Introduction to Data Mining

Mining Massive Datasets
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Topic 01

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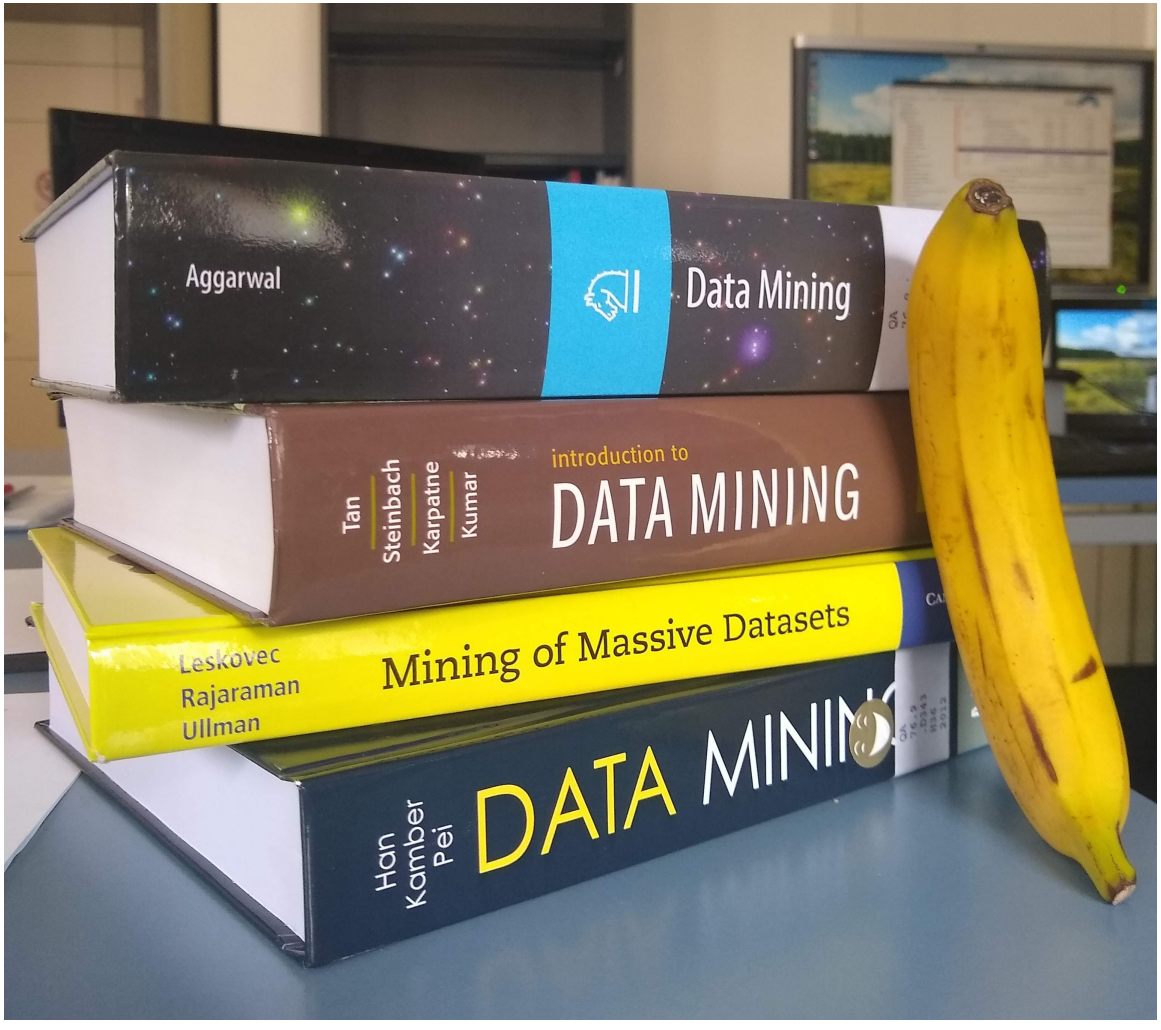


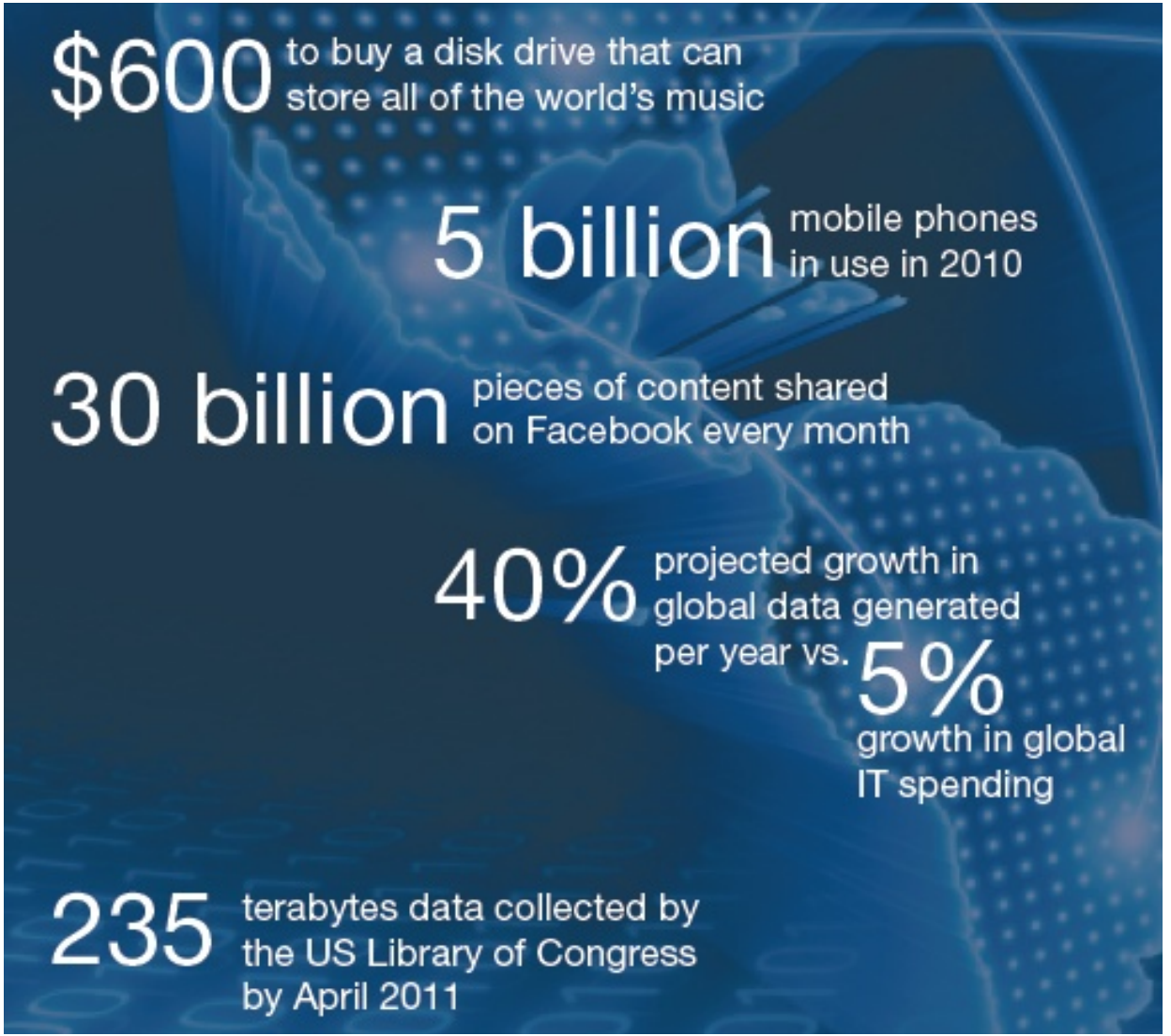
(Banana for scale)

Main Sources

- Data Mining, The Textbook (2015) by Charu Aggarwal (Chapter 1) + slides by Lijun Zhang
- Mining of Massive Datasets, 2nd edition (2014) by Leskovec et al. (Chapter 1)
- Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al. (Chapters 1-2)

Data Mining

The age of "Big Data"



Wikipedia definition

- **Data mining** is the process of
  - discovering patterns in
  - large data sets
  - involving methods at the intersection of
    - machine learning,
    - statistics, and
    - database systems.

