02450: Introduction to Machine Learning and Data Mining

Introduction

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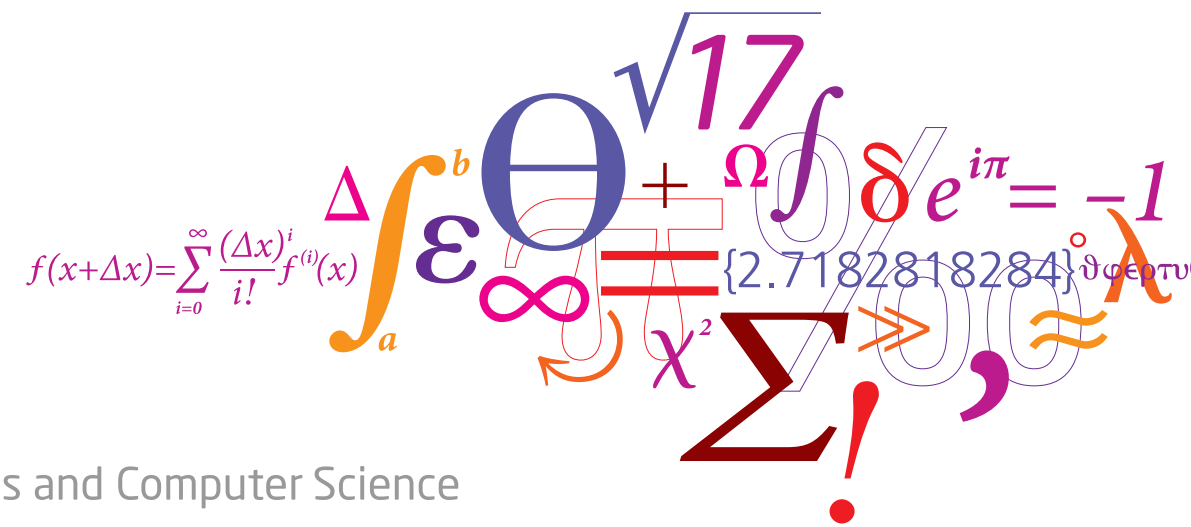


DTU Compute
Department of Applied Mathematics and Computer Science

Lecture Schedule

1. **Introduction**
   7 October: C1

   Data: Feature extraction, and visualization
2. Data, feature extraction and PCA
   7 October: C2, C3
3. Measures of similarity, summary statistics and probabilities
   7 October: C4, C5
4. Probability densities and data Visualization
   7 October: C6, C7

   Supervised learning: Classification and regression
5. Decision trees and linear regression
   8 October: C8, C9
6. Overfitting, cross-validation and Nearest Neighbor
   8 October: C10, C12
7. Performance evaluation, Bayes, and Naive Bayes
   9 October: C11, C13
8. Artificial Neural Networks and Bias/Variance
   9 October: C14, C15
9. AUC and ensemble methods
   10 October: C16, C17

   Unsupervised learning: Clustering and density estimation
10. K-means and hierarchical clustering
    10 October: C18
11. Mixture models and density estimation
    11 October: C19, C20
12. Association mining
    11 October: C21

    Recap
13. Recap
    11 October: C1-C21

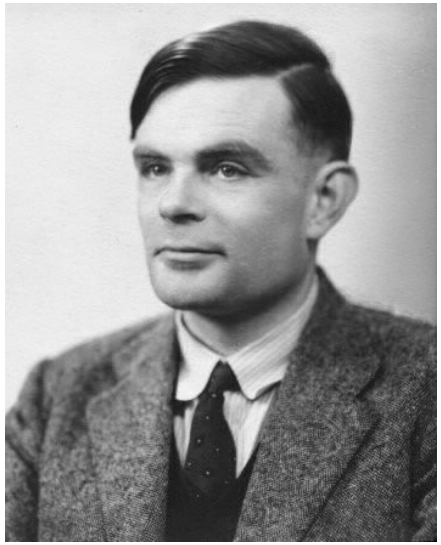
Piazza online help: `https://piazza.com/dtu.dk/fall2019/october2019`

Outline

- What is machine learning?
- Why do we learn different methods?
- Impact of machine learning
- This course
- Lecture 1, basic terminology

Alan Turing (1946)

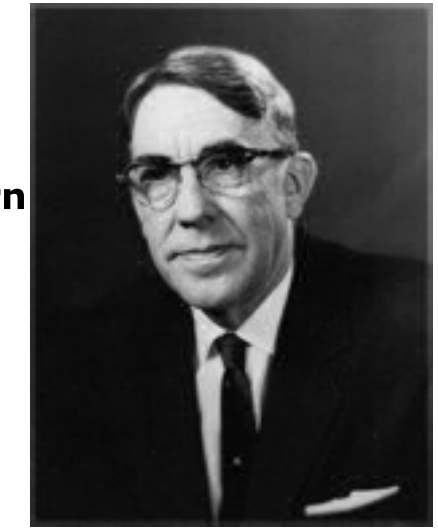
- Proved universal computation
- We are not in a position to answer if a machine can think because the terms machine and think are undefined. Rather we should ask if a machine can imitate a human (**the Turing test**)
- Proposed we should consider machines that were able to learn like children



Alan Turing
(1912-1954)

Arthur Samuel (1959)

- ***Machine learning:*** **"Field of study that gives computers the ability to learn without being explicitly programmed"**
  - Samuels wrote a checkers playing program
    - Had the program play 10000 games against itself
    - Work out which board positions were good and bad depending on wins/losses



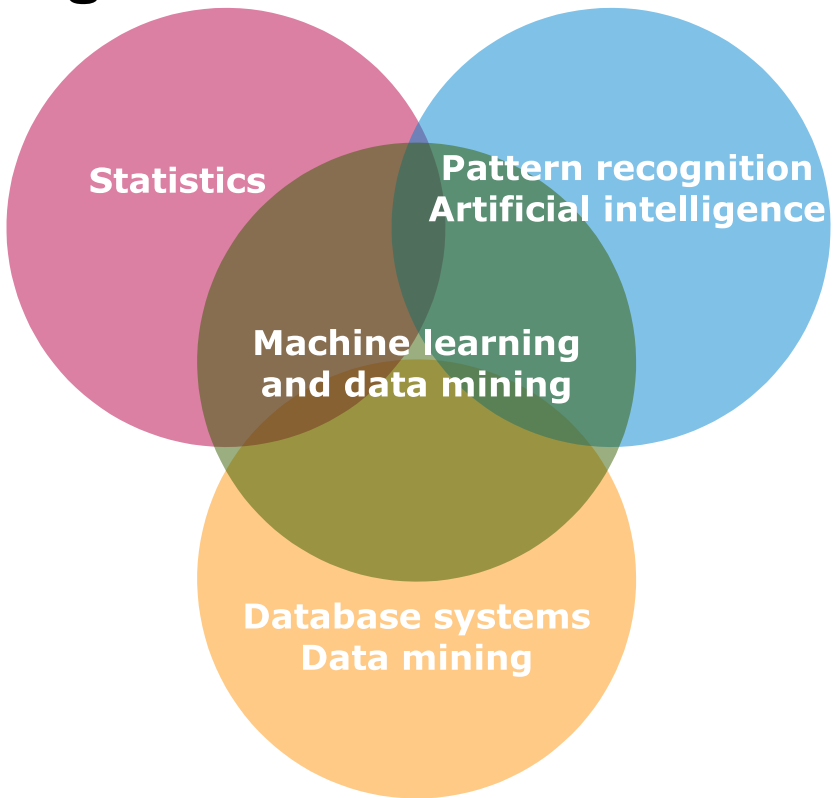
Arthur Samuel
(1901-1990)

Tom Michell (1999)

- ***Well posed learning problem:*** **"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."**
  - The checkers example,
    - E = 10000 games
    - T = playing checkers
    - P = if you win or not

