
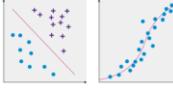


	Image Net Image Classification	MNIST Digit Classification
# features	270 000	784
# outputs	1000	10
# model parameters	~50 000 000	< 50 000
# data samples	14 000 000	42 000
Training time on 1 GPU	1-2 weeks	2 minutes

# Deep Learning Summary

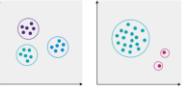
**Supervised Learning**  
Build a predictive model by using training data with known output (labels)



**Classification:** Categorize observed data into discrete categories based on learned decision boundary

**Regression:** estimate mathematical relationship ("line of best fit") between continuous variables

**Unsupervised Learning**  
Describe "hidden" structure in unlabeled data

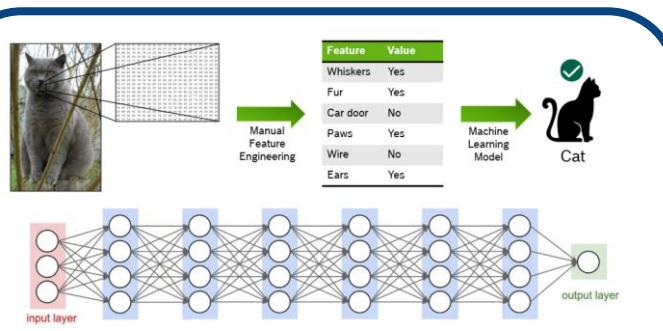


**Clustering:** group data based on similarity of certain features

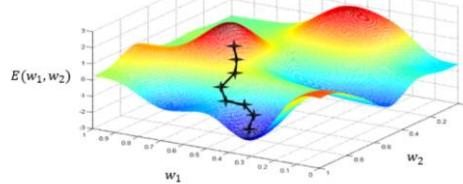
**Anomaly detection:** identify data which does not conform to expected patterns

**Density estimation:** approximate distribution from observed data

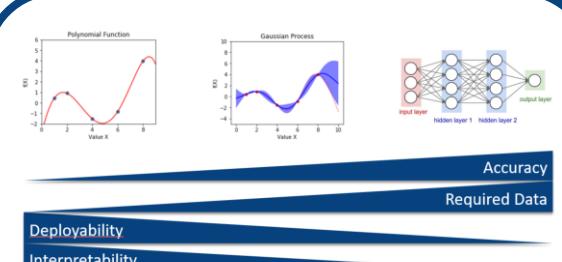
What tasks can DL solve?



Classical ML vs DL



Training of DL Models



When to use DL



Why CNNs?

# IMPLEMENTATION— ROLES, TRAINING AND CONSULTING

# Roles, Training and Consulting

## AI Roles and Competencies



### Executive

Understands strategic relevance of data, has tools overview, knows staff requirements



### Data Analyst

Has a data-driven mindset, expert in visualizing data from various sources, knows basics of statistical data analysis



### Data Scientist

Expert in statistics, machine learning, artificial intelligence and big data technologies and methodologies



### Data Engineer

Builds links to big data systems, provides clean data, develops deployment strategies and drives IT enhancement

### Existing training portfolio available

Webbased Training "Data & AI": Chapters 1-5 available

Management & Project Leads      Technical Trainings

### Concept phase Pilot in Q2 2020



### DAX

Data Analytics Expert Program



### DSX

Data Science Expert Program



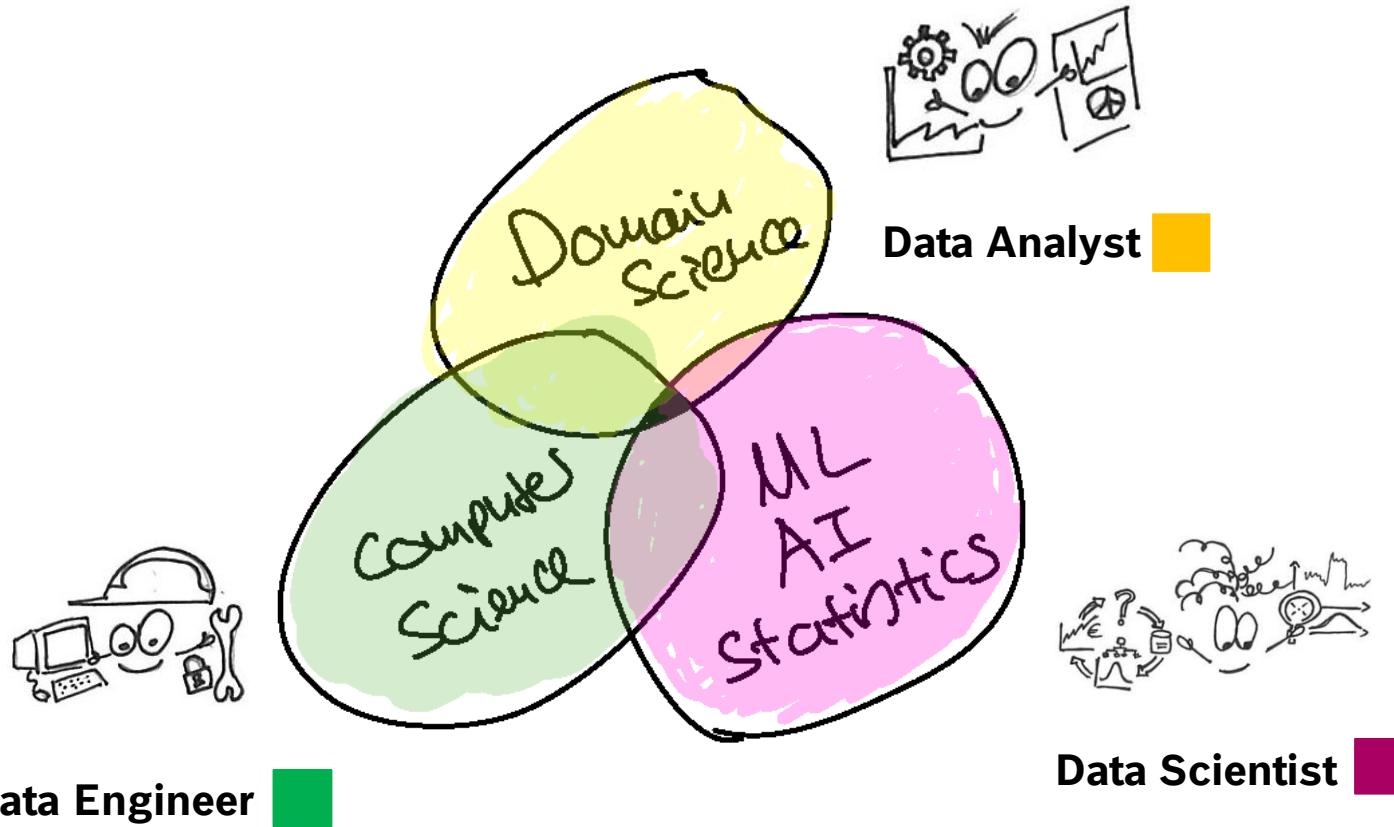
### DEX

Data Engineering Expert Program

Create AI Awareness in Executives and set standards of qualification for AI expert roles

# Roles, Training and Consulting

## Data Analyst, Data Scientist and Data Engineer



Data-driven projects are a team effort where **domain experience, analytical skills and technological expertise** go hand in hand.

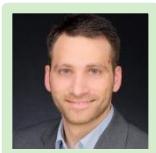
# Roles, Training and Consulting Interplay at controlling use case



**Michael Binder (G2/PJ-FCE-IT)**

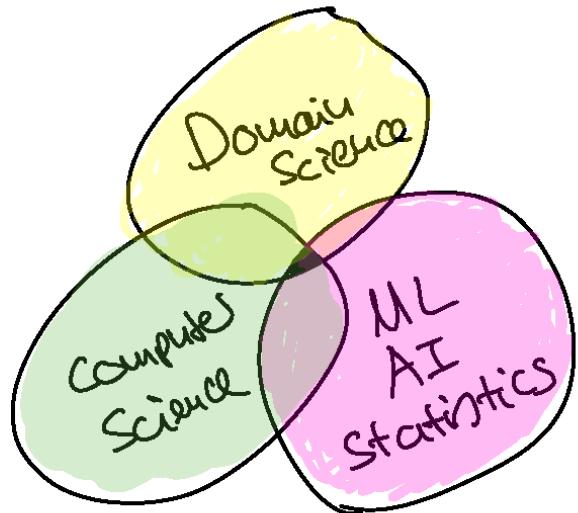
Background: Controlling

Project topics: Product lead



**Dominik Mayer**

Background: Hadoop and Linux administration



**Phil Gaudreau (CR/PJ-AI-S1)**

Background: Mathematics

Project topics: Design of prediction algorithm



**Cinar Goktug (CR/PJ-AI-S1)**

Background: PhD in Machine Learning

Project topics: Design and implementation of prediction algorithm

# Data Engineering Expert Program (DEX)

## Expert in building reliable data infrastructure

	Junior Expert			Senior Expert	
	Basics	Methodical Overview	Project 1	Specialization	Project 2
Content	<ul style="list-style-type: none"> <li>Required programming languages</li> <li>Collaborative Software Design</li> </ul>	<ul style="list-style-type: none"> <li>Data sources and architectures, data warehouse/lake</li> <li>Designing of reliable data pipelines</li> </ul>	<ul style="list-style-type: none"> <li>Project ideation and proposal</li> <li>Execution with BCAI mentoring</li> </ul>	<ul style="list-style-type: none"> <li>Deployment and continuous X</li> <li>Operation and maintenance</li> <li>Security and resource management</li> </ul>	<ul style="list-style-type: none"> <li>Project ideation and proposal</li> <li>Execution with BCAI mentoring</li> </ul>
Duration	3 months	4 months	3 months	4 months	6 months
Grading	Certificate	Certificate	Final presentation	Assignment grading	Final presentation & FEBER
Trainee Effort	~100 h	~150 h	~ 120 h	~ 150 h	~ 230 h
Provider	Coursera	BCAI, Udacity, Coursera	BCAI	BCAI, Udacity, Coursera	BCAI