Informal definition

Given **lots of data,** discover **patterns** and **models** that are:

- **Valid**: hold on new data with some certainty
- **Useful**: should be possible to act on them
- **Unexpected** or **novel**: non-obvious
- **Understandable**: interpretable
- **Complete:** contain most of the interesting information

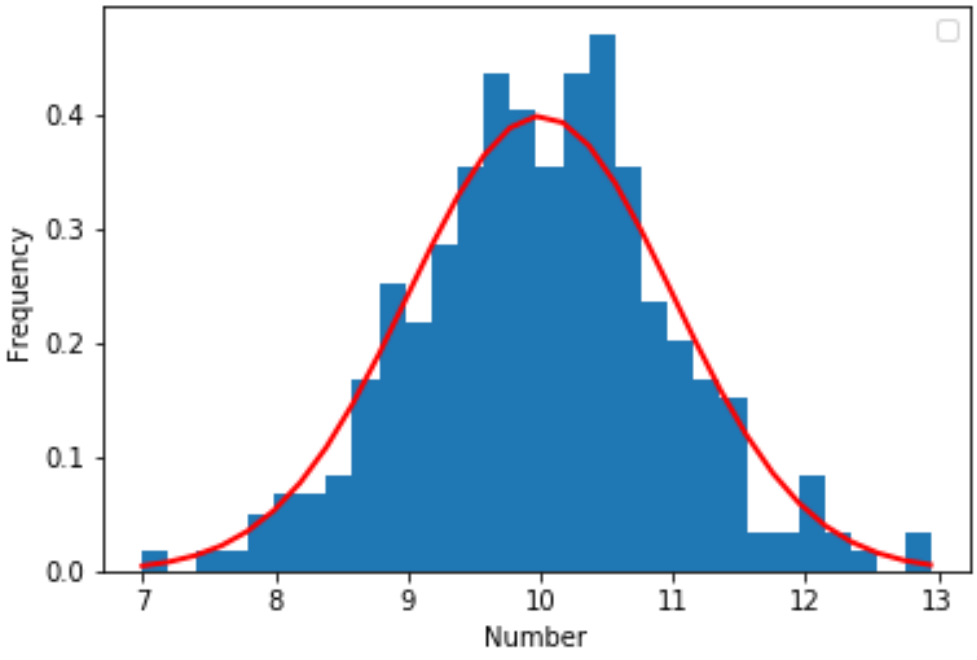
Example: 300 numbers

8.5998019 10.82452538 10.25496714 9.9264092 10.26304865 8.80526888 8.96569273 9.00883512 9.82813977 10.19311326 9.6545295
10.83958189 12.20970744 10.41521275 10.15902266 9.86904675 10.17021837 10.58768438 12.07341981 8.45713965 9.62152893 11.2494364
9.30073426 10.12753479 11.06429886 9.80406205 9.74418407 11.15815923 10.87659275 10.39190038 10.52911904 10.84125322 11.98925384
10.63545001 9.07420116 10.48011257 11.32273164 9.4831463 10.67973822 10.87064128 9.35940084 9.51149749 11.13211644 9.23292561
8.4767592 9.64339604 9.91374069 9.84184184 9.85576594 9.18523161 10.27107348 8.7511958 8.70297841 10.50609814 11.1908866
10.59484161 10.60027882 9.06375121 10.48534475 9.34253203 10.37303225 9.27441407 11.27229628 12.88441445 9.80825939 9.09844847
10.82873991 8.89169535 10.43092526 7.43215579 10.29787802 9.87946998 8.3799398 10.21263966 9.93826568 9.17325487 10.22256677
10.04892038 11.01233696 9.6145273 9.9495437 10.51474851 9.19288505 7.87728009 9.987364 10.94639021 10.01814962 9.40505023
8.87242546 10.23686131 8.90710325 10.31678617 10.4571519 9.04315227 9.85321707 11.89885306 6.99926999 10.71534924 10.29215034
10.59516732 9.8807174 9.01321711 8.45289144 9.1739316 7.90909364 9.42165081 10.37087284 9.57754821 9.60350044 10.75691005
8.24594836 10.33419146 9.7779209 9.51609087 10.25712725 12.1256587 9.53397549 9.44765209 9.53901558 9.8006768 9.633075
11.17692346 11.00022919 8.38767624 8.63908897 8.10049333 10.66422258 10.70986552 10.82945121 10.45206684 9.21578565 10.21230495
10.28984339 9.4130091 10.54597988 10.8042254 10.52795479 10.76288124 11.3554357 11.484667 10.36068758 8.18239896 11.20998409
9.88574571 9.8811874 10.64332788 8.67828643 9.23619936 10.71263899 9.36036772 8.80204902 8.84117879 9.60177677 8.82383074
9.85787872 10.30883419 10.09771435 10.33417508 8.94003225 9.63795622 8.88926589 8.51484154 10.61543214 10.10520145 10.23046826
11.22923654 10.25575855 10.4210496 9.79970778 7.70796076 9.56309629 10.82893108 10.4055698 10.12121772 9.38935918 9.48947921
9.53357322 9.87589518 10.5455508 9.98665703 9.440398 9.67368819 12.94191966 10.01303924 12.14295086 9.58399348 10.92799244
10.4654533 10.14613624 9.29818262 9.25613292 11.59370587 8.62517536 10.29703335 9.11065832 10.68766309 9.86507094 10.58314944
10.65232968 8.13400366 11.04148688 10.16883849 10.23649503 11.51859843 9.4754405 10.88103754 8.6249062 9.64581983 8.80660132
10.3794072 11.7687303 9.6768357 10.83753706 12.39138541 9.45756373 10.4746549 11.44321655 10.70109831 8.36186335 8.99123853
10.7221973 9.25735885 10.11287178 9.77908247 10.05372548 12.32358117 9.09128196 10.27487412 8.31704578 9.67337192 11.17123559
11.33146049 10.44967579 9.58649468 9.5908432 10.53829167 10.16738708 10.45433891 10.79223358 11.3936216 9.27709756 8.91159056
8.67186161 7.83968452 11.00207472 10.61085929 11.15868605 10.13873855 9.29370024 10.49794191 10.49884897 9.77150045 8.80503866
10.08775177 11.38167004 10.42724794 11.11626475 10.68890453 10.49280739 9.53675721 9.74560138 10.34343033 10.19711682 9.20212506
9.06407316 10.07228419 11.06791431 12.10523742 8.72119193 10.04645774 11.47090441 8.92472486 10.04585273 10.41149437 9.90118185
9.02229964 8.66708035 11.53976046 11.40609367 9.73014878 8.94607876 11.562354 9.58552216 9.74172847 9.64220948 9.69459042
9.58460199 11.14917832 9.49543794 9.46369271 10.16544667 9.92277128 9.61975057 11.11679747 9.42894032 9.25751891 11.44948256
8.16601628 10.11500258 9.42431821