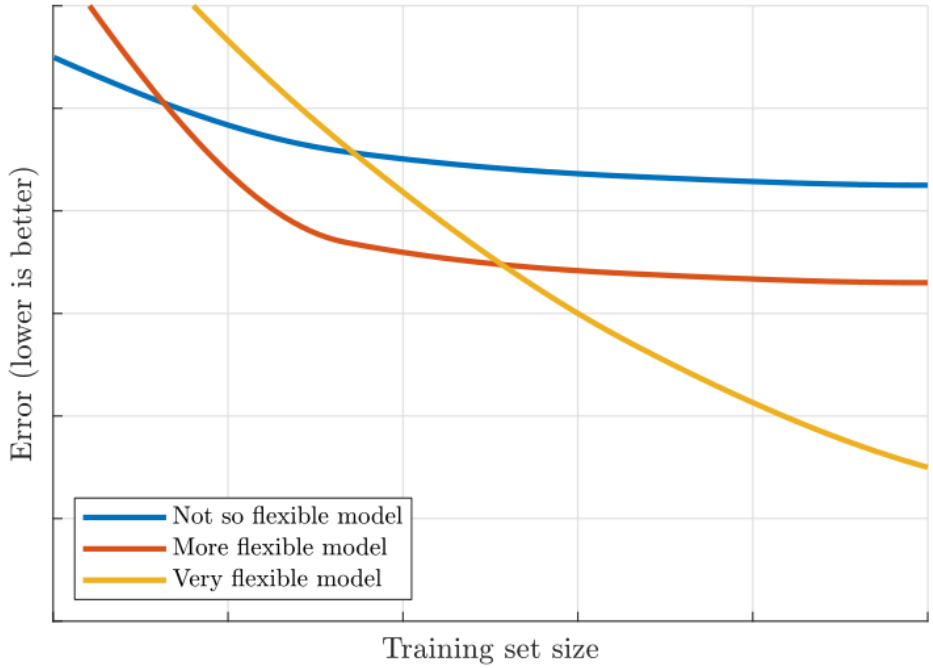
Tom Michell

Machine-learning as a research area

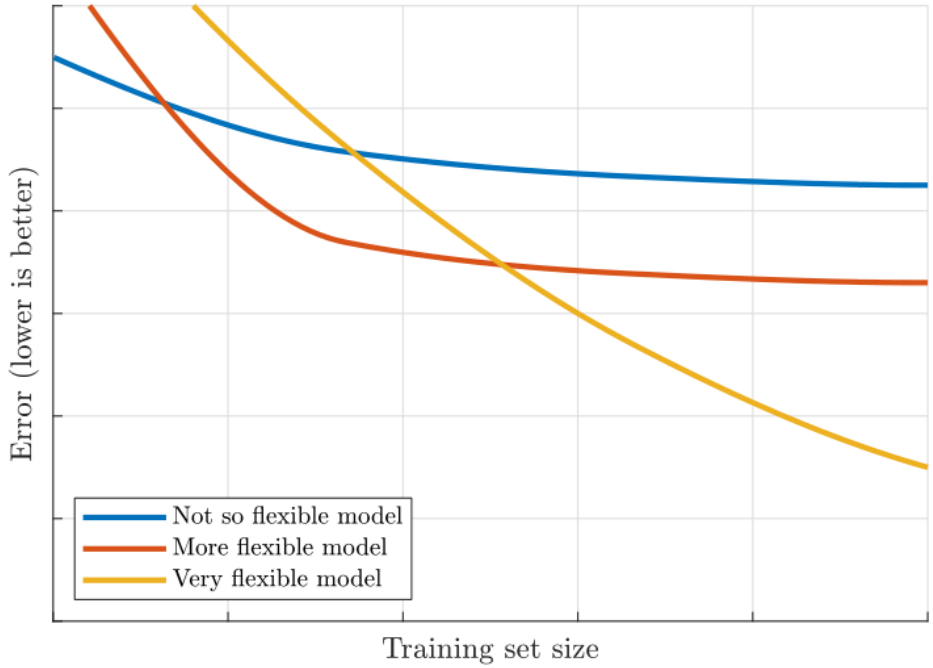


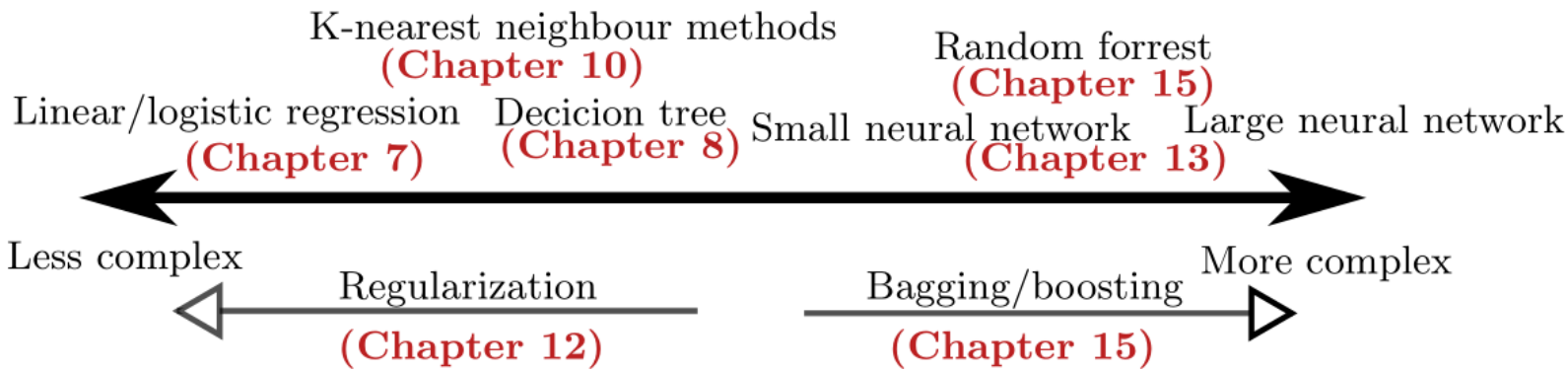
- Focus on a *learning algorithms* (rather than search, pathfinding, etc.)
- De-emphasis of explicit knowledge representations, etc.
- Gradual improvements (training time, amount of data)
- *General* algorithms (or algorithmic ideas)

Machine-learning as a research area



Machine-learning as a research area





Can machines really compete against humans?

- Humans have wisdom
- Humans have intuition
- Humans are moral

Image source: https://pixabay.com/da/meditation-\%C3\%A5ndelig-yoga-meditere-1384758/

Human abilities examined

source: https://www.boredpanda.com/dangerous-distracted-driving/?utm_source=google&utm_medium=organic&utm_campaign=organic

Man vs. Machine

2019, Lung cancer Outperform six doctors with a 5% reduction in false negatives (Deepmind / Nature Medicine)

2019, Starcraft 1v1: OpenAI deep reinforcement learning exhibit high-level performance in SC2

2018, BERT: Superhuman performance on the SQuADv1.1 wikipedia question-answer task

2018, alphago: superhuman chess/go learned from scratch

2017, Dota2 1v1: OpenAI deep reinforcement learning bot beats top professionals in 1v1 DOTA

2017, Texas hold'em no limit: Libratus (Carnegie Mellon) beats top professional

2017, Go: Superhuman Go by reinforcement learning + imitation of expert games

2016, libreading : Superhuman libreading from Oxford and Google Deepmind

2016, conversational speech: Microsoft research demonstrate superhuman speech recognition

2016, Geoguessing Google PlaNet win 28 of 50 rounds; median localization error of 1132km vs. 2321km

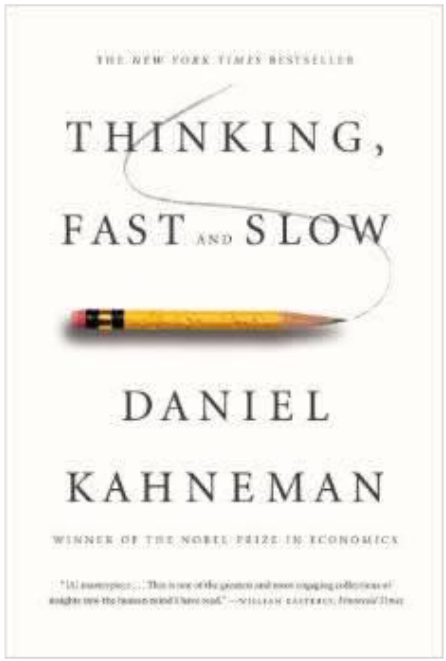
2015, closed-world image recognition Microsoft report error of 4.94% on ImageNet vs. 5.1% for top-human labeler

2015, Atari Google Deepmind obtain better-than-expert human performance on many Atari video games

List inspired by:
`https://finnaarupnielsen.wordpress.com/2015/03/15/status-on-human-vs-machines/`

Human abilities examined

The number of studies reporting comparisons of clinical and statistical predictions has increased to roughly two hundred (...) About 60% of the studies have shown significantly better accuracy for the algorithms. The other comparisons scored a draw in accuracy, but a tie is tantamount to a win for the statistical rules, which are normally much less expensive to use than expert judgement. No exception has been convincingly documented.