**DEX: Expert in distributed data-intensive applications based on profound Software Engineering expertise**

# Data Science Expert Program (DSX)

## Expert in functionality and application of ML methods

	Junior Expert			Senior Expert	
	Basics	Methodical Overview	Project 1	Specialization	Project 2
Content	<ul style="list-style-type: none"> <li>Python for Data Science</li> <li>Visualization</li> <li>Linux basics</li> <li>Version control</li> <li>SQL</li> </ul>	<ul style="list-style-type: none"> <li>Classroom Trainings on basics of Data Science, Statistics and Machine Learning</li> <li>Exercises in Python</li> </ul>	<ul style="list-style-type: none"> <li>Project ideation and proposal</li> <li>Execution with BCAI mentoring</li> </ul>	Options: <ul style="list-style-type: none"> <li>Deep Learning</li> <li>Embedded</li> <li>NLP</li> <li>DevOps</li> <li>Autonomous vehicles</li> </ul>	<ul style="list-style-type: none"> <li>Project ideation and proposal</li> <li>Execution with BCAI mentoring</li> </ul>
Duration	2 months	2 months	4 months	4 months	6 months
Grading	Certificate	Assignment grading	Final presentation	Certificate	Final presentation & FEBER
Trainee Effort	~ 100 h	~ 90 h	~ 180 h	~ 200 - 400 h	~ 270 h
Provider	Coursera	BCAI	BCAI	Depends on specialization	BCAI

**DSX: Expert in Statistics, Machine Learning and implementing advanced algorithms**

# Data Analytics Expert Program (DAX)

## Expert in data analysis & visualization

		Expert		
		Basics	Advanced	Project
Content	• Introduction to Python and Jupyter Notebooks • Python at Bosch • Python for Data Science • Visualization • SQL	• Basics of Statistical Data Analysis • Tableau • Power BI	• Project ideation and proposal • Execution with BCAI mentoring	
	6 weeks	6 weeks	3 months	
	Certificate	Assignment grading	Final presentation	
	~ 80 h	~ 80 h	~ 140 h	
	Coursera, BCAI	Coursera, BCAI, CI	BCAI	

### DAX: Expert in Data Analytics & Visualization

# BCAI Classroom Training Portfolio

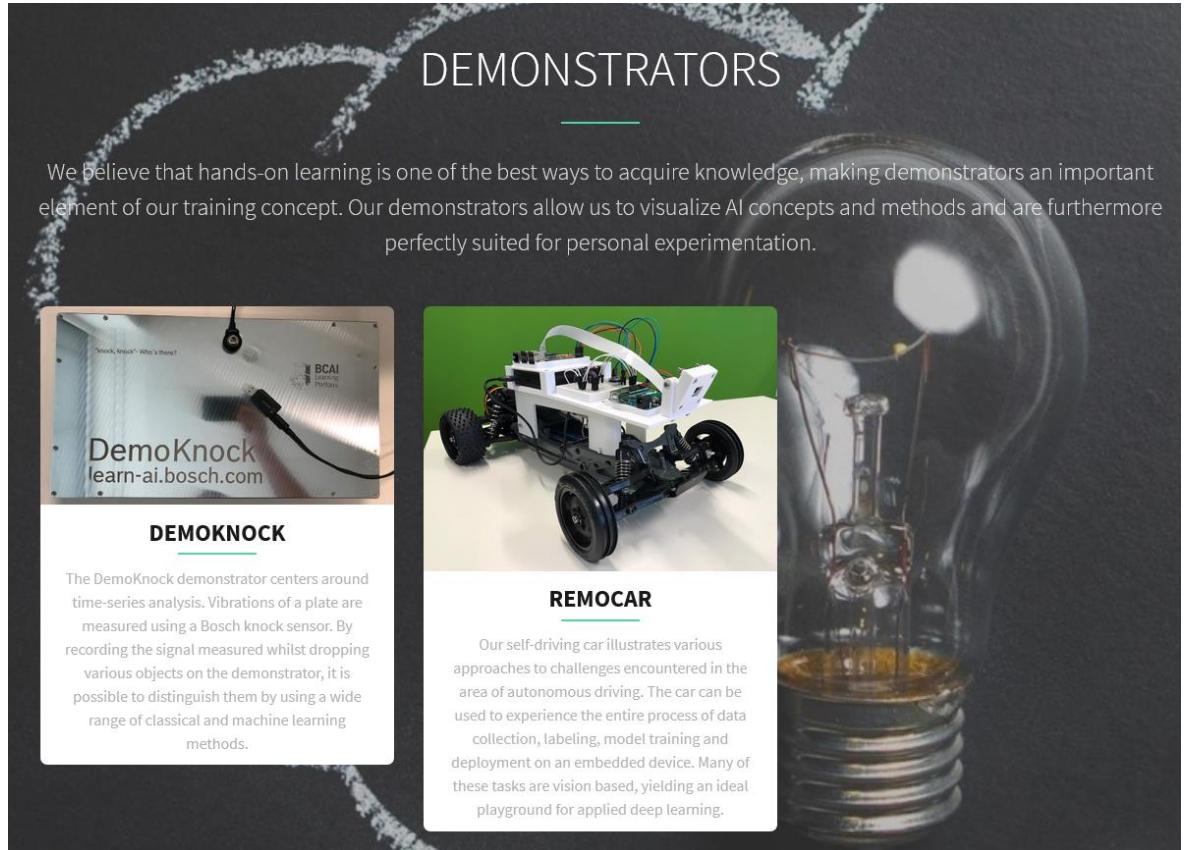
					Executives, Managers, Project Leaders	Engineers, Experts
					Also covered in [FT-AI-ML-01]	
					Recommended	
	[EDT-AI-100] Introduction to Big Data and Artificial Intelligence	[FT-AI-DDP-01] Leading Data-Driven Projects	[FT-AI-DL-01] Deep Learning Deep Dive	[FT-AI-STL-01] Statistical Learning and Gaussian Processes	[FT-AI-ML-01] Machine Learning and Deep Learning	
Summary	AI Introduction	Short methodical introduction	Introduction to deep neural networks	Basics of statistics and Gaussian models	Classical machine learning, deep learning	
Prerequisites	None	General understanding of AI	General understanding of AI	Basic Python skills recommended	Basic understanding of statistics, Python skills	
Content	General overview of AI and data value Ability to see data-driven opportunities in the area of expertise	Overview of basic methods for regression, clustering and classification with a focus on model validation for AI project leads	Basics of deep neural networks, architectures for image classification and object detection, hands-on workshop	Introduction to statistics, Bayesian statistics, hypothesis tests, regression analysis, Gaussian mixture models, Gaussian processes	Data Science workflow, machine learning tasks, concepts and models, data-preprocessing, time series analysis, deep neural networks, CNNs	
Duration Price (Germany)	1 day 750 EUR	1 day 750 EUR	1 day 750 EUR	2 days 1450 EUR	3 days 2175 EUR	
Next Dates (Germany)	Online Format: 28 <sup>th</sup> - 29 <sup>th</sup> Jul 2020	To be added	To be added	Online Format: 7 <sup>th</sup> - 10 <sup>th</sup> Jul 2020	Online Format: 14 <sup>th</sup> - 22 <sup>th</sup> Jul 2020	
	<a href="#">Link for more details</a>	<a href="#">Link for more details</a>	<a href="#">Link for more details</a>	<a href="#">Link for more details</a>	<a href="#">Link for more details</a>	
	Alternative: <a href="#">free web-based training [EDT-AI-100_WBT]</a>					
	In case of questions/remarks please contact <a href="mailto:Jennifer.Thompson2@de.bosch.com">Jennifer.Thompson2@de.bosch.com</a>					
Info Online Format:	Training days split up in double amount of half-days					

# Demonstrators

## Experience AI in a hands-on tutorial

### Philosophy

- ▶ Growing palette
- as the next one a catapult for Bayesian Optimization
- ▶ Purposes
  - ▶ Part of trainings
  - ▶ Keynotes, conferences
- ▶ Can be used as demonstration material for groups to get excited about AI
  
- ▶ See instructions for assembly below:
  - ▶ [DemoKnock](#)
  - ▶ [RemoCar](#)



# Train the Trainer

## Scaling concept for class room trainings

### Trainers

- ▶ Requirements for candidates
  - ▶ Skills/Background (ML/AI)
  - ▶ Motivation
  - ▶ Strong recommendation: team of min. two trainers
- ▶ Participate in 3 trainings (6 training days) to be certified for full portfolio:
  - ▶ EDT-AI-100, FT-AI-STL-01, FT-AI-ML-01
- ▶ Proposed workload: 5-10 training days/year

### Benefits

- ▶ Profit by local organizations:
  - ▶ Direct local trainings in the right language
  - ▶ Additional local business context (use cases can be added)
- ▶ Cost reduction

### Process

#### Local manager:

- suggest candidates

#### Candidates:

- participate in trainings in Germany
- get materials and additional training by BCAI trainers

#### BCAI with local BTC and manager:

- clarify training conditions (fee, dates, ...)
- clarify license fee process

#### Candidates → Local trainers:

- conduct pilot training
- evaluate the feedback with BCAI

#### Local trainers and BTC:

- schedule and conduct trainings

### Training

- ▶ Already up and running/in development in Turkey, Portugal & Spain, US, Mexico, France, China, Japan, Brazil
- ▶ Types of training
  - ▶ General AI awareness
  - ▶ Deep methodical knowledge
- ▶ We start with the awareness training to establish the processes

### Price Structure

- ▶ BCAI: license fee 150 Euro/Participant per day (materials, infrastructure, support, quality meetings)
- ▶ Local: trainer cost defined by local manager with BTC/HR
- ▶ Local: organizational costs (training, organization, room, catering, etc...)