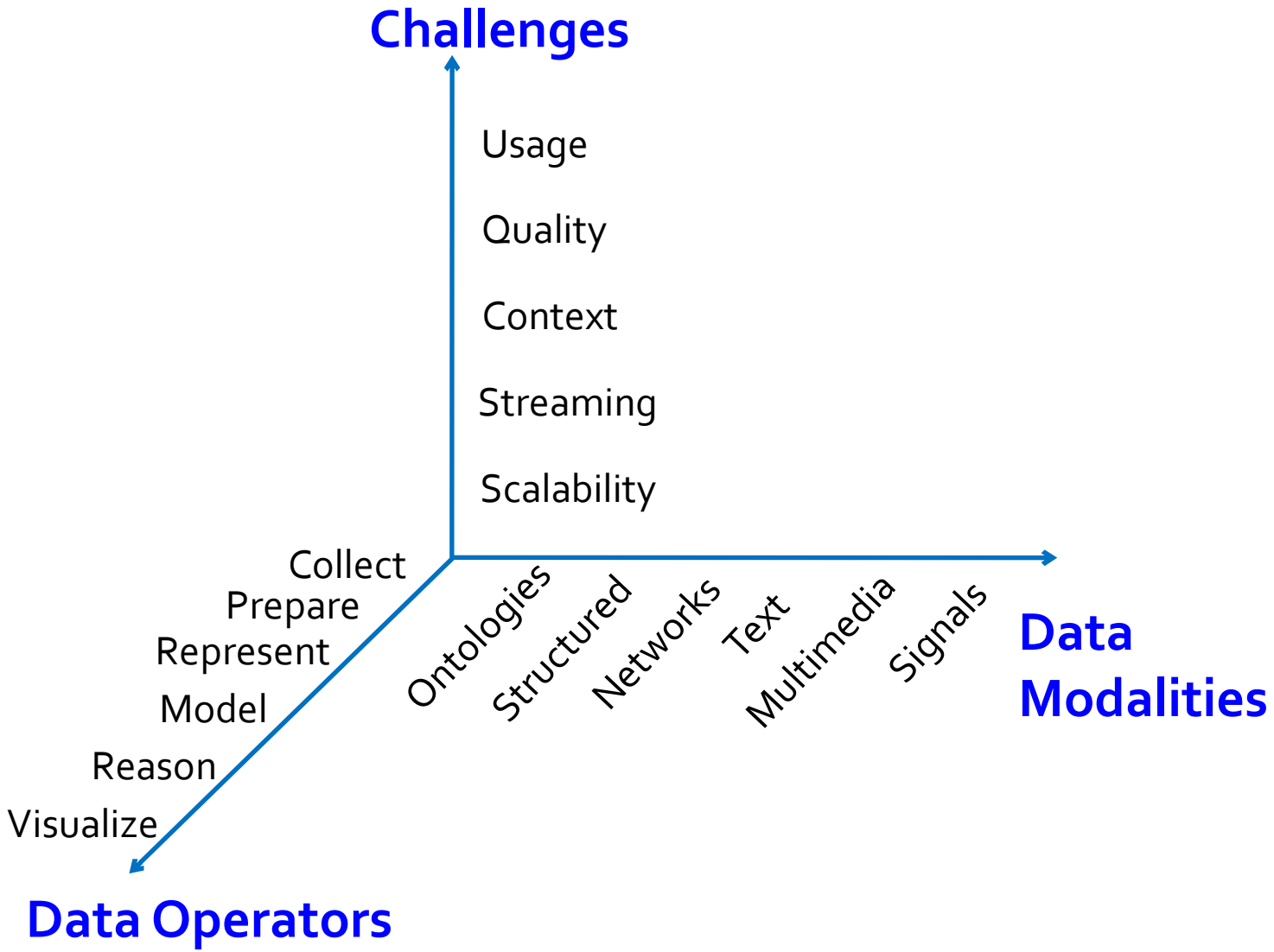
Example: 300 numbers (cont.)

Through *statistical modeling* we can find the data comes from a Normal distribution with mean 10 and standard deviation 1

- **Normal(μ=10,σ=1)** is a *model* for the data



```
import numpy as np
import matplotlib.pyplot as plt
mu=10
sigma=1
sample = np.random.normal(mu, sigma, 300)
out, bins, ignored = plt.hist(sample, 30, density=True)
plt.plot(bins, 1/(sigma * np.sqrt(2 * np.pi)) * np.exp(
- (bins - mu)**2 / (2 * sigma**2) ), linewidth=2,
color='r')
plt.xlabel("Number")
plt.ylabel("Frequency")
plt.show()
```


Challenges
Usage
Quality
Context
Streaming
Scalability
Collect
Prepare
Represent
Model
Reason
Visualize
Ontologies
Structured
Networks
Text
Multimedia
Signals
Data Modalities
Data Operators

Describing vs Predicting

Descriptive methods

- Find human-interpretable patterns that describe the data
- Example: Clustering

Predictive methods

- Use some variables to predict unknown or future values of other variables
- Example: Recommender systems

Characterizing vs Distinguishing

Data characterization methods

- A summarization of the general characteristics or features of a target class of data

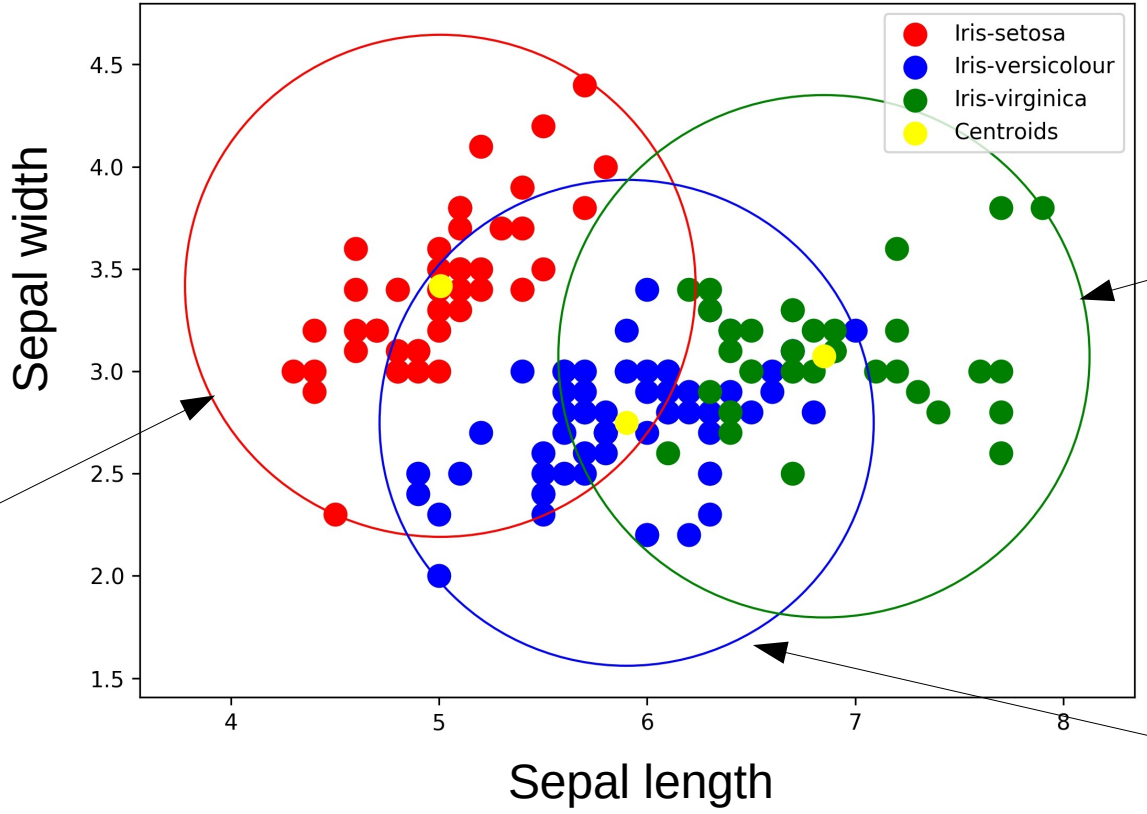
Data discrimination methods

- A comparison of the general features of the target class data objects against the general features of objects from one or multiple contrasting classes