The range of predicted outcomes has expanded to cover medical variables such as longevity of cancer patients, the length of hospital stayes, the diagnosis of cardiac disease, and the susceptibility of babies to sudden infant death syndrome; economic measures such as the prospect of success for new businesses, the evaluation of credit risks by banks, and the future career satisfaction of workers; questions of interest to government agencies, including assessment of the suitability of foster parents, the odds of recidivism among juvenile offenders, and the likelihood of other forms of violent behaviour; and the miscallaneous outcomes such as the evaluation of scientific presentations, the winners of football games, and the future prices of Bordeaux wine. Each of these domains entails a significant degree of uncertainty and unpredictability. We describe them as “low-validity environments.”. **In every case, the accuracy of experts was matched or exceeded by a simple algorithm.** (Kahneman 2011)

Why now?

Scientific Advances in algorithmic ideas

Emperical Increased availability of large/good datasets

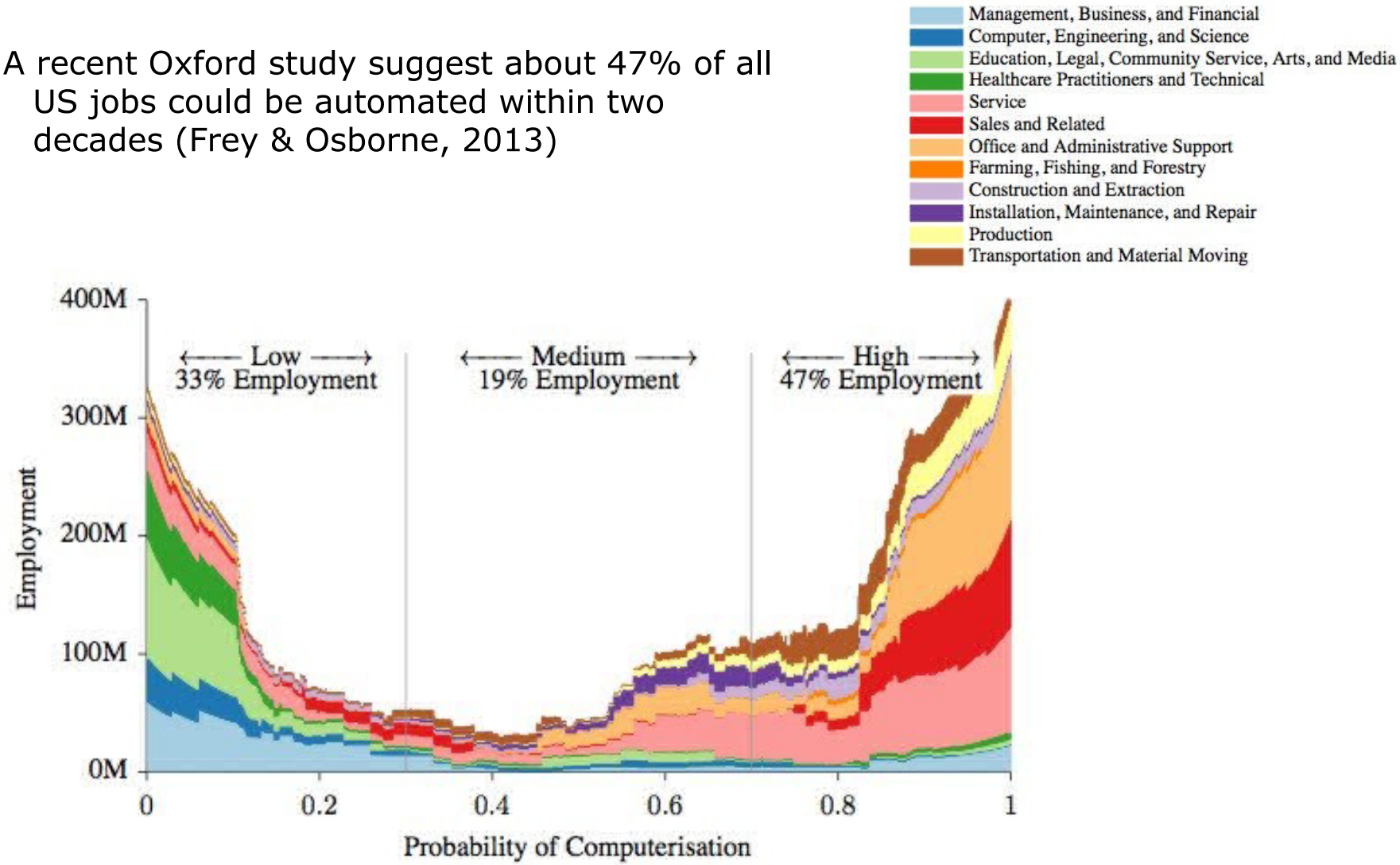
Technological Faster computers

Social Libraries which automate routine tasks; increased sharing of code, etc.

Economical Greatly increased resource allocation

Machine learning as a disruptive technology

- A recent Oxford study suggest about 47% of all US jobs could be automated within two decades (Frey & Osborne, 2013)



Economical impact I

- Basic economics: When things become cheap, we will use it in more places
- Example: Microprocessors perform computations
- Microprocessors did not change the world because people did a lot of computations in 1950, but because nearly everything can at least partially be turned into a computation problem (bookkeeping, telephony, photography, entertainment, navigation, design, education, economics, science, etc.)
- We should not ask what situations are as of now a machine-learning problem, but which can be turned into one

Economical impact II

Many jobs match this description

1. Recognize what situation you are in
2. Collect relevant data
3. Given data about situation make a prediction such as: (i) outcome of performing a given action in the situation or (ii) which action is appropriate
4. Perform action
5. repeat

Machine learning can, in principle, learn 3

https://en.wikipedia.org/wiki/William_Lee_(inventor)
William Lee (1563–1614) was an English clergyman and inventor who devised the first stocking frame knitting machine in 1589

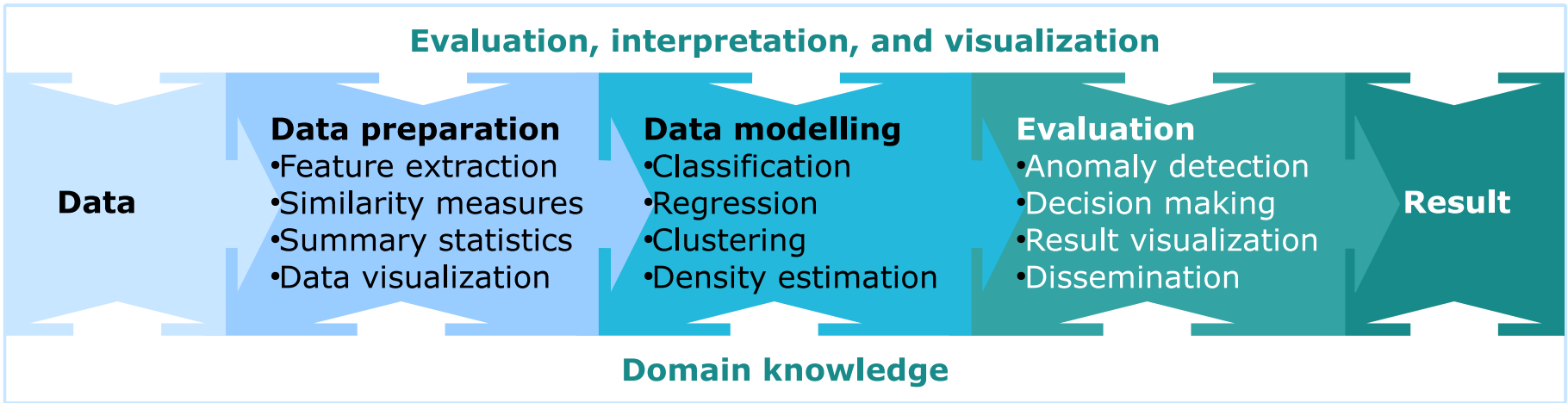
Elizabeth I: ”Thou aimest high, Master Lee. Consider thou what the invention could do to my poor subjects. It would assuredly bring to them ruin by depriving them of employment, thus making them beggars."