# Training: Intro to Big Data and Artificial Intelligence

Training duration: 1 day  
Max. 15 participants



## BD & AI: What and why?

- ▶ Basic definitions
- ▶ Why AI and why now?
- ▶ Real world applications
- ▶ Bosch Use Cases

## Data as an asset: Value creation

- ▶ Relevance of data
- ▶ Big Data handling
- ▶ Data mining
- ▶ Roles and processes

## Technical foundations: Machine Learning

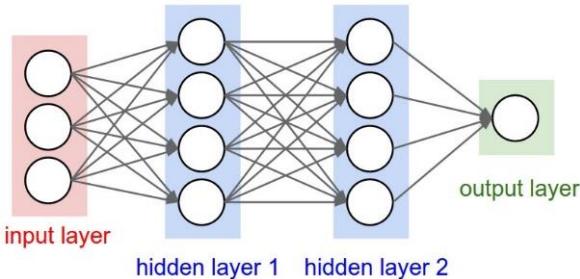
- ▶ What is machine learning?
- ▶ Strategies
- ▶ Tasks
- ▶ Methods

## Get started: Data mining in your BU

- ▶ Interactive session
- ▶ Find business opportunities
- ▶ Learn how to tackle them
- ▶ Discuss & exchange

# Training: Deep Learning Deep Dive

Training duration: 1 day  
Max. 15 participants



## LO1: Understand Deep Learning Functionality

- ▶ Basic structure
- ▶ Terminology
- ▶ Training and inference
- ▶ Important architectures

## LO2: Identify Deep Learning Applications

- ▶ Image Classification
- ▶ Object Detection
- ▶ Natural Language Processing

## LO3: Know Project Requirements

- ▶ Data
- ▶ Infrastructure
- ▶ Algorithms

## LO4: Work on a Real Deep Learning Problem

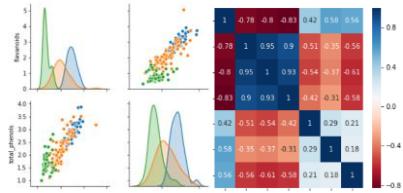
- ▶ Incrementally learn to develop a neural network for autonomous lane keeping
- ▶ Deploy your network on a model car and see it in action

Leftmost image: <http://cs231n.github.io> (MIT license)

# Training: Leading Data-Driven Projects

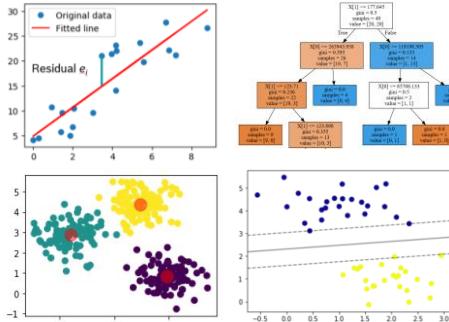
Training duration: 1 day  
Max. 15 participants

## Data Exploration



- ▶ Exploratory analysis
- ▶ Visualization

## Modelling

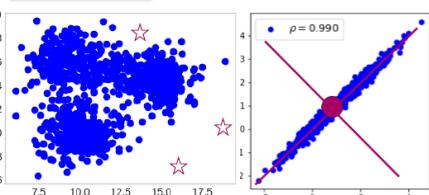


- ▶ Train an appropriate model
  - ▶ Regression
  - ▶ Clustering
  - ▶ Classification

## Deployment

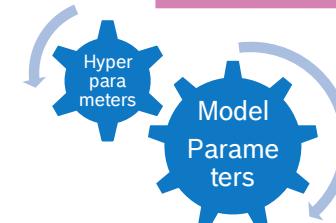
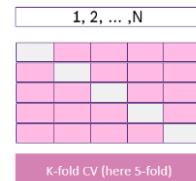


- ▶ Implement your model in a production system



## Data pre-processing

- ▶ Feature (predictor) selection
- ▶ Outlier treatment
- ▶ Dimensionality reduction
- ▶ Model-specific processing

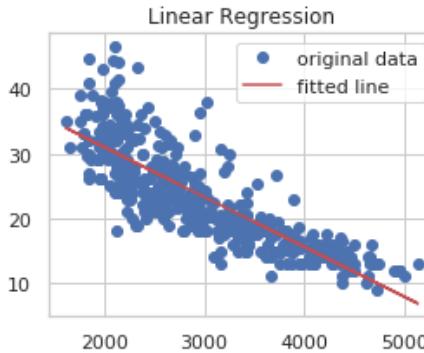
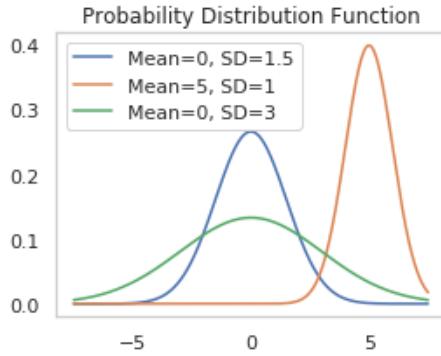


## Validation

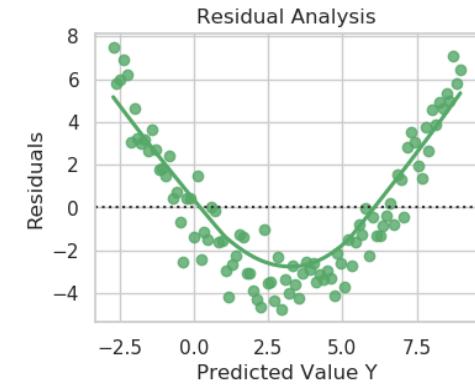
- ▶ Cross-validation
- ▶ Test model on an independent dataset
- ▶ Tune hyperparameters

# Training: Statistical Learning & Gaussian Processes

Training duration: 2 day  
Max. 15 participants



Decision	The Null Hypothesis	
	True	False
Accept $H_0$	$(1-\alpha)$	$\beta$
Reject $H_0$	$\alpha$	$(1-\beta)$



## LO1: Understand Basic Statistical Terminology

- ▶ (Conditional) probabilities
- ▶ Location and distribution parameters
- ▶ Common distributions

## LO2: Correlation and Linear Regression

- ▶ Correlation
- ▶ Linear regression
- ▶ Parameter interpretation

## LO3: Parameter Estimation and Statistical Tests

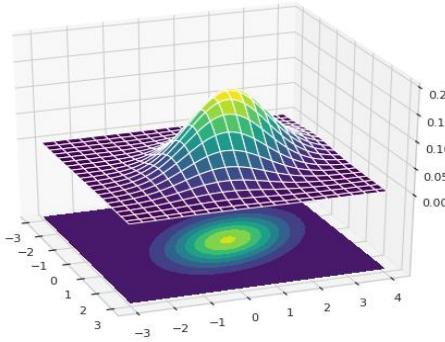
- ▶ Parameter estimation
- ▶ Hypothesis tests
- ▶ Confidence intervals

## LO4: Linear Regression Assumptions and Diagnostics

- ▶ Basic assumptions, tests and remedies against assumption violation
- ▶ Residual analysis

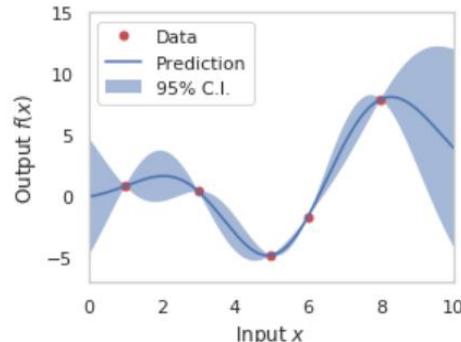
# Training: Statistical Learning & Gaussian Processes

Training duration: 2 day  
Max. 15 participants



## LO5: Gaussian Mixture Models

- ▶ Multivariate Gaussian distribution
- ▶ Gaussian mixture models
- ▶ Estimation by expectation maximization



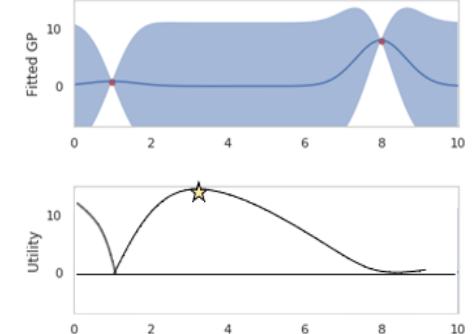
## LO6: Understanding Gaussian Processes (GP)

- ▶ Covariance function
- ▶ Noise-free vs. noise case
- ▶ Hyperparameters (signal and noise variance, length-scale)

1	3	8	2	6	4	1
0	1	2	7	5	2	9
3	5	7	8	0	9	3
6	9	4	2	7	1	4
7	2	1	0	3	5	8

## LO7: Advanced Topics and Applications of GP

- ▶ Types of covariance functions
- ▶ Regression and classification with GP
- ▶ Model estimation and selection

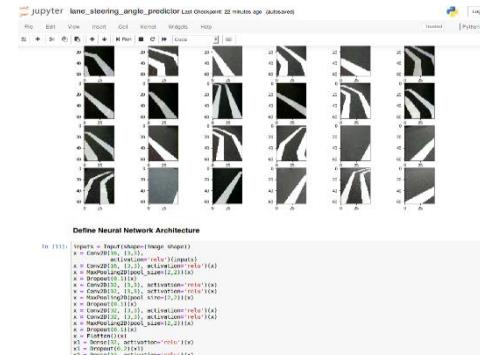
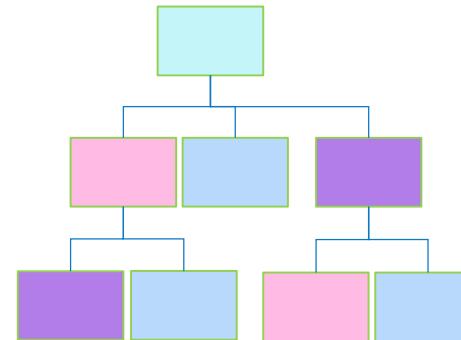
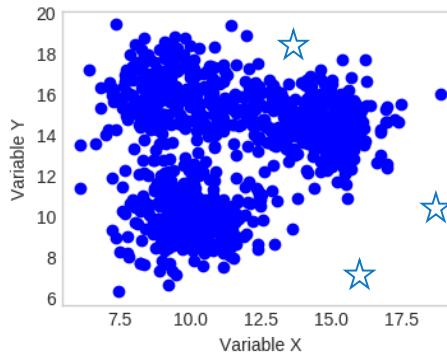
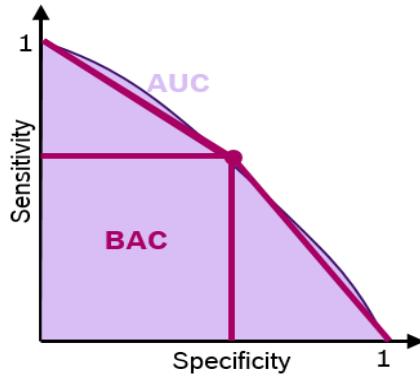