Data mining has several goals

- To produce a **model**
  - E.g., a regression model for a numerical variable, or a classification model for a categorical variable
- To create a **summary**
- To extract **prominent features**

Example summary: clustering



Example: feature extraction

- Given shopping baskets of previous customers, determine:
  - **Frequent itemsets** (bought together)
  - **Similar items** (e.g., for recommendations)

Risk #1: Spurious patterns

- A risk with “Data mining” is that an analyst can “discover” patterns that are **meaningless**
- *If you look in more places for interesting patterns than your amount of data will support, you are bound to find something (~Bonferroni principle)*

If you interrogate data
hard enough
it will tell you
what you want to hear

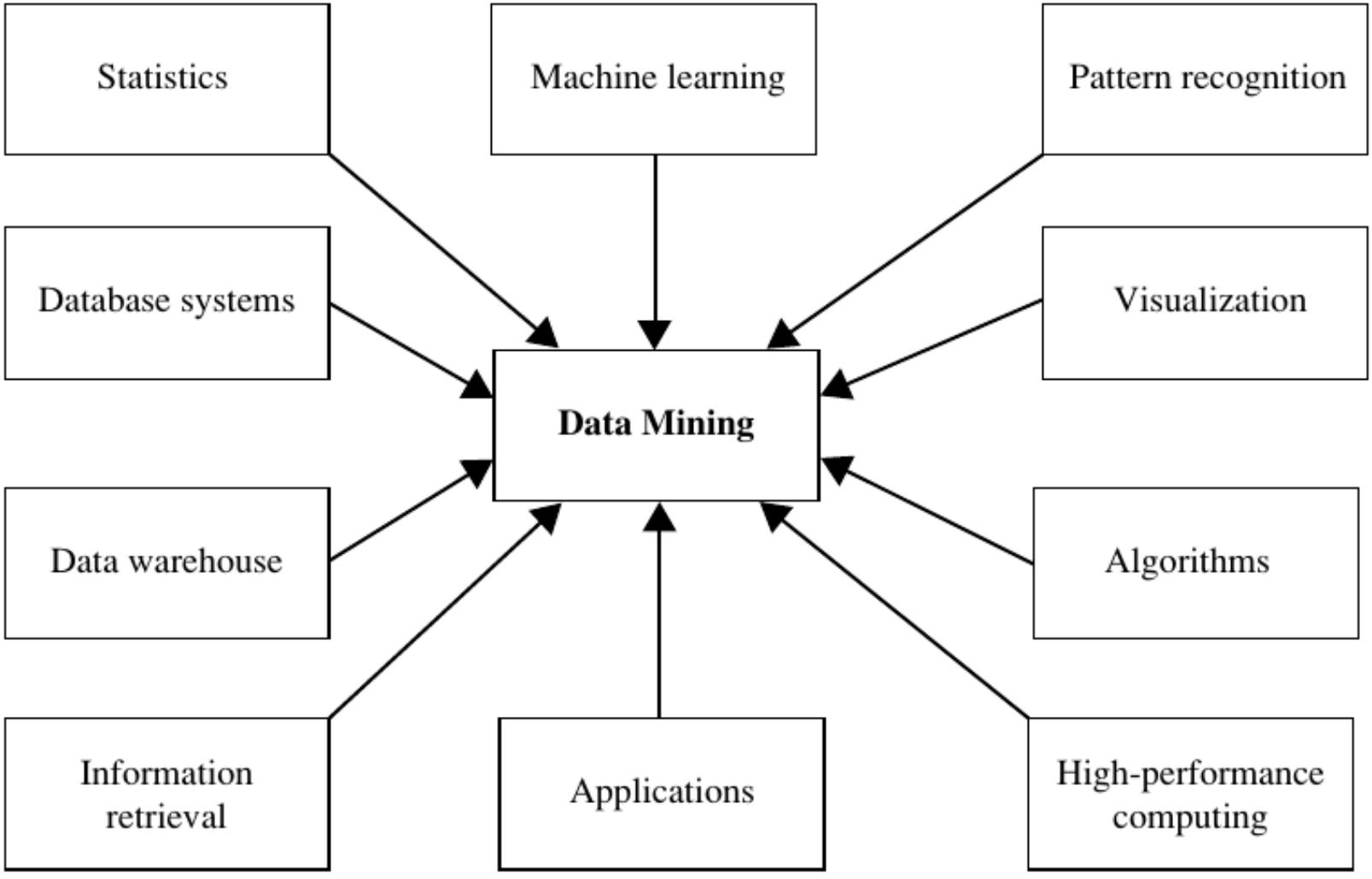
Risk #2: Surveillance state

- Attention-grabbing evil actions are also very rare, with consequences:
  - Suppose 1 in a million in a suicide bomber
  - Catching one suicide bomber a year on average means examining 999.999 innocent people
- A system with 1% false positive rate will flag ~10K people as potential suicide bombers