”our discovery of means of economising the use of labour can outrun the pace at which we can find new uses for labour, as Keynes (1933) pointed out. ***The reason why human labour has prevailed relates to its ability to adopt and acquire new skills by means of education (Goldin and Katz, 2009). Yet as computerisation enters more cognitive domains this will become increasingly challenging*** *(Brynjolfsson and McAfee, 2011).”*
(Taken from Frey & Osborne, 2013)

Economical impact III

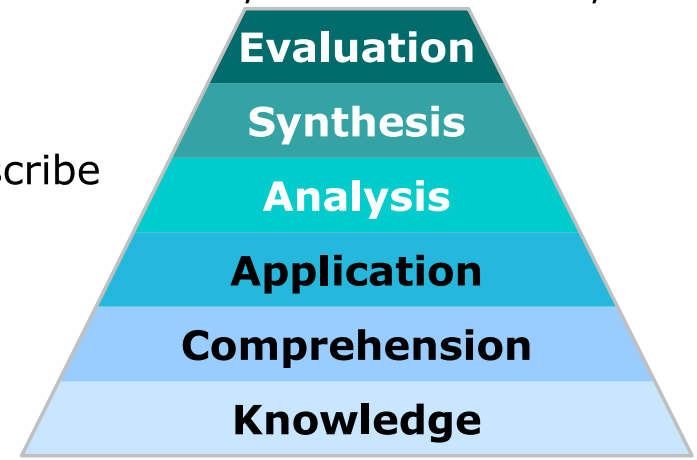
- We don't know what will happen
- Plausibly, many tasks will become so cheap humans will no longer perform them. Macroeconomics suggests:
  - Essential, non-automated tasks will both become more valuable, inhibit progress
  - Humans will do fewer jobs, play a relatively smaller role in the economy (the share of capital will increase relative to labor)
  - The most destructive forms of automation is when tasks are only slightly better done by a machines

Machine learning and data mining pipeline of this course



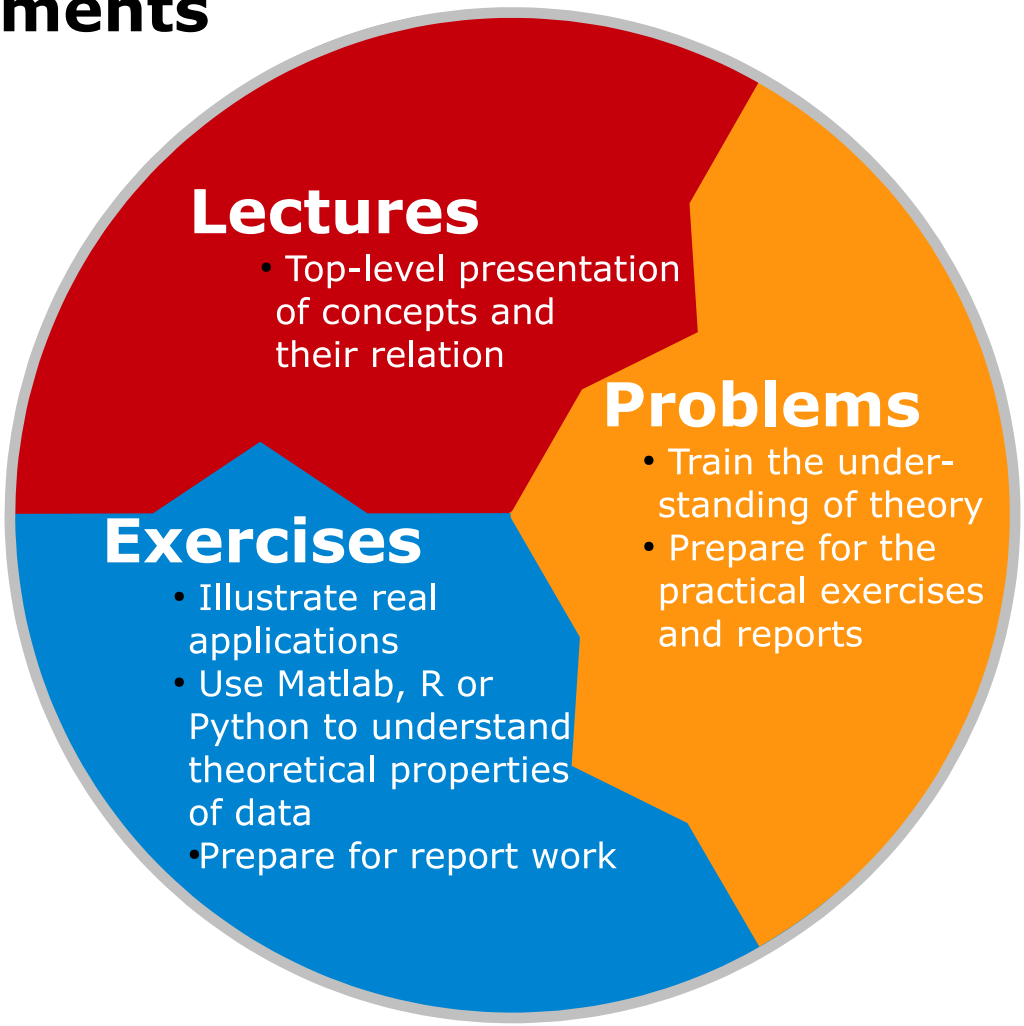
Learning objectives

1. Describe the major steps involved in data modeling from preparing the data, modeling the data to evaluating and disseminating the results.
(Knowledge)
2. Discuss key machine learning concepts such as feature extraction, cross-validation, generalization and over-fitting, prediction and curse of dimensionality.
(Comprehension)
3. Sketch how the data modeling methods work and describe their assumptions and limitations.
(Knowledge and Comprehension)
4. Match practical problems to standard data modeling problems such as regression, classification, density estimation, clustering and association mining.
(Comprehension and Application)

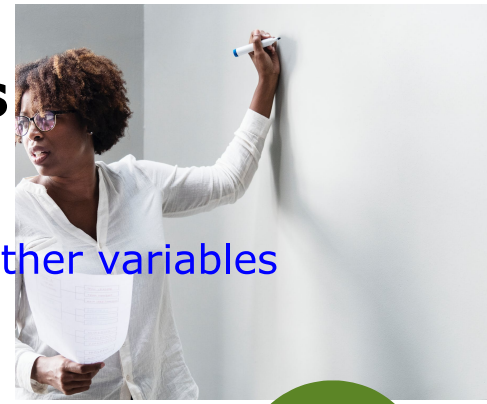


5. Apply the data modeling framework to a broad range of application domains in medical engineering, bio-informatics, chemistry, electrical engineering and computer science.
(Application)
6. Compute the results of the data modeling framework by use of Matlab, R or Python.
(Application)
7. Use visualization techniques and statistics to evaluate model performance, identify patterns and data issues.
(Analysis)
8. Combine and modify data modeling tools in order to analyze a data set of their own and disseminate the results of the analysis.
(Application, Analysis, Synthesis and Evaluation)

Course elements



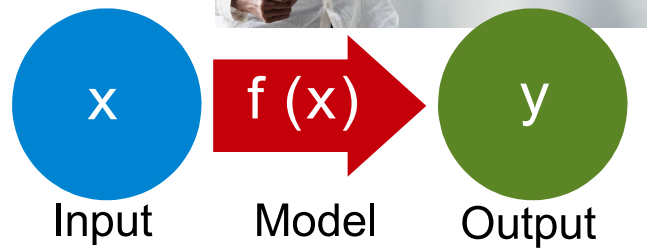
Data Mining and Machine Learning Tasks



Predictive tasks (Supervised learning)