## LO8: Bayesian Optimization (for Hyperparameters)

- ▶ General purpose
- ▶ Acquisition functions
- ▶ Exploration vs. Exploitation
- ▶ Application for GP

# Training: Machine Learning & Deep Learning

Training duration: 3 day  
Max. 15 participants



## LO1: Machine Learning (ML) Concepts

- ▶ ML workflow
- ▶ Model complexity
- ▶ Regularization
- ▶ Ensembles

## LO2: Data Science Workflow

- ▶ Data exploration and dimensionality reduction
- ▶ Outlier detection
- ▶ Model validation and selection

## LO3: Algorithms and Methods

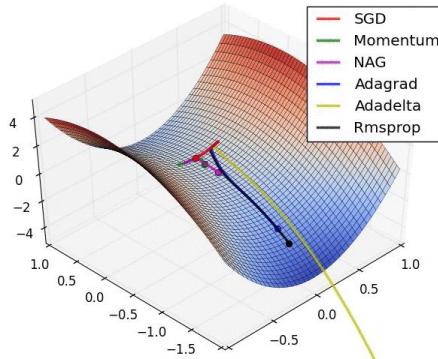
- ▶ Clustering
- ▶ Decision trees
- ▶ Support vector machines
- ▶ Time series analysis

## LO4: Application of Learned Concepts using Python

- ▶ Implementing the models
- ▶ Performance comparison
- ▶ Use cases at Bosch and potential in BUs

# Training: Machine Learning & Deep Learning

Training duration: 3 day  
Max. 15 participants

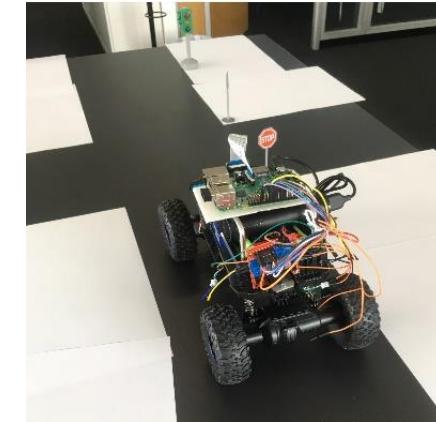
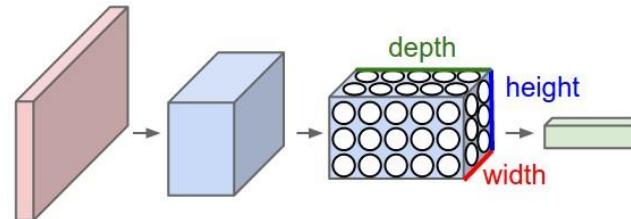


## LO5: Basics of Neural Networks

- ▶ Training and inference
- ▶ Optimization
- ▶ Activation and loss functions
- ▶ Weight initialization
- ▶ Transfer learning

## LO6: Deep Learning

- ▶ Vanishing gradient problem
- ▶ Convolutional Neural Networks (CNN)
- ▶ Word embeddings
- ▶ Bosch use cases



## LO7: Work on a real Deep Learning Problem

- ▶ Incrementally learn to develop a neural network for autonomous lane keeping
- ▶ Deploy your network on a model car and see it in action

Images: <http://cs231n.github.io> (MIT), A. Radford <https://imgur.com/a/Hqolp>

# AI Roles and Competencies

## Learning journey for executives

### Before:

#### No AI Background

You have been hearing Artificial Intelligence on every corner but except for the utopic picture of machines taking over you have no further ideas about it?

### Step 1:

#### AI Awareness Class Room



OR

#### WBT AI Awareness



Use a series of eight episodes from our web-based training to get an initial overview over the most prominent AI topics, methods, and some of Bosch use cases

If you need more methodical knowledge in machine learning and/or deep learning you have the opportunity to have a one-day methodical deep dive

### Step 2:

#### Leading Data-Driven Projects



AND/OR

#### Deep Learning Deep Dive



### After:

You are aware of what the chances and risks of AI are, what words machine learning, deep learning mean, have seen some use cases and have decided how to proceed on your own

#### Training Bar

After you know what keyword to look for we can offer you a wide palette of further training offers (internal/external) in different formats (online vs. class room, priced vs. free). If you want a practical implementation experience in Python in addition to a methodical introduction, see our landing page

# Web-based Training “Data & AI”

## Target Groups



### Executive

Understands strategic relevance of data & AI, has tools overview, knows staff requirements



### Employee

Understands strategic relevance of data & AI, has tools overview, knows the basics of these topics

## Learning Objectives

- Build a mindset for the importance and **value of data** and data mining
- Understand **the value proposition and the limitations** of (big) data and artificial intelligence
- Identify **commercial opportunities** of deploying (big) data and artificial intelligence in our products, services, and processes
- Prepare for the **chances and challenges** coming with the rise of artificial intelligence technologies
- Gather a **high-level understanding of the technologies** behind (big) data and artificial intelligence, including machine learning and deep learning

## Cost

Our [web-based training](#) is free of charge!

## Time Effort

8 x 25 min of interactive web-based learning

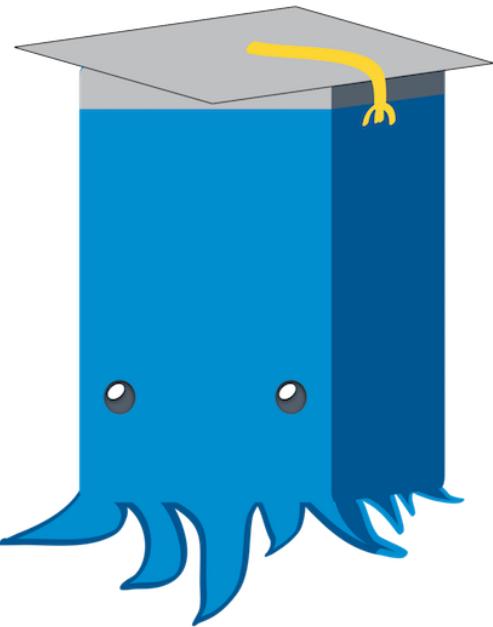
## Requirements

Interest and willingness to dive into the topics of data & AI

# AI Learning Platform

## Supporting AI enthusiasts

### Target Group



- Motivated AI enthusiasts

### Training Offers

A screenshot of a Jupyter notebook interface. The title bar says "Early-Adopter-Network neural\_networks\_intro (unsaved changes)". The menu includes File, Edit, View, Insert, Cell, Kernel, Widgets, Help. The toolbar has icons for file operations and a Python 3 button. A "Validation" section is shown with text about minimizing prediction error on validation data. Below it is a line graph showing training and validation error over 300 epochs.

#### Validation

The goal of training is minimizing the prediction error on data, which the network has not seen before, so-called **validation data**. This ensures, that the network generalizes to new data and does not simply memorize the training data. To track the validation error during training, it is evaluated after each **epoch**, i.e. after all training data has been used for backpropagation once.

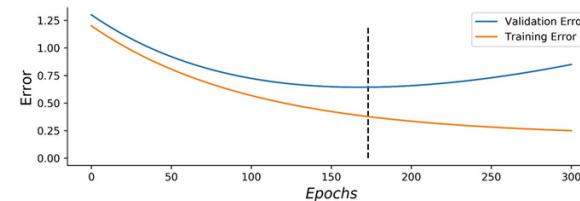


Figure: Network error on training and validation data over the number of epochs, for which a network was trained