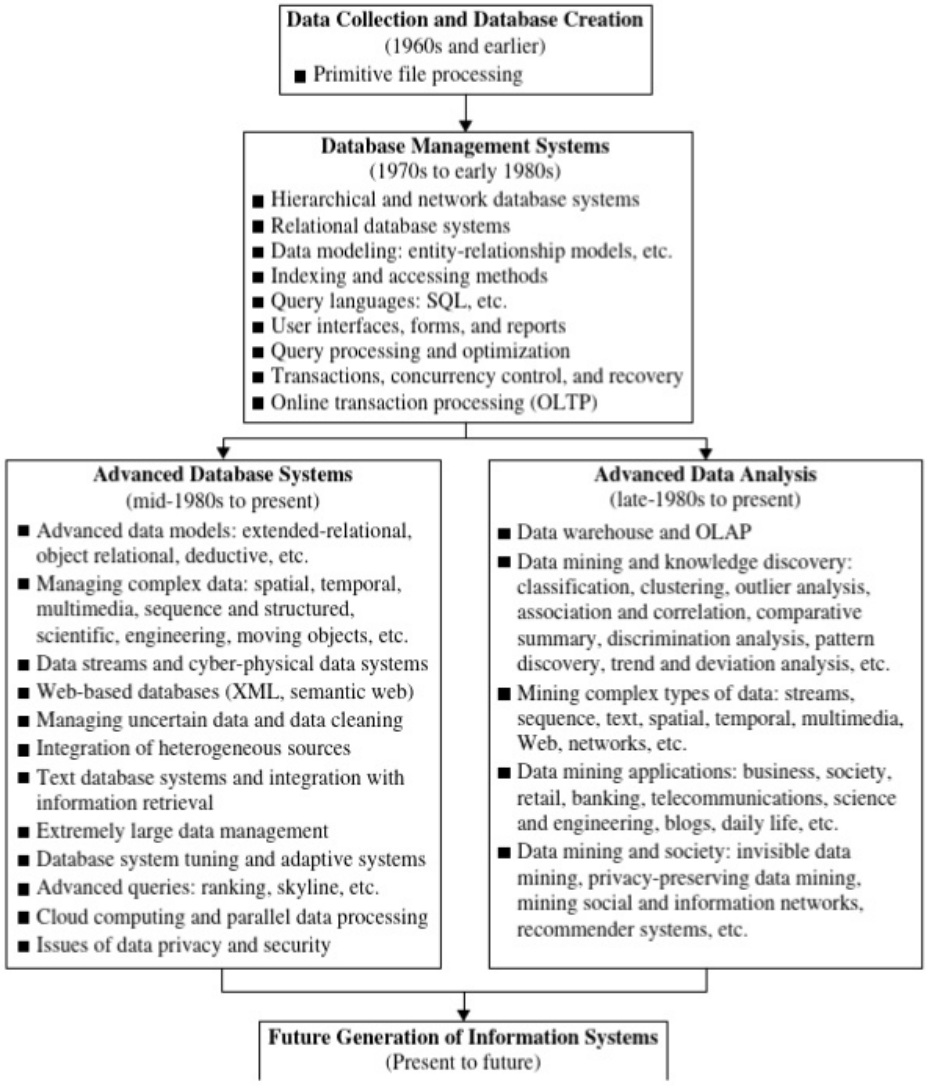
Data mining (DM) vs other disciplines

- For a database person, DM=analytic processing
- For a machine learning person, DM=modeling
- For an algorithms person, DM=efficiency

- Our focus will be on **scalable algorithms**



Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al.



Data mining is a descendant of methods for Online Analytical Processing (OLAP) done over Data Warehouses

Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al.

Data rich but information poor

- Fast-paced data streams become data archives that become data tombs
- Decisions could be better made by using data that already exists but is hard to “mine”

Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al.

Knowledge Discovery from Data

- KDD, a popular acronym
  - "Discovery" is Data Mining
- Other names: knowledge mining from data, knowledge extraction, data/pattern analysis

Data Mining Concepts and Techniques, 3rd edition (2011) by Han et al.

Typical stages of KDD

1) Data Cleaning
2) Data Integration
3) Data Selection
4) Data Transformation
5) Data Mining ← application of a DM algorithm
6) Pattern Evaluation
7) Knowledge Presentation

Typical stages of KDD

1) Data Cleaning
2) Data Integration
3) Data Selection
4) Data Transformation

Pre-processing phase

5) Data Mining
6) Pattern Evaluation
7) Knowledge Presentation

Analytical phase

Data Types

Nondependency / Dependency

- Nondependency oriented data can be structured so items are separate
  - Relational data, text data
- Dependency oriented data includes relationships between items
  - Graphs, time series

Mixed attribute data

- Most attributes we will deal with are numerical, they quantify something
- Sometimes attributes are categorical
  - Categorical
    - Example: elephant, tiger, moose, ...
  - Binary (two categories)
    - Example: present, absent
  - Ordinal (two or more categories that can be naturally sorted)
    - Example: low, medium, high
- Real-world datasets include both types

Binary attributes, sets, dummy vars.

- Every binary attribute can be used as a marker of belonging to a set and viceversa

Name	Age	Gender	Race	ZIP Code
John S.	45	M	African American	05139
Manyona L.	31	F	Native American	10598
Sayani A.	11	F	East Indian	10547
Jack M.	56	M	Caucasian	10562
Wei L.	63	M	Asian	90210

- **One-hot encoding**: every categorical attribute taking one of k values can be encoded as k “dummy” binary attributes

Question

- Suppose you encode race and gender using one-hot encoding. How many columns do you obtain?

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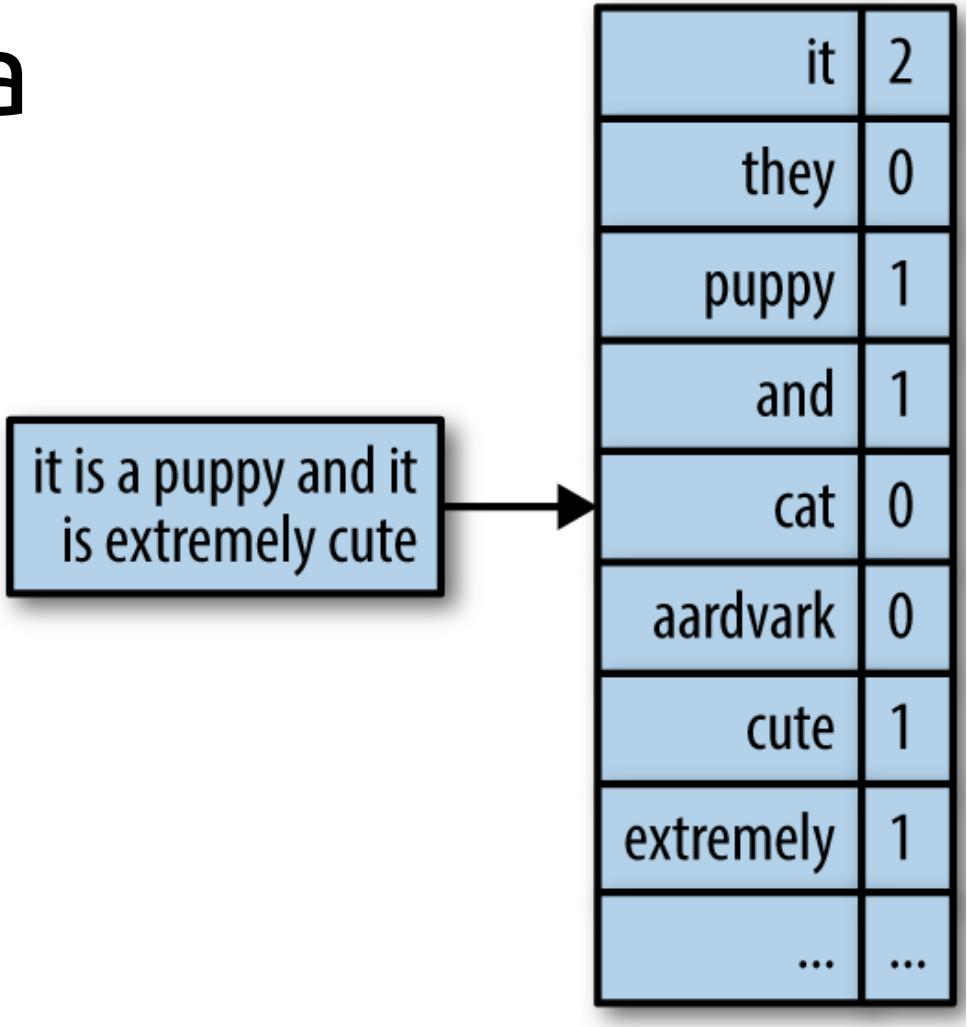
Textual data