– Use some variables to predict unknown or future values of other variables

- **Classification**
  - Discrete output
  (Determine which class a new data object belongs to)
- **Regression**
  - Continuous output
  (Determine the output value from the input variables)



Descriptive tasks (Unsupervised learning)

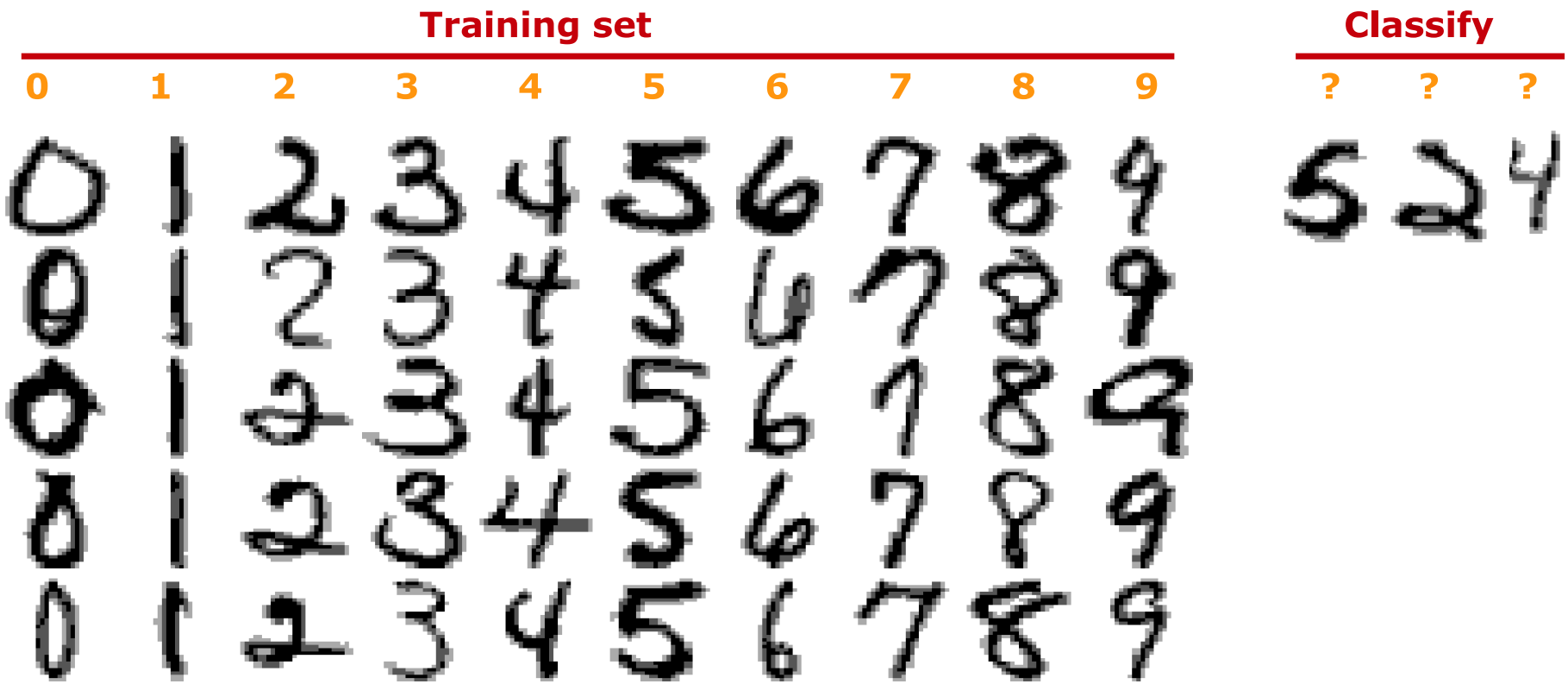
– Find human-interpretable patterns that describe the data

- **Clustering**
  – Discover group structure in data
- **Association rule discovery**
  – Discover how data objects relate to each other
- **Anomaly detection**
  – Find data objects that are abnormal

Classification: Definition

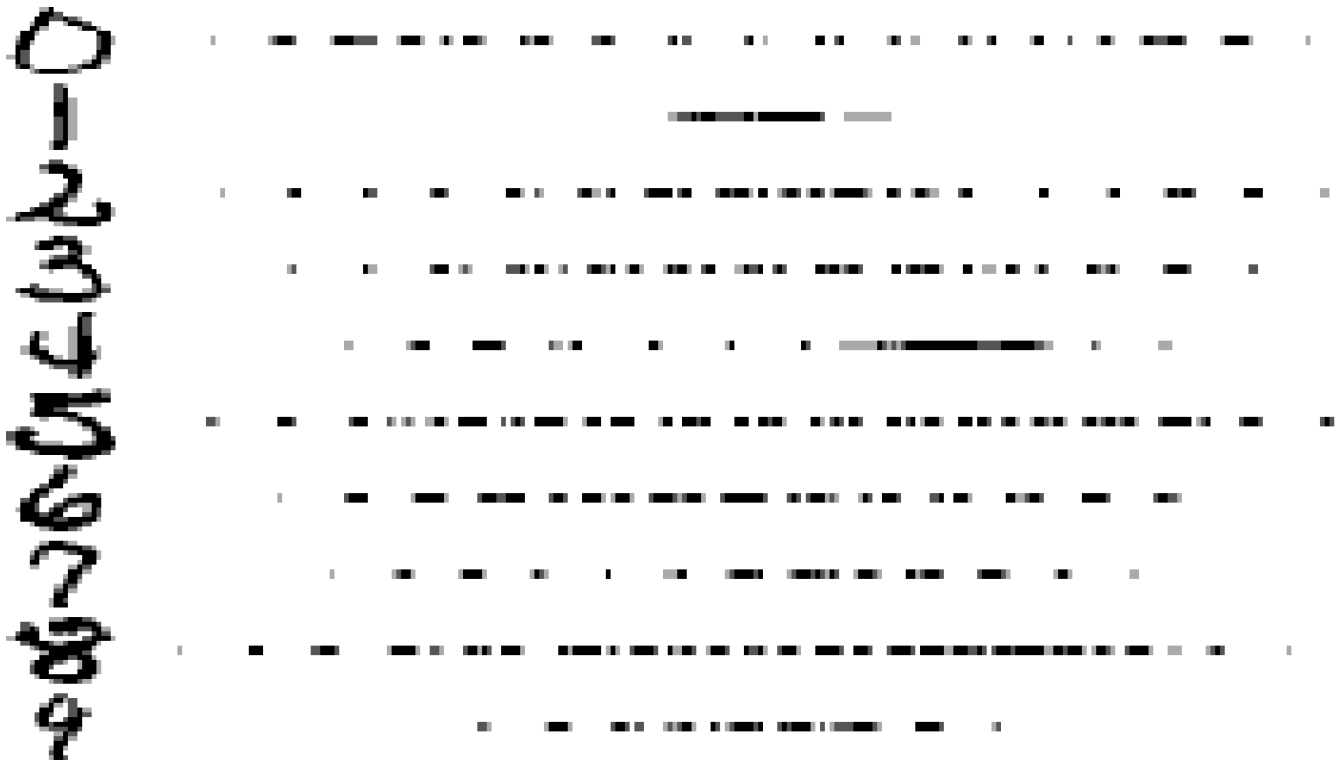
- Given a collection of data objects (**training set**)
  - Each object has associated a number of features
  - Each object belongs to a certain class
- Define a **model** for the class given the other features
- Goal: Assign a class label to a **previously unseen object**