#### Titanic Dataset: Exploration

Let's get started with applying Neural Networks to a real problem. We read the file containing our dataset into a [Pandas DataFrame](#) and output some descriptive information:

```
In [1]: import pandas as pd #module for convenient handling of tabular data
```

```
In [2]: titanic = pd.read_csv('input/titanic.csv')
```

```
Out[2]:
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	796.000000	796.000000	796.000000	619.000000	796.000000	796.000000	796.000000
mean	448.146985	0.38191	2.327889	29.54336	0.527638	0.373116	31.336735

- Self-paced learning on Jupyter notebooks
- Prerequisites:
  - Basic Python skills
- Linked with our community

### Access Links

- [Visit Our Learning Platform](#)
- [Visit Our Community](#)

# AI Competitions on “Baggle” (Kaggle for Bosch)

## Facts

- ▶ Pilot together with CC and hosted on the AI learning platform
- ▶ **5 challenges** online, 1 more to come based on real use cases and data
- ▶ [Bosch Connect community](#)
- ▶ About **200 registered participants** from 600 addressed in the keynote
- ▶ Over 100 submissions after approx. 3 weeks



## Competitions (2019)



**Highway Detection** by Automated Driving - Perception  
Classify if a car is driving on a highway  
🕒 launched 17 days ago   ⏳ close in about 2 months

👤 15 teams  
📄 16 submissions



**Driver Fatigue Detection** by Advanced Development Projects  
Classify the awareness of a driver  
🕒 launched 2 months ago   ⏳ close in about 2 months

👤 11 teams  
📄 0 submissions



**First Level Support** by Engineering Software Coordination, Methods and Tools  
Classify support tickets by tool  
🕒 launched 2 months ago   ⏳ close in about 2 months

👤 83 teams  
📄 234 submissions



**Loose Wheel Detection** by Engineering Software for Controllers  
Predict a loose wheel from speed sensor data  
🕒 launched 2 months ago   ⏳ close in about 2 months

👤 35 teams  
📄 187 submissions

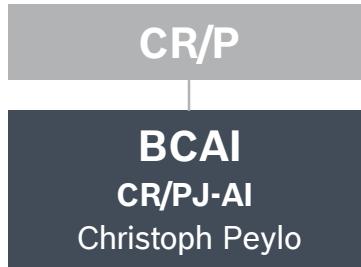


**Noise prediction for ESP devices** by Engineering Components and Hydraulic Functions  
Generate what a driver hears from sensor data  
🕒 launched 2 months ago   ⏳ close in about 2 months

👤 30 teams  
📄 78 submissions

[See this link for more details](#)

# BCAI Organization & Contacts



AI Research	AI Enabling	AI Marketing	AI Consulting	AI Services
gain best in class AI technology	accelerate digital business	raise awareness of BCAI	support project strategies	drive commercialization
<ul style="list-style-type: none"><li>▶ Generate technical differentiation</li><li>▶ Realize cutting-edge AI into lead application USP's</li><li>▶ Establish BCAI as a major player in the academic community</li><li>▶ <b>CR/PJ-AI-R</b> Alexander Müller</li></ul>	<ul style="list-style-type: none"><li>▶ Build up AI competence in business units</li><li>▶ Drive data as an asset mindset</li><li>▶ Facilitate transfer of research results</li></ul> <p>See: <a href="http://learn-ai.bosch.com">learn-ai.bosch.com</a></p> <ul style="list-style-type: none"><li>▶ <b>CR/PJ-AI-E</b> Martin Thomas</li></ul>	<ul style="list-style-type: none"><li>▶ Drive internal and external communication</li><li>▶ Active Stakeholder Management</li><li>▶ Develop Market Intelligence</li></ul> <ul style="list-style-type: none"><li>▶ <b>CR/PJ-AI-M</b> Christoph Röscher</li></ul>	