- Text be represented as:
  - As a string
  - As a set of binary variables, one for each word in the dictionary, with value True iff the word belongs to the text (the “bag-of-words” model)
  - As a set of numerical variables indicating number of occurrences (the “vector space” model)



http://uc-r.github.io/creating-text-features

Time series data

- Contextual attributes
  - Timestamps, sequence number, …
- Behavioral attributes
  - Readings of a sensor, value of the variable, …

- *Multivariate* time series data has multiple behavioral attributes

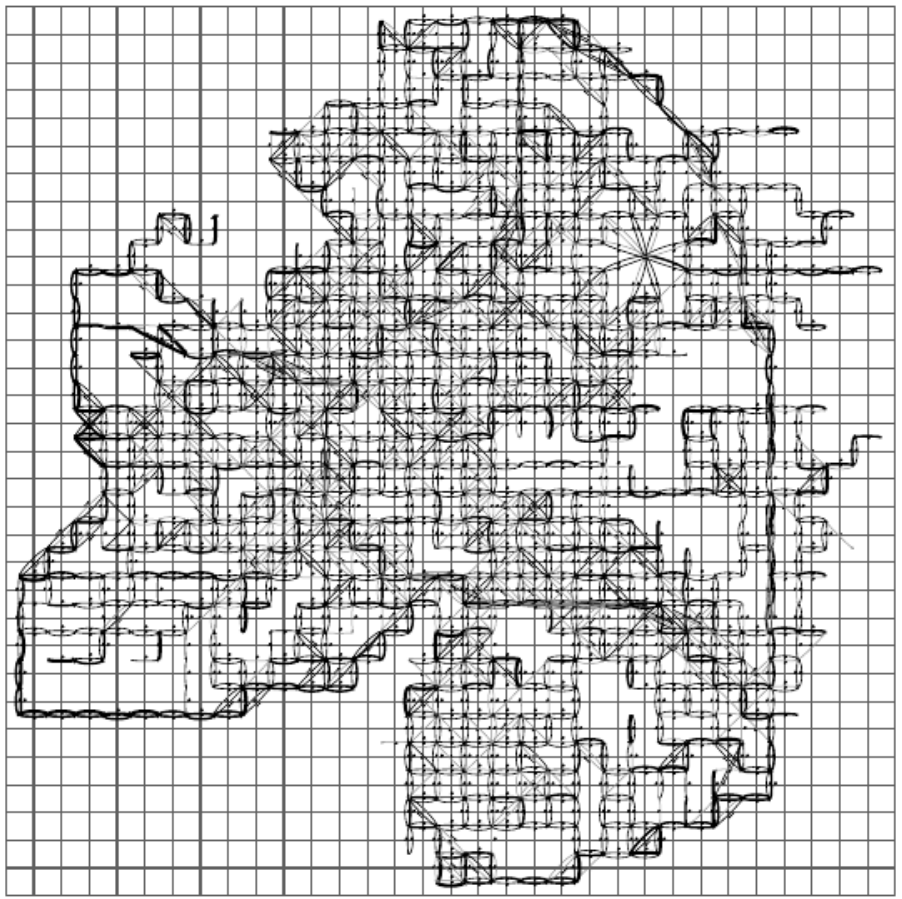
Spatial data

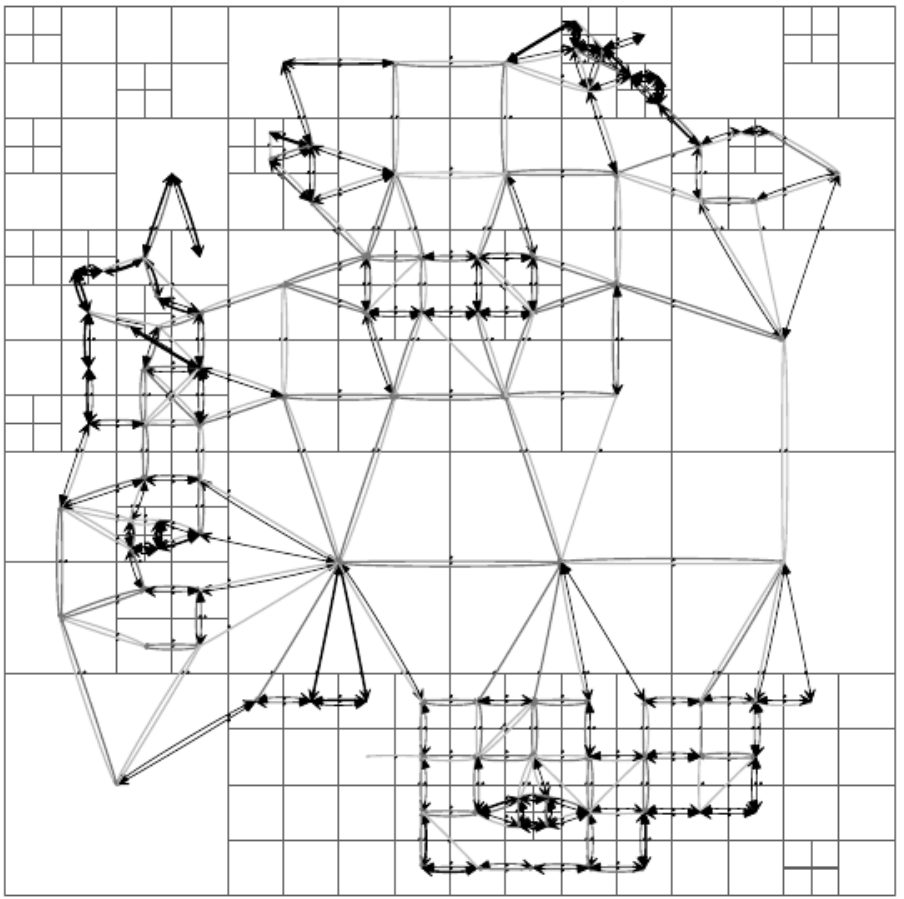
- Two (lat/long) or three (lat/long/elevation) spatial attributes
- Represented by images
- Remote sensing data

Spatiotemporal data

- Spatial and temporal attributes are contextual
  - Example: sea surface temperature
- Temporal attribute is contextual, spatial attribute is behavioral
  - Example: trajectories

Aggregating trajectory data





Bonchi, F., Castillo, C., Donato, D., & Gionis, A. (2009). Taxonomy-driven lumping for sequence mining. Data Mining and Knowledge Discovery, 19(2), 227-244.

Key elements

Which kind of relationships? Columns or Rows?

- Between columns
  - Find associations, correlations, …
  - If there is one key column: classification, prediction, ...
- Between rows
  - Find clusters
  - Detect outliers

Association pattern mining

- Sparse binary databases representing, e.g., items a person is interested in

$$\begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix} \in \{0,1\}^{5\times 4}$$

- The relative frequency of a pattern is its support

Frequent Patterns	Support
{2,3}	3/5
{1,4}	2/5

https://cs.nju.edu.cn/zlj/Course/DM_15.html

Association pattern mining (cont.)

- Given a binary $n \times d$ data matrix D,
  - determine all subsets of columns such that all the values in these columns take on the value True for at least a fraction *min_support* of the rows in the matrix.
- The relative frequency of a pattern is referred to as its support

Association pattern mining (cont.)