Classification: Example



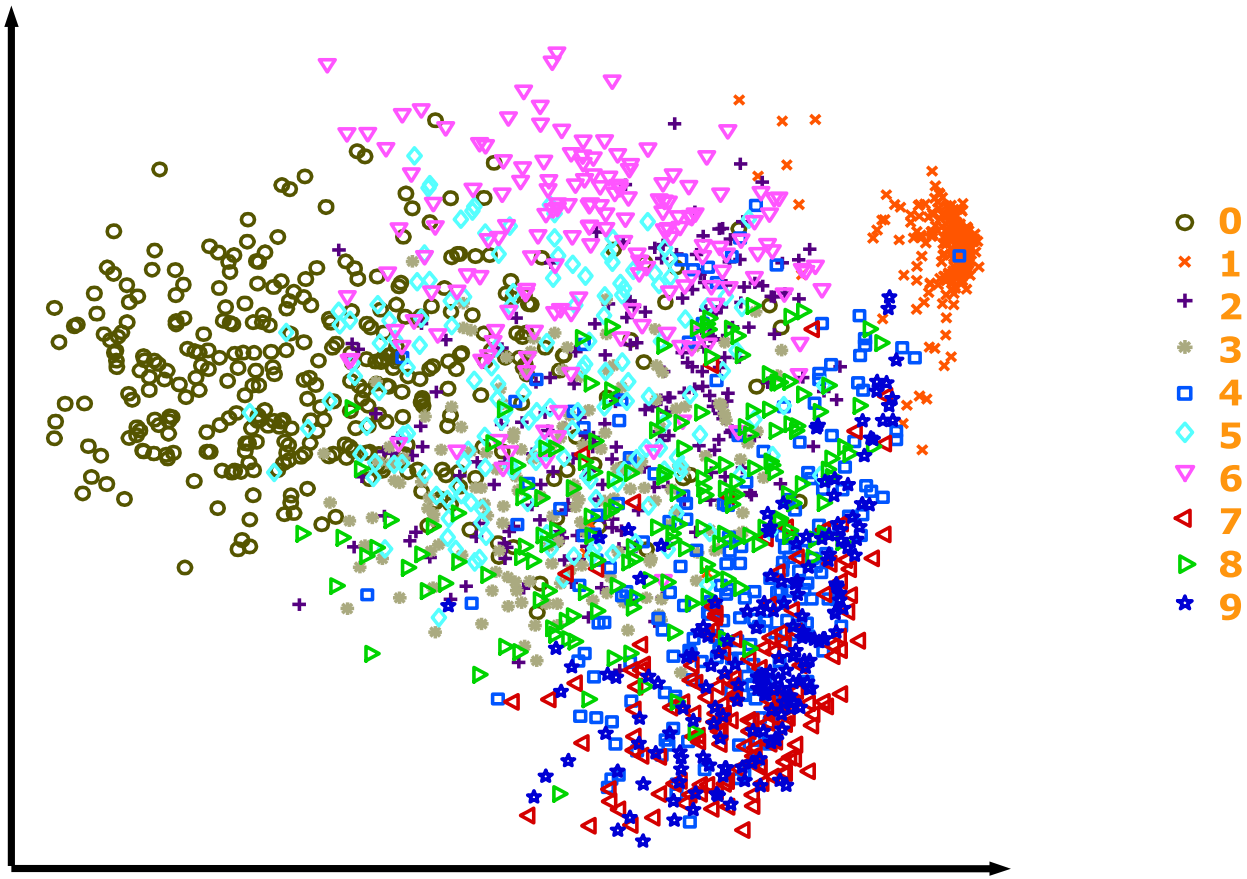
Classification: Example

Data representation



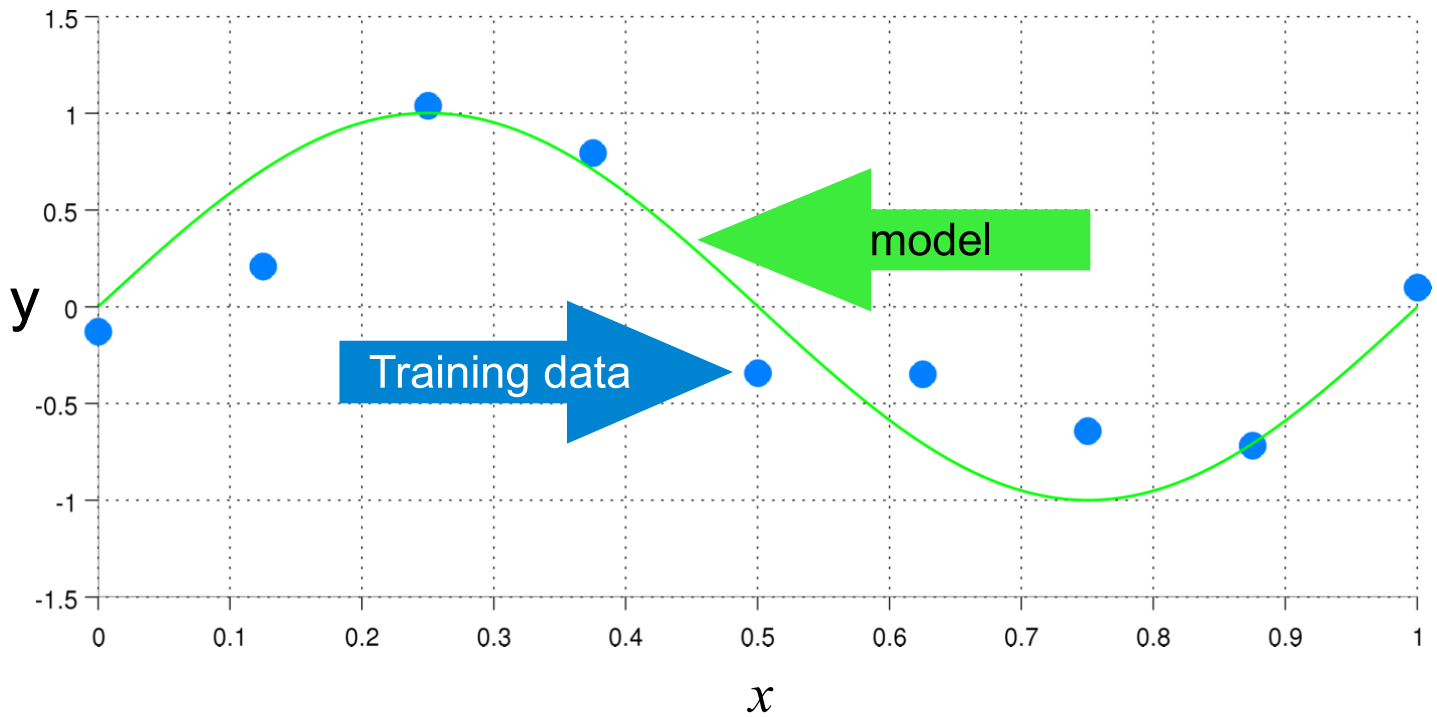
Classification: Example

Visualization



Regression: Definition

- Given a collection of data objects
  - Each object has associated a number of features
  - Each object has associated a **continuous valued variable**
- Define a **model** for the variable given the features
- Goal: Predict the value of the variable for a **previously unseen object**



Regression: Example

- Predict **sales amounts** of new product based on
  - advertising expenditure
- Predict **wind velocity** as a function of
  - temperature, humidity, and air pressure
- Predict the value of a **stock market index** based on
  - previous index time series and market indicators

Regression: Example

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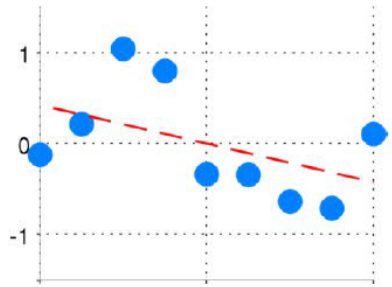
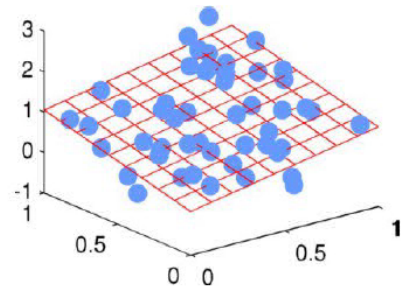
1-dimensional inputs