<ul style="list-style-type: none"><li>▶ AI project ideation and incubation</li><li>▶ AI project preparation and execution</li><li>▶ AI strategy support</li></ul> <ul style="list-style-type: none"><li>▶ <b>CR/PJ-AI-C</b> Thomas Geiler</li></ul>	<ul style="list-style-type: none"><li>▶ Projects that apply state of the art AI to solve business problems for BUs</li><li>▶ AI platform to fast-track AI project and solution development</li></ul> <ul style="list-style-type: none"><li>▶ <b>CR/PJ-AI-S</b> Rahul Kapoor</li></ul>
<b>External Scientific Advisory Board</b>				
<b>Consultancy Board</b>				

# Bringing your ideas to life with BCAI CONSULTING



SEND US YOUR USE CASE

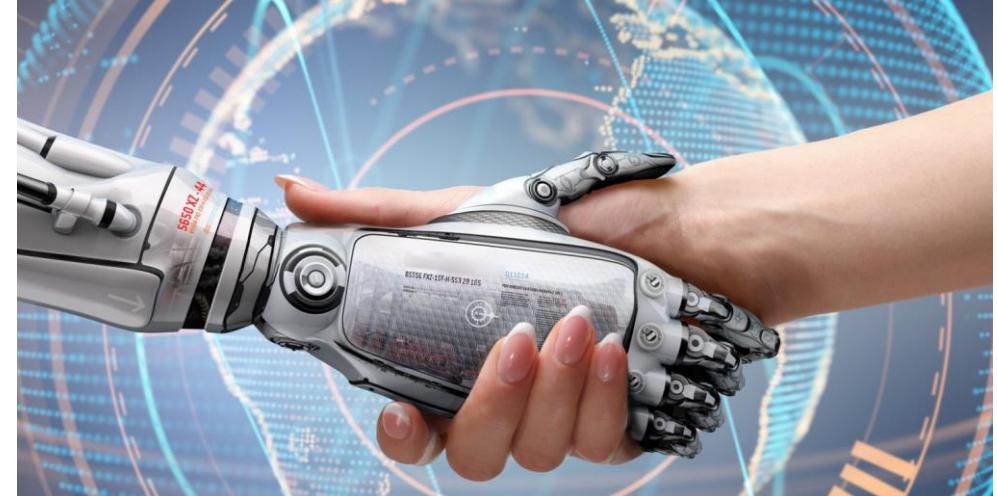
<https://bcaic-ai-demo.learn-ai.bosch.com/contact/form/>

# AI code of ethics

## Bosch sets company guidelines for the use of artificial intelligence

### At a glance: guidelines in Bosch's AI code of ethics

- All Bosch AI products should reflect our “Invented for life” ethos, which combines a quest for innovation with a sense of social responsibility.
- AI decisions that affect people should not be made without a human arbiter. Instead, AI should be a tool for people.
- We want to develop safe, robust, and explainable AI products.
- Trust is one of our company’s fundamental values. We want to develop trustworthy AI products.
- When developing AI products, we observe legal requirements and orient to ethical principles.



Bosch Zündler

Processes will be established to ensure that the AI codex stays a “living document”.

# Check out our landing page for all our offers

The screenshot shows the BCAI Academy landing page with a teal gradient background. At the top left is a white speech bubble containing the text "learn-ai.bosch.com". Below it is a white rocket ship icon. The top navigation bar includes links for Home, Mission, Testimonials, Services, Demonstrators, Team, and Stats. A central call-to-action button says "Start your AI learning journey today." Below it, a green box contains a COVID-19 update message. The main content area features six training program cards arranged in two rows of three:

- Classroom Trainings**: Fundamentals of Machine Learning. Description: Dive deep into AI topics with the guidance of our experts. Experience practical use-cases in collaborative hands-on sessions. Accelerate your learning progress by interaction within the group. Buttons: EXPLORE CLASSROOM TRAININGS, EXPLORE EXPERT PROGRAMS.
- Expert Programs**: In-depth development of AI skills. Description: Our expert programs have been carefully designed to develop expertise in one of three specializations - data science, data engineering or data analysis. Each program consist of classroom trainings as well as dedicated project phases where participants work on problems of their business units. We also provide a certificate for the participants of these expert courses. Buttons: EXPLORE EXPERT PROGRAMS.
- Web Based Trainings**: Awareness of AI Impact. Description: Globally available trainings, everywhere and at any time. Get a basic understanding of data driven methods. Learn at your own pace. Buttons: EXPLORE WEB BASED TRAININGS.

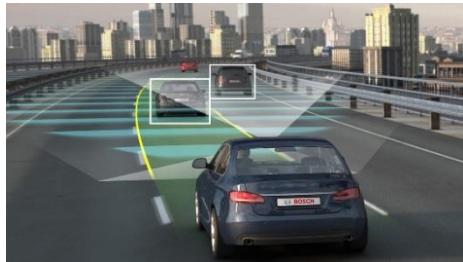