- Given a binary $n \times d$ data matrix D,
  - determine all subsets of columns such that all the values in these columns take on the value True for at least a fraction *min_support* of the rows in the matrix.
- The relative frequency of a pattern is referred to as its support

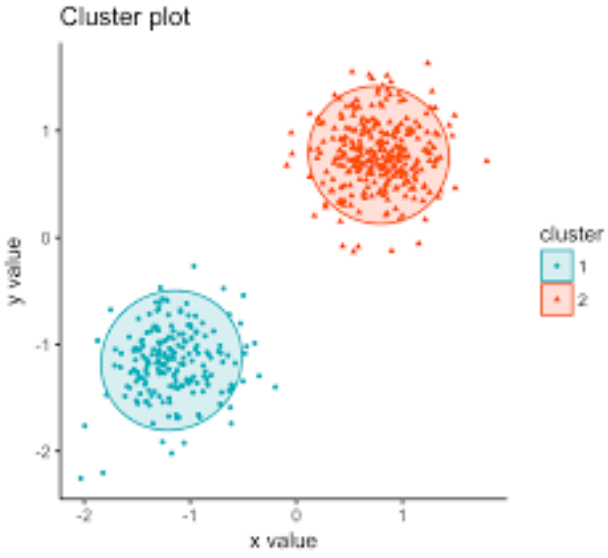
Association pattern mining (cont.)

- The confidence of a rule A→B is
  - support(A U B) / support(A)
- Example:
  - { Chips, Olives } → { Beer }

Try it!

- The confidence of a rule A→B is
  - support(A U B) / support(A)
- Suppose
  - 10 people buy only Chips and Beer
  - 20 people buy only Chips and Olives
  - 30 people buy only Olives and Beer
  - 40 people buy all three: Chips, Olives, and Beer.
- What is the confidence of the rule
  { Chips, Olives } → { Beer } ?

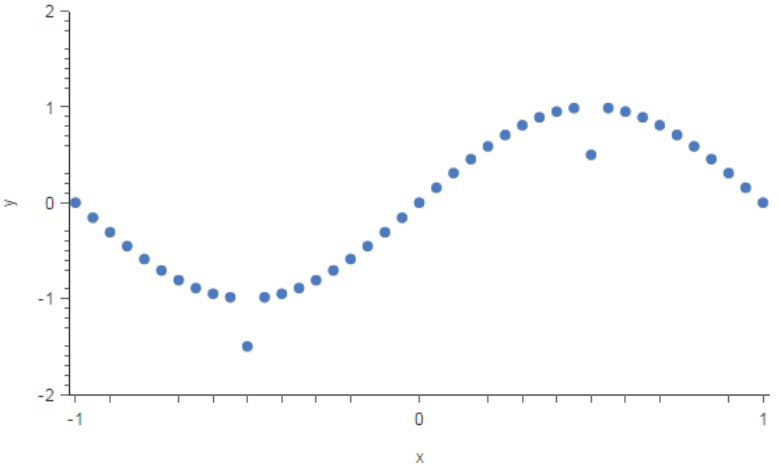
Clustering



- Partition records/rows in a way that
  - elements in the same partition are similar
  - elements in different partitions are different
- *But what does it mean to be similar? How many sets? Can a record/row belong to two sets? To zero sets? …*
- Applications:
  - Segmentation, summarization, …
  - Sometimes a step in a larger DM algorithm

Image credit: http://www.sthda.com/english/articles/tag/pam-clustering/

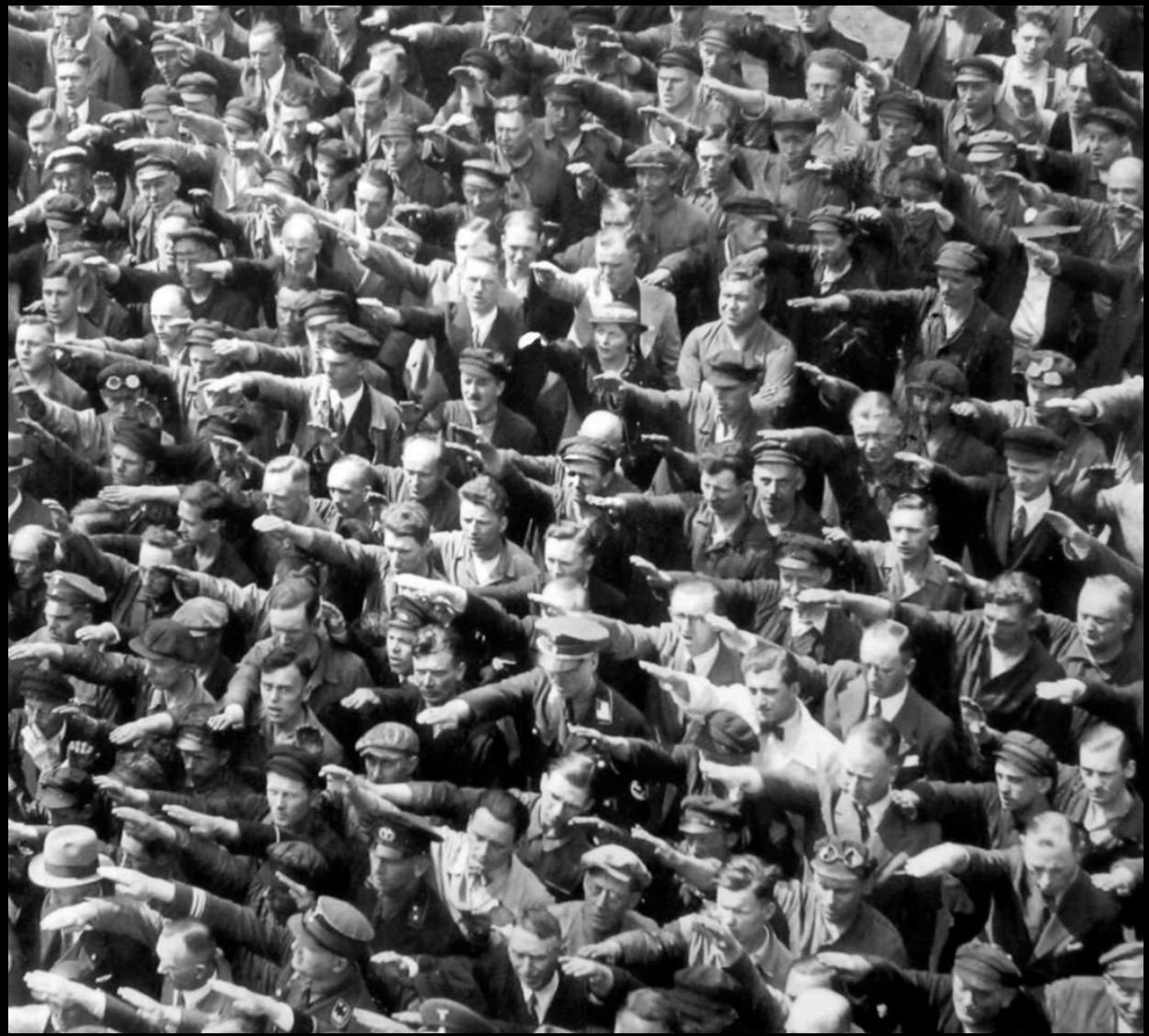
Outlier detection



- Given a database, find records/rows that are different from the rest of the database
- *But what does it mean to be different? How many can be different? How different should they be?*
- Applications:
  - Intrusion detection, credit card fraud, interesting sensor events, medical diagnosis, ...