$$f(x) = w_0 + w_1 x$$



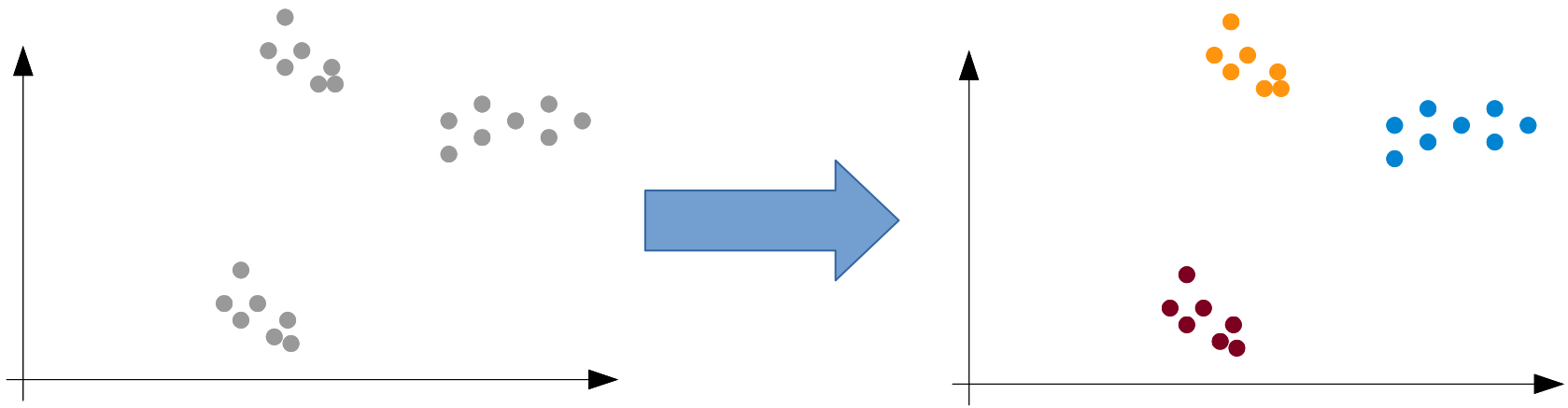
2-dimensional inputs

$$f(\boldsymbol{x}) = w_0 + w_1 x_1 + w_2 x_2$$



Clustering: Definition

- Given a collection of data objects
  - Each object has associated a number of features
  - A measure of **similarity** between objects is defined
- Goal: **Group the objects** into clusters such that
  - Objects within each cluster are similar
  - Objects in separate clusters are less similar



Clustering: Example

Document clustering

- **Goal**
  - Find groups of similar documents based on the words appearing in them
- **Approach**
  - Identify frequently occurring words in each document
  - Define a similarity measure based on the word frequencies
  - Perform clustering to find groups of documents
- **Motivation**
  - Use the clusters to relate a new document to existing documents
  - Better search algorithms: Return documents that are similar but do not have the exact search keywords

Association rule discovery: Definition

- Given a set of **records**
  - Each containing a number of **items from a set**
- Goal: Produce dependency rules
  - Predict the occurence of an item based on occurences of other items

Association rule discovery: Example

Market basket analysis

Training set

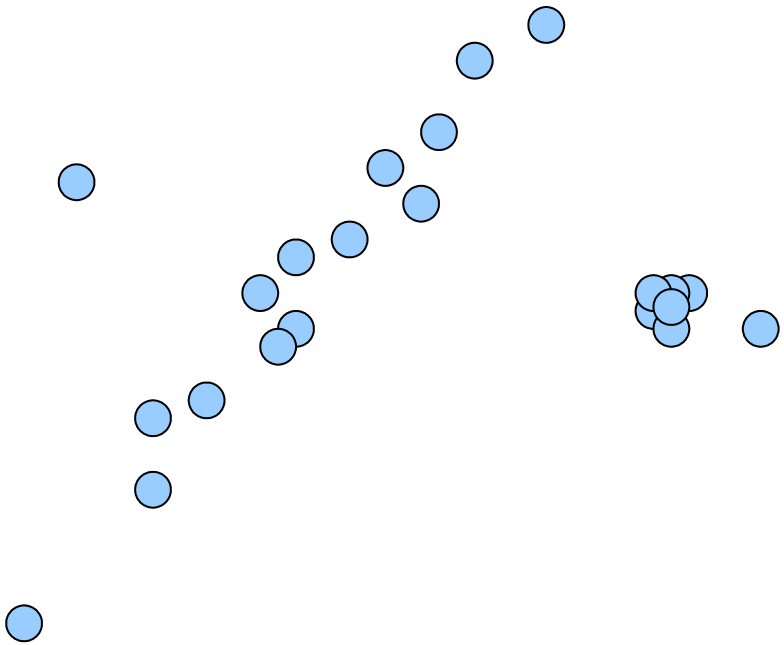
1.{Bread, Coke, Milk}
2.{Beer, Bread}
3.{Beer, Coke, Diaper, Milk}
4.{Beer, Bread, Diaper, Milk}
5.{Coke, Milk}

Rules discovered

{Milk} ▸ {Coke}
{Diaper, Milk} ▸ {Beer}

Anomaly detection: Definition

- Given a collection of data objects
  - Each object has associated a number of features
- Detect which objects **deviate from normal** behaviour



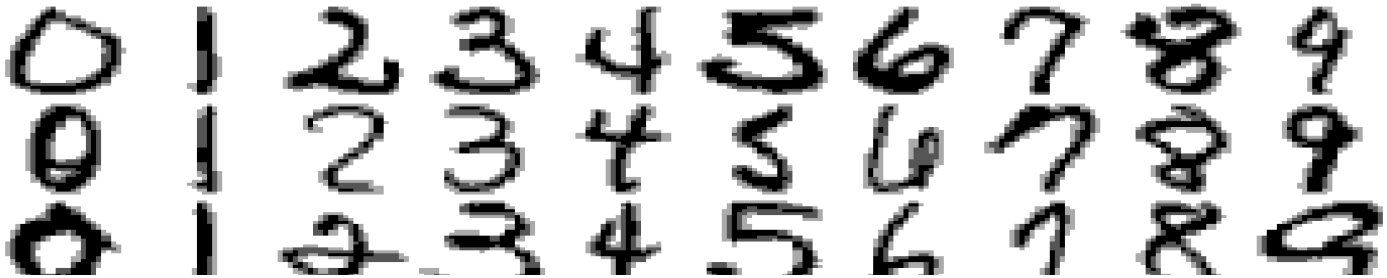
Anomaly detection: Example

- Credit card **fraud detection**
  - Recognize dubious credit card transactions based on the transaction history of the card holder
- Detection of **outliers** in data measurements
  - Remove erroneous measurements due to misreading from an instrument
- **Fault detection** in system health monitoring
  - Detect when a wind turbine performs poorly due to ice coating on blades

Models in machine learning

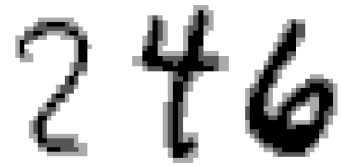
Training set

0	1	2	3	4	5	6	7	8	9



Test set

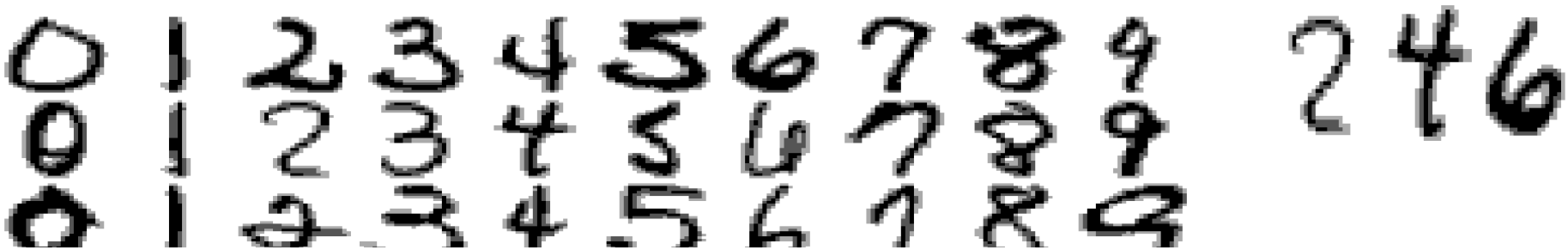
?	?	?