- Train the Trainer**: Become an AI trainer. Description: This program enables you to give classroom trainings as one of our accredited trainers. You can spread your AI knowledge locally and join an international community of AI trainers just like you. Learn, teach, share. Buttons: LEARN MORE.
- Learning Platform™**: Beginner to expert hands-on AI practice. Description: Enable yourself today! Learn about AI methods and Bosch use-cases with self-paced online material. No setup required. Buttons: GET STARTED.
- Community**: Share your thoughts. Description: Join our community and get in touch with other Bosch AI enthusiasts. Ask questions, exchange ideas and empower your AI learning journey with the help of the community. Buttons: JOIN THE COMMUNITY.

# IMPLEMENTATION- PLATFORM PROVIDERS

# Platform Providers

## CI/OST – CoC Big Data platforms

### Mobility Analytics



Autonomous Driving Platform  
for CC

### Connected Industry



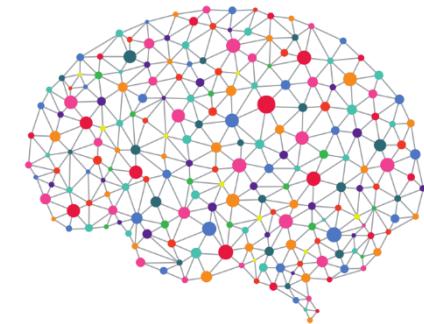
RB i4.0 Analytics Platform  
for AE, PS, CC, DC and CM

### Cloud Operations



Big Data Platform  
capabilities making use of  
the cloud

### Deep Learning



GPU Computing Platform  
for BCAI, CR and CC

- ▶ CoC Big Data Director: Dr. Michael Peters (CI/OST)
- ▶ Bosch Connect: <https://connect.bosch.com/communities/community/bigdata>

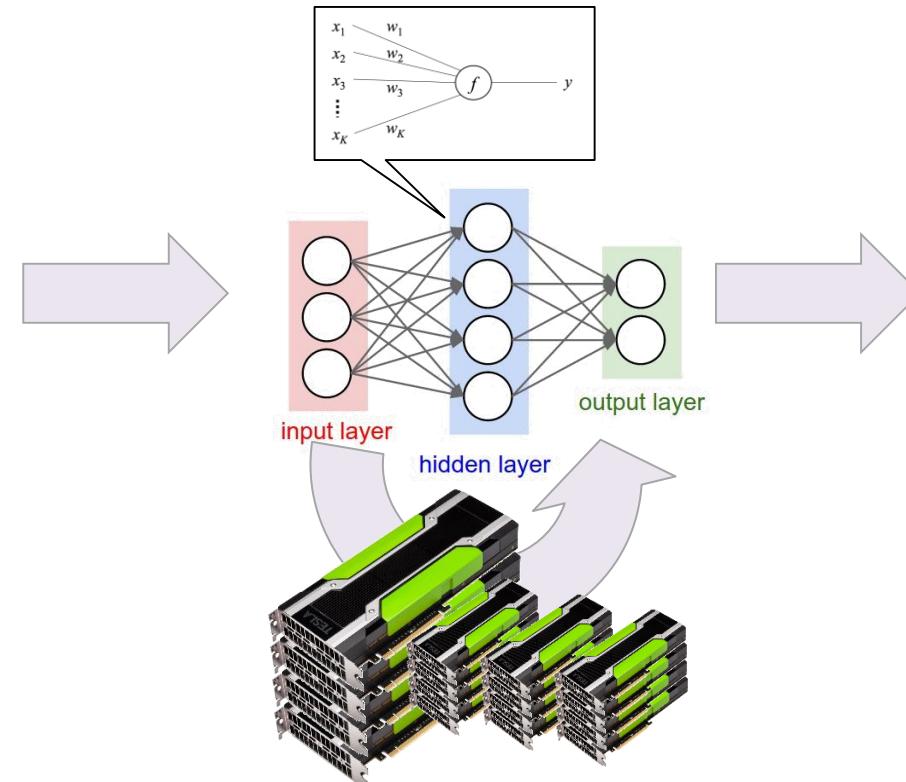
# Platform Providers

## GPU cluster: Infrastructure for Deep Learning applications

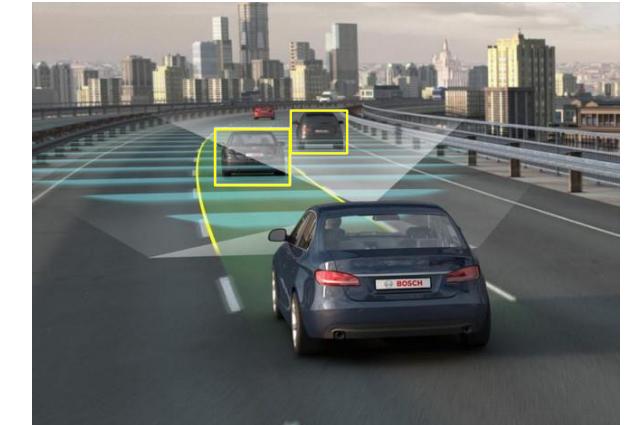


### Data sets

for training and validation



**GPU Cluster**  
to accelerate model training

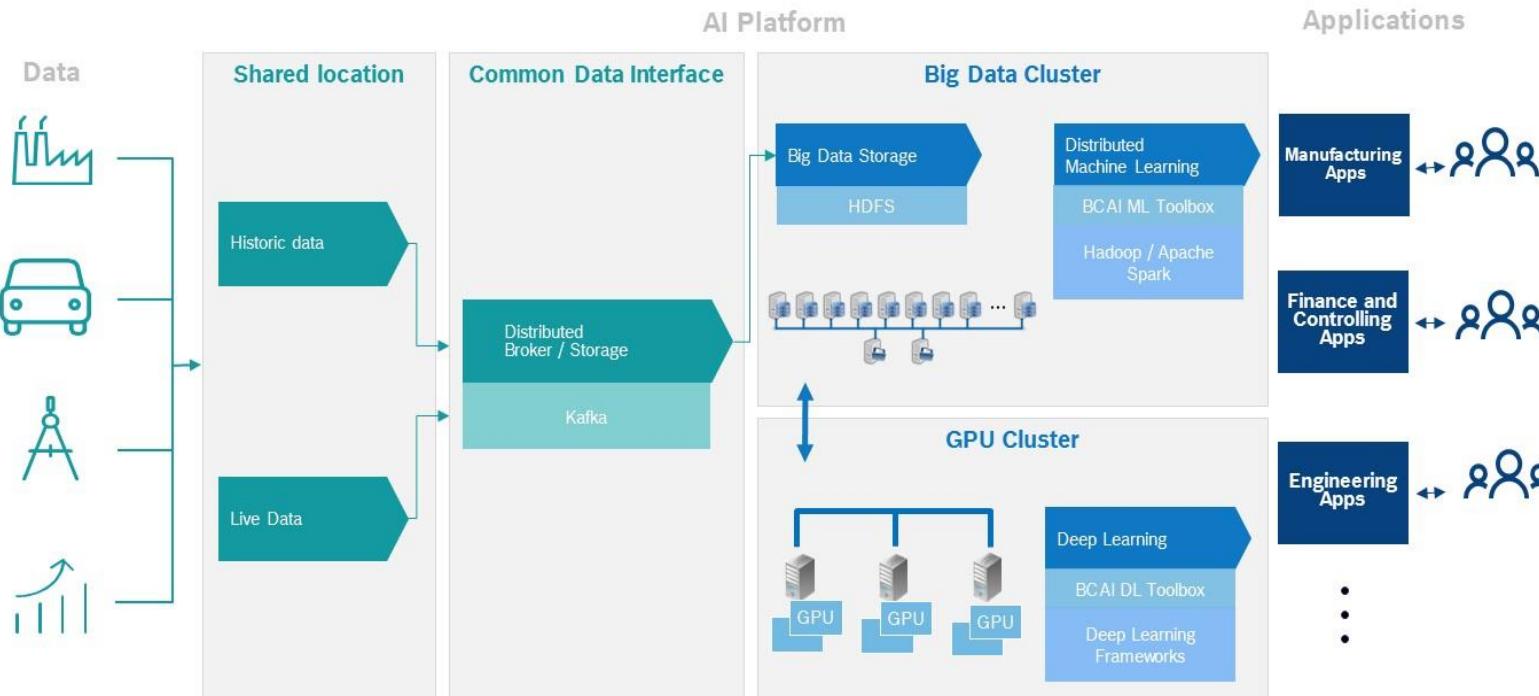


### Inference

Application of models  
to unknown (e.g. live) data

# Platform Providers

## AI platform: Bring key ingredients together to scale AI at Bosch



**BCAI platform provides framework to accelerate AI deployment in BUs**

- ✓ Adjacent, curated data sets speed up AI development and enable cross domain use cases
- ✓ Access for BU data scientists to state-of-the-art AI tools and Big data infrastructure minimizes lead time for own set-up and invest for BU.
- ✓ Domain-specific applications, pre-trained AI models unlock immediate value from data for BUs.

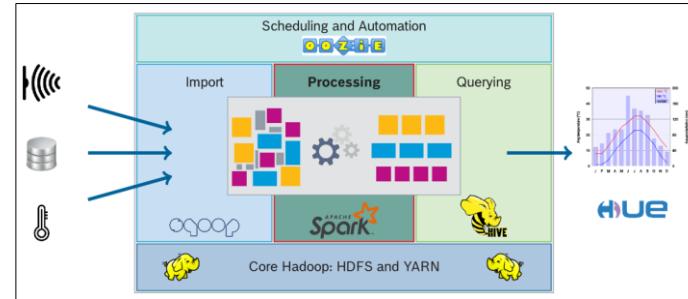
AI platform developed by integration of off-the-shelf components with in-house AI assets

# Roles, Training and Consulting

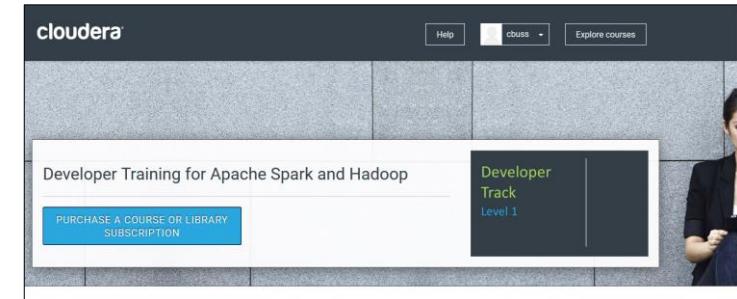
## Big Data Analytics training portfolio



[IT-BD-120] Intro to Data Science



[IT-BD-110] Hadoop Hands-On Tutorial



[IT-BD-210-A] Hadoop and Spark Developer

# IMPLEMENTATION- DATA-DRIVEN MINDSET

# Data-Driven Mindset

## Example: Data-driven mindset at Amazon

- ▶ Everything that can be **measured**, is measured: web design, product features, HR, finance, operations processes ...
  - ▶ Example: impact of website load times on sales
- ▶ Prove the opportunities of a new idea with a **live test** and **result data**
- ▶ Everyone, regardless of seniority, has **access to data** and tools to test their ideas and intuitions

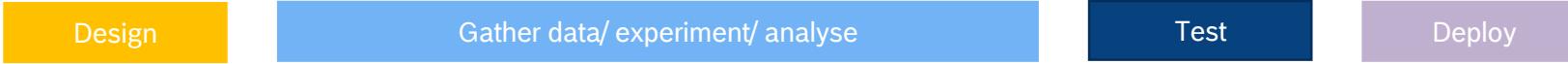
Direct access to data and computing capabilities are of fundamental importance.

Source: <https://www.entrepreneur.com/article/237326>

# Data-Driven Mindset

## Data worker process

Most



Some

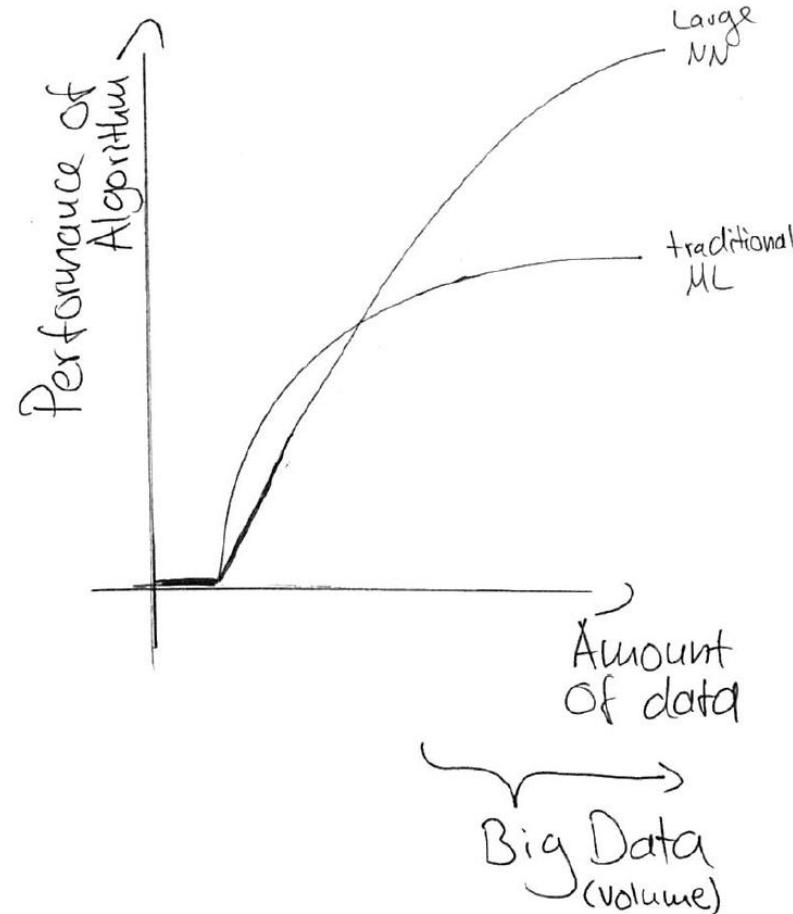


Desired



# Data-Driven Mindset

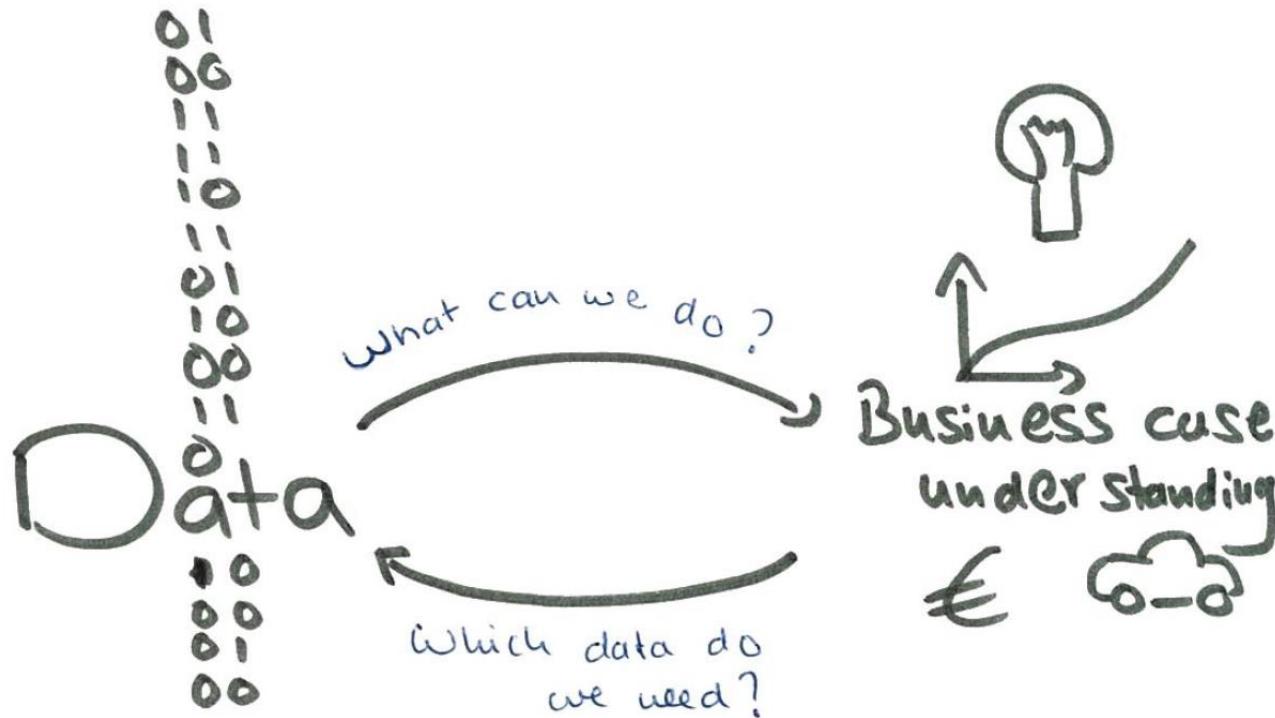
## The value of data



Not only algorithms **win the game** but also data.

# Data-Driven Mindset

## What is first: data or the business case?

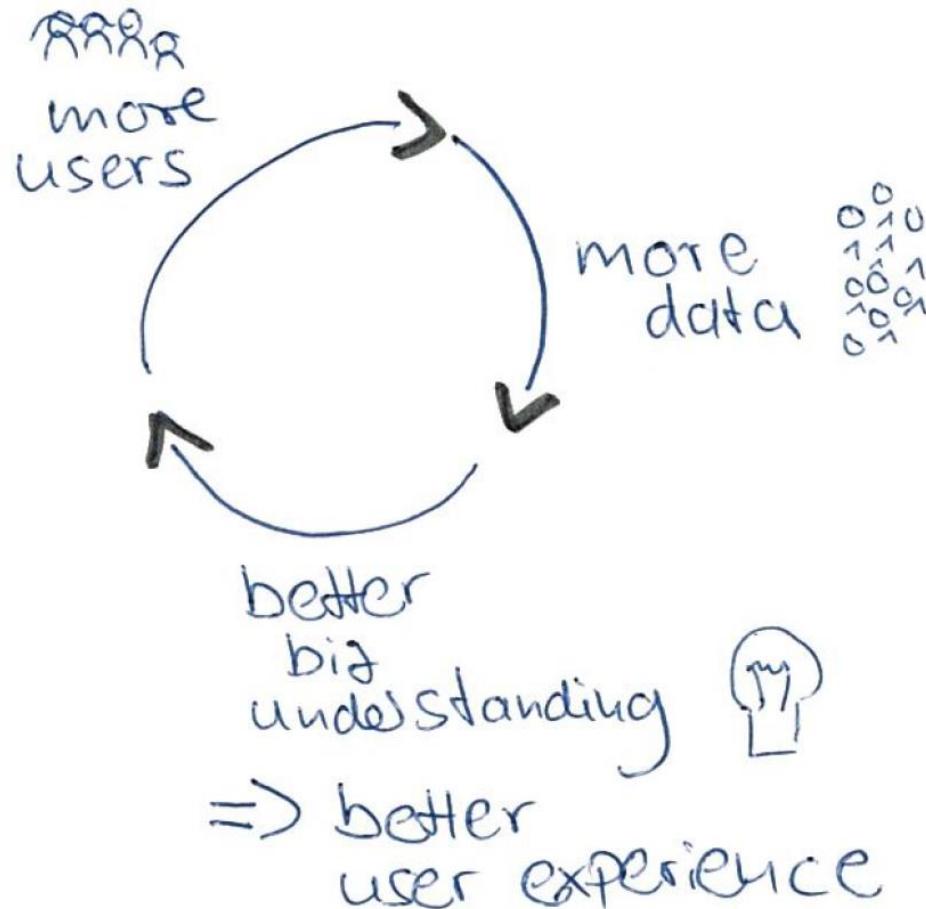


**Data first:** collecting data early is the start of **data strategy**.

Surely data can be collected before a fully defined business case. The earlier you start, the better.

# Data-Driven Mindset

## The positive data feedback loop / data advantage



**Data is the defensible barrier** in data-driven business.

It may lead to a continuous self-enhancing improvement cycle.

# Data-Driven Mindset

## Sensors: the data approach to vision ...

- Software defined camera with 16 lenses
- 10 pictures per lens at once from **small inexpensive photo sensors**
- Result are higher-quality, higher-resolution, and 3D pictures for a **fraction of the cost** of sophisticated sensors and lenses
- **51 Megapixel image** including depth map
- Possibly can be used instead of LiDAR and for smartphones
- Valuated with 147M\$ in 2017

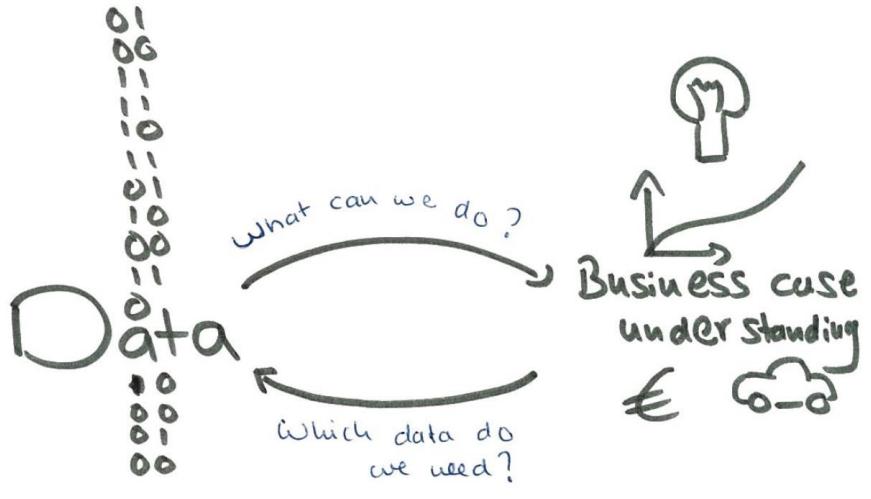


**Light L16**

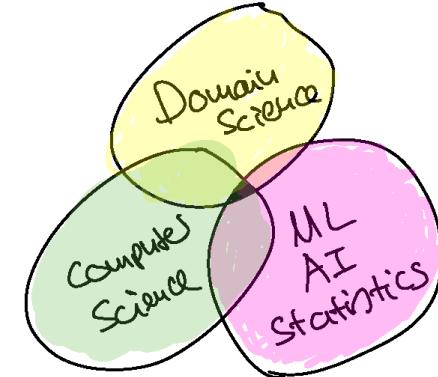
# CLOSING

# Retrospective Closing remarks

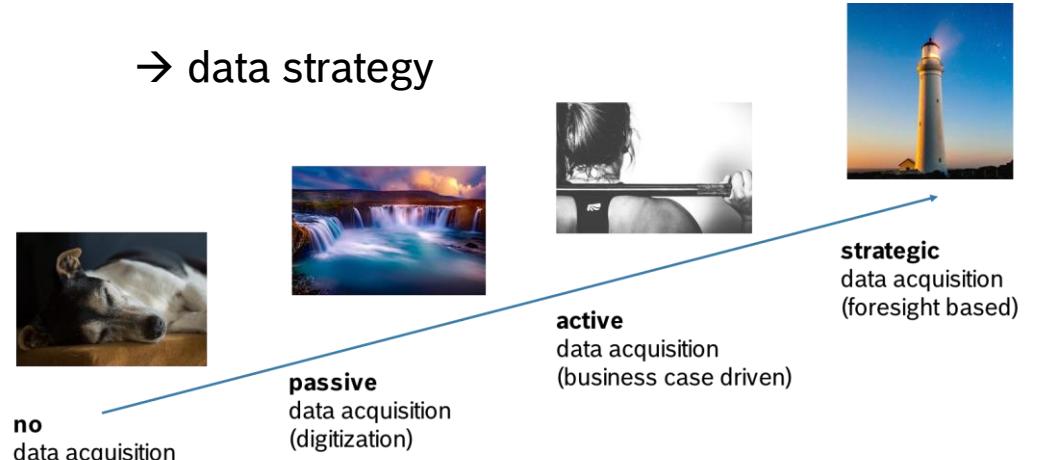
Data as an asset becomes more and more important!



→ competences in data science,  
data engineering, domain



→ data strategy



# Retrospective Closing remarks

AI is neither a panacea nor work of the devil – it is a [useful toolbox!](#)



There are almost endless [new possibilities](#) to apply the new methods and technologies!

# Retrospective Closing remarks

Bosch is in a very good position to be **successful in data-driven innovations**, too!



Start your journey and **contact us** any time with your questions, ideas, project proposals ...

# INTERACTIVE SESSION

# Data-driven problem finding and solving

## Objectives and scope

Introduction (5 min)

↓ 3 groups

Idea brainstorming (10 min)

↓ Discuss on ideas

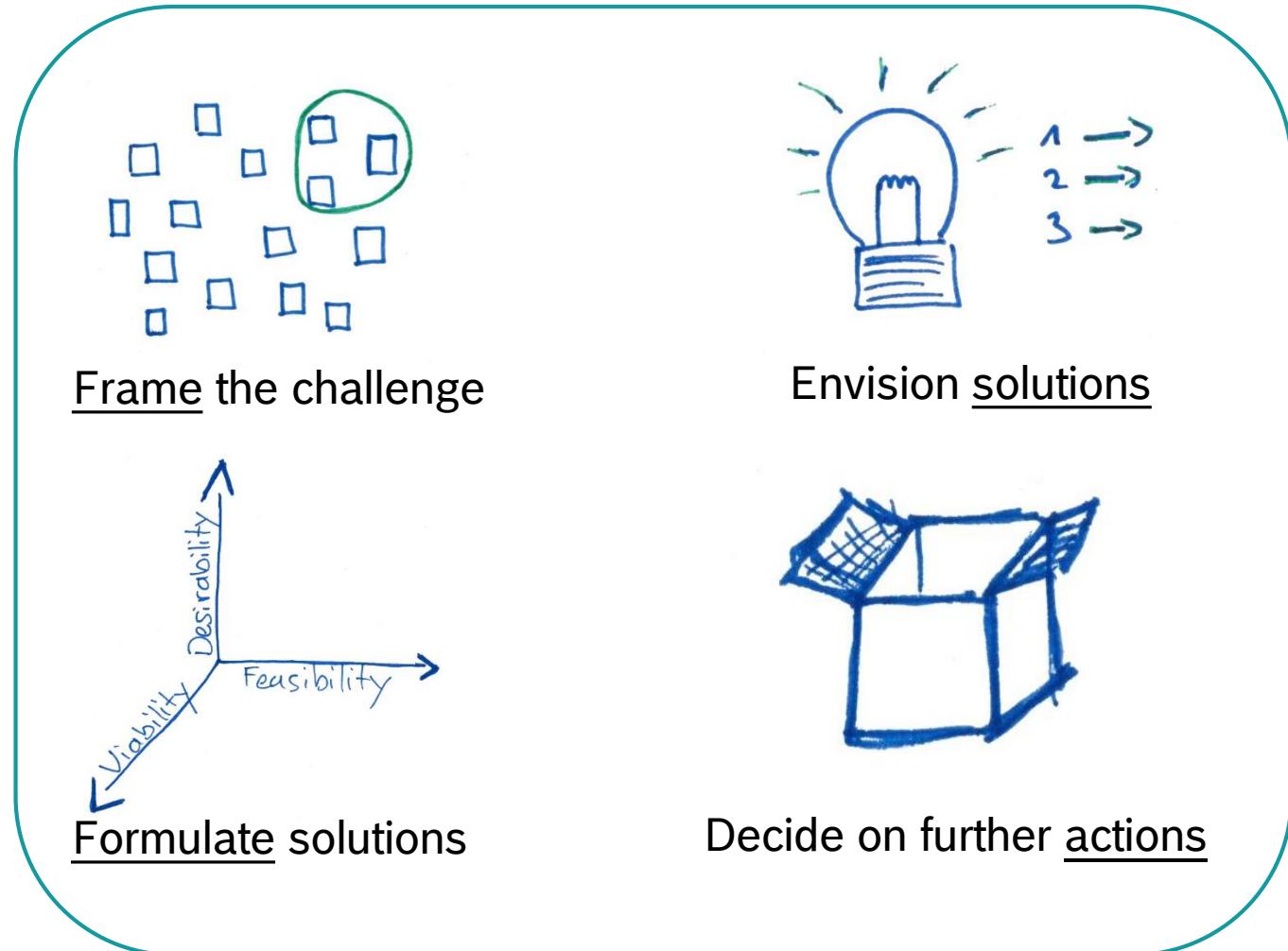
Decide on one idea (5 min)

↓ Working on one idea

Detailed Solution (20 min)

↓ Define further steps

Final Presentation and  
Discussion (20 min)



# Data-driven problem finding and solving (Online Version)

## Objectives and scope

### Introduction (5 min)

↓ Everyone alone

### Idea brainstorming (10 min)

↓ Gather in 2-3 groups

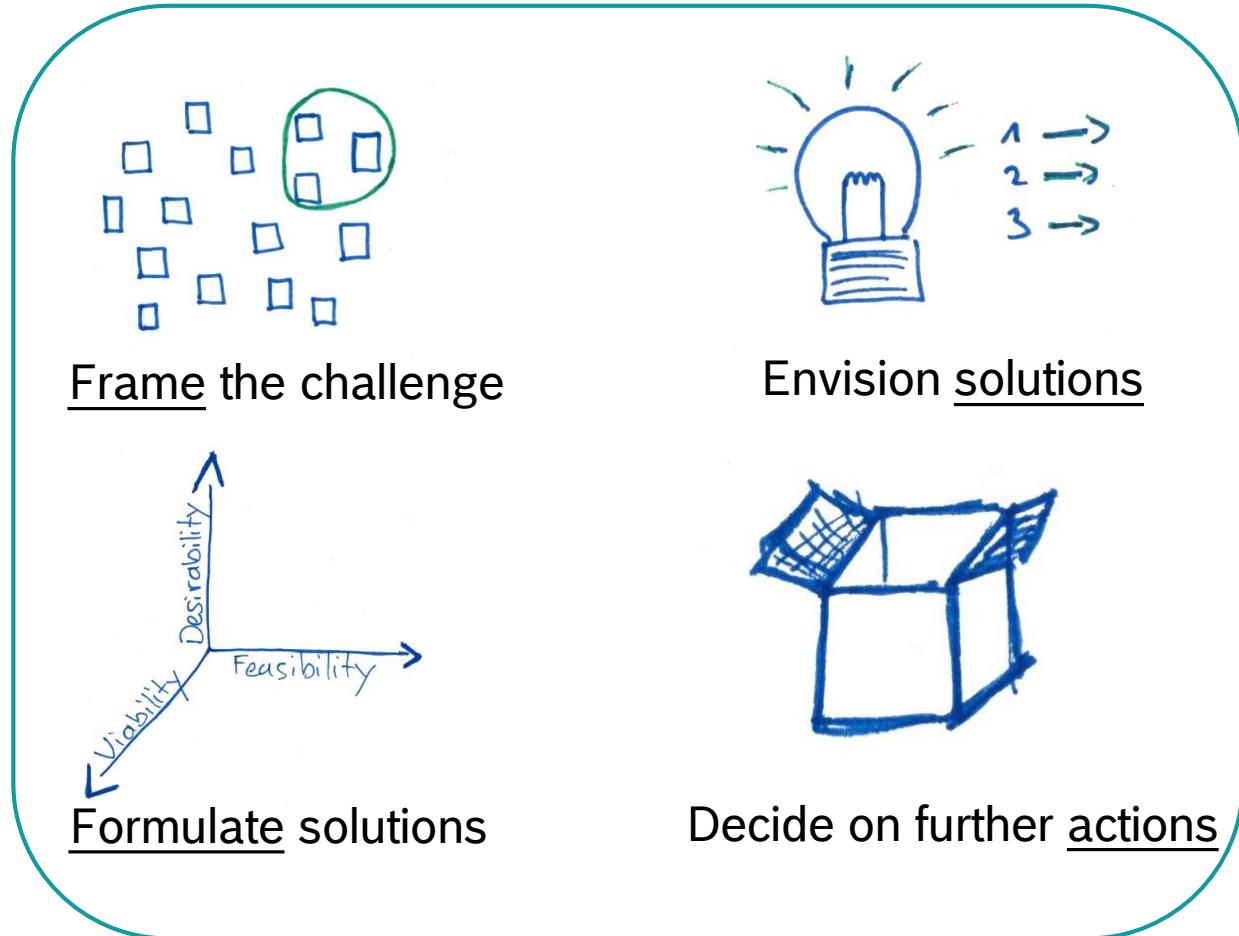
### Discuss and decide on one idea (10 min)

↓ Working on one idea

### Detailed Solution (20 min)

↓ Define further steps

### Final Presentation and Discussion (15 min)



# Data-driven problem finding and solving

## Potential domains and dimensions

- Frame the challenge
- Envision solutions
- Formulate solutions
- Decide on further actions

### Engineering

Example: Designing for data (capacity, data transfer, frequency, ...)?

### Manufacturing

Example: Using sensors for early scrap reduction?

### Field/Aftersales

Example: Reliability and revenue using predictive maintenance?

### 4 Dimensions: Product – Process – People – Profit

Potential interfaces and implications for other groups?

# Retrospective Disclaimer for pdf handout

License statement of document: not allowed to publish external to Bosch.

Usage of training material in products only after

- ❖ Written agreement,
- ❖ Disclaimer of liability,
- ❖ Reference on use of third party sources (Pictures, Logos)