Models in machine learning

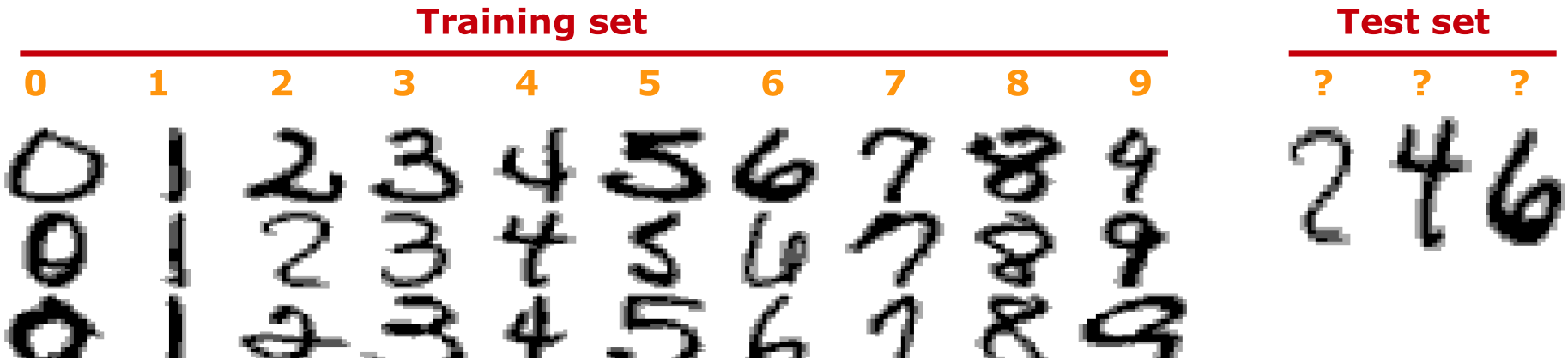
Training set

Test set



Classifying digits is a mapping $f : \mathbb{R}^M \rightarrow \{0, 1, \ldots, 9\}$

Models in machine learning



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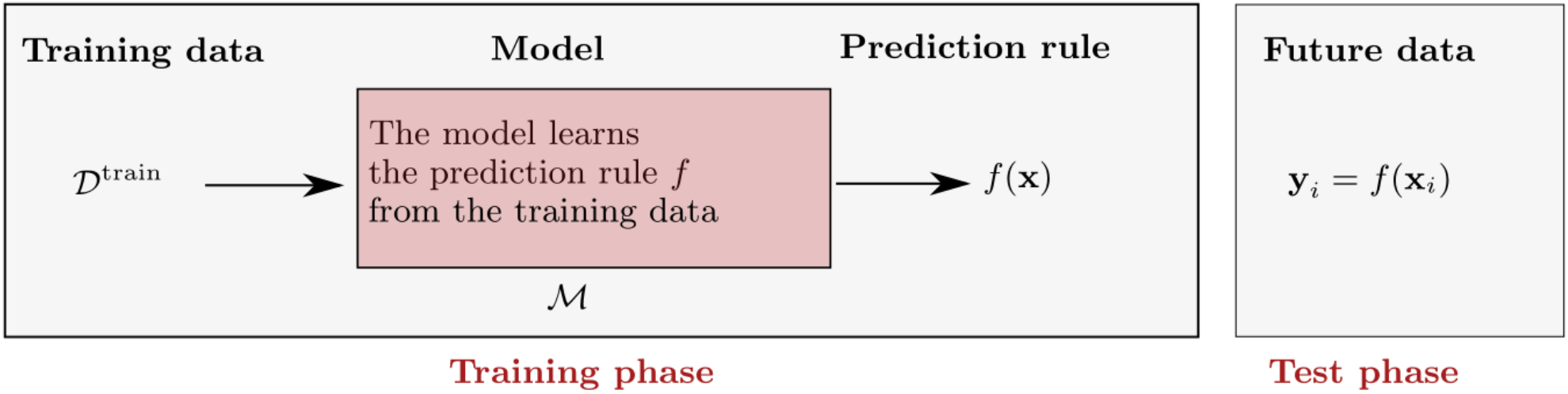
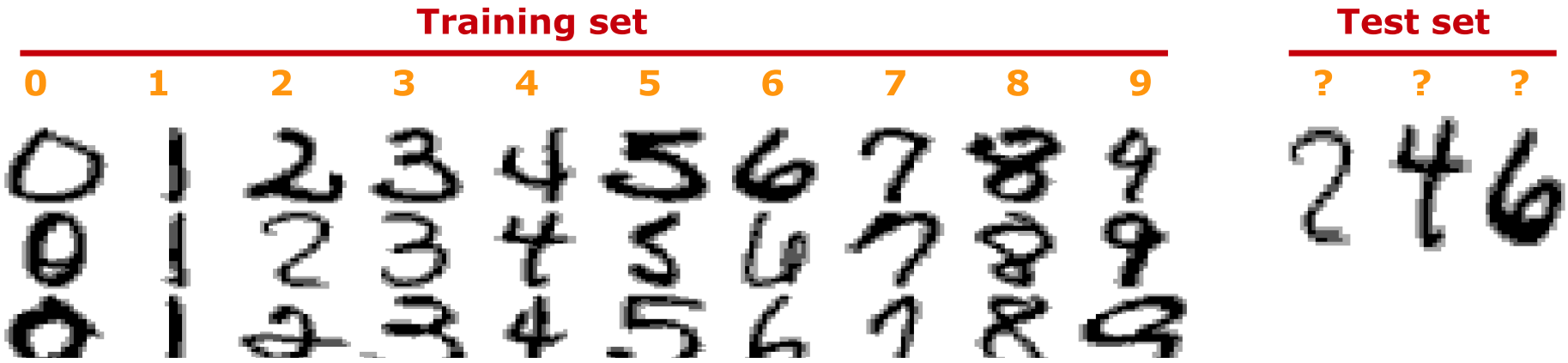


Models in machine learning



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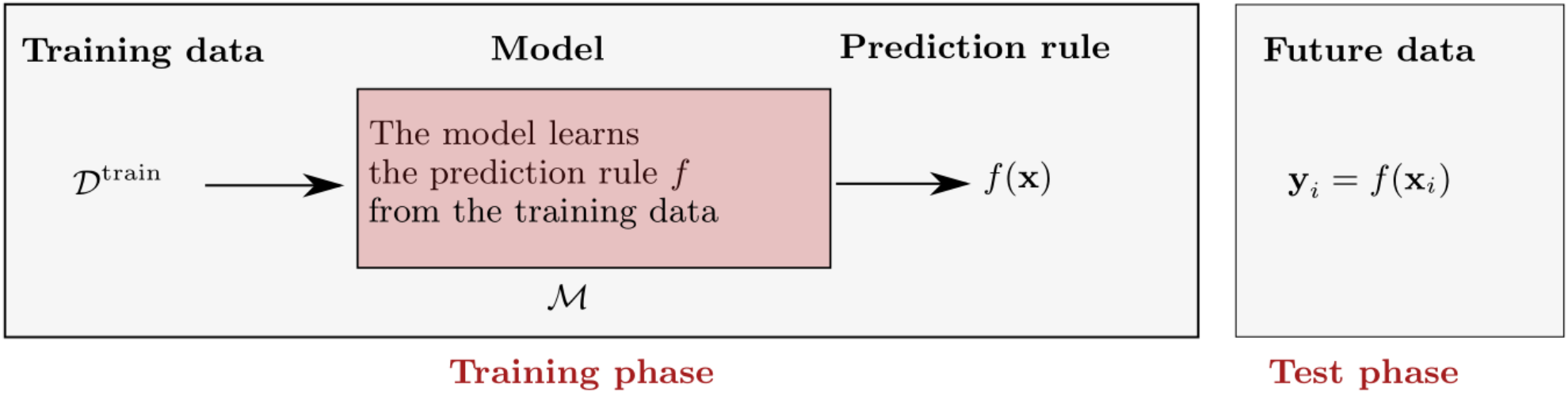

How often the learned function f makes errors in the future is the **generalization error**

Resources

https://www.mckinsey.com Impact assessment of automation by McKinsey (https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy)

https://towardsdatascience.com Another introduction to machine learning basics (https://towardsdatascience.com/introduction-to-machine-learning-db7c668822c4)

https://www.economicsofai.com conference on modelling economical impact of AI (https://www.economicsofai.com/nber-conference-toronto-2017/)

https://deepmind.com Obviously google-focused, but otherwise a great resource for what is hot right now (https://deepmind.com/)