Image credits: https://www.kdnuggets.com/2017/01/3-methods-deal-outliers.html

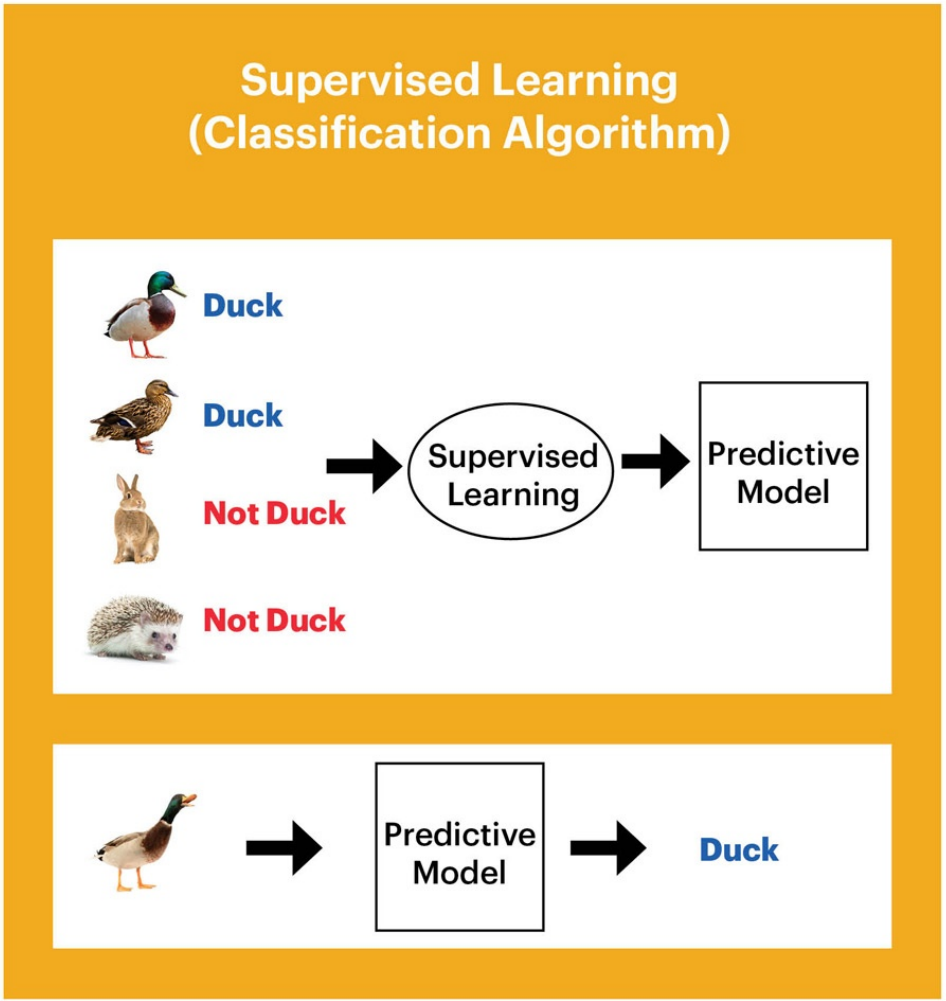
Outlier detection (cont.)

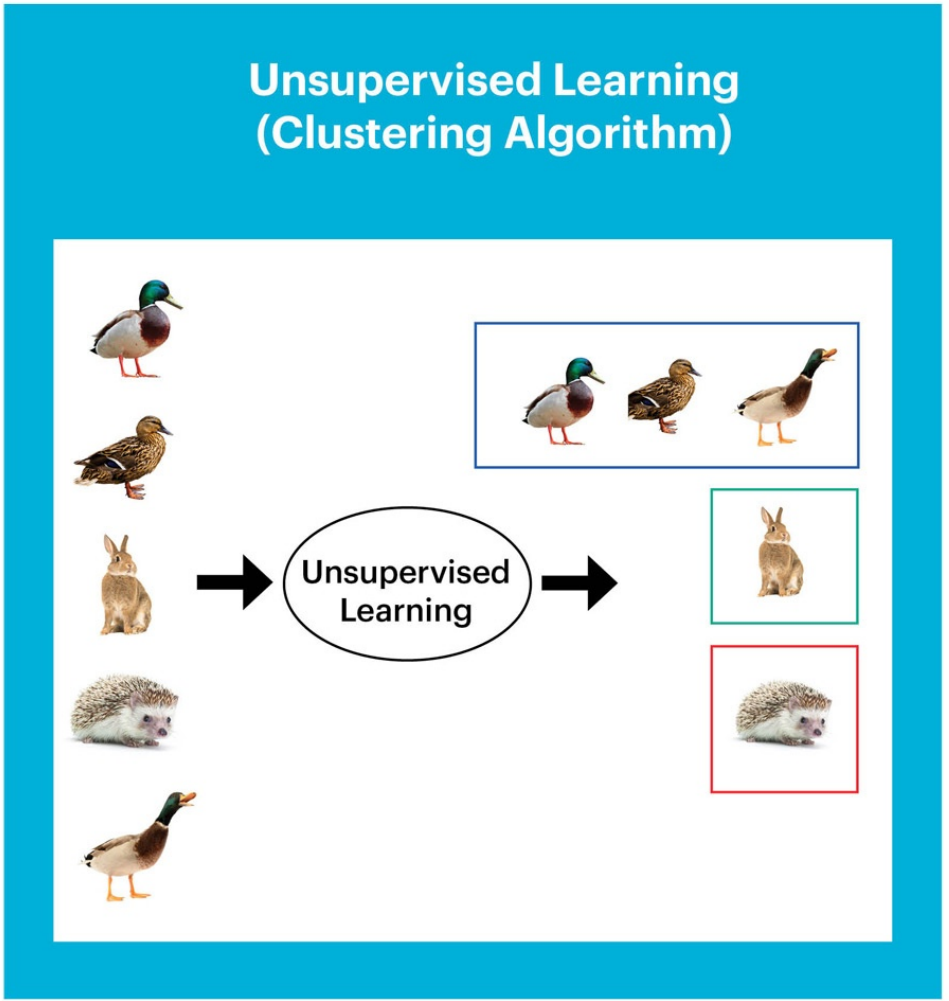


August Landmesser in 1936

Data classification

- When data has a special feature known as a class label
- A model can learn from previous data to associate a record/row to a class label
- Applications:
  - Too many to list here :-)





https://blog.westerndigital.com/machine-learning-pipeline-object-storage/

Western Digital.

Tasks with complex data types

- Frequent temporal patterns
- Time series motifs
- Graph motifs
- Trajectory clusters
- Collective classification
- ...

Data types x Prototypical problems

Problem	Time series	Spatial	Sequence	Networks
Patterns	Motif-mining Periodic pattern	Colocation patterns	Sequential patterns Periodic Sequence	Structural patterns
	Trajectory patterns			
Clustering	Shape clusters	Spatial clusters	Sequence clusters	Community detection
	Trajectory clusters			
Outliers	Position outlier Shape outlier	Position outlier Shape outlier	Position outlier Combination outlier	Node outlier Linkage outlier Community outliers
	Trajectory outliers			
Classification	Position classification Shape classification	Position classification Shape classification	Position classification Sequence classification	Collective classification Graph classification
	Trajectory classification			

Data Mining, The Textbook (2015) by Charu Aggarwal

Example scenarios

Example scenario 1

- Place products in a store to maximize co-purchases of items frequently bought together
  - Input data: baskets
  - Output: similar pairs
  - Algorithm: frequent pattern mining

Example scenario 2

- Recommend movies to users in a video-on-demand platform
  - Input data: viewing history
  - Output: recommendations for a user
  - Simple algorithm: k nearest neighbors

Example scenario 3

- Help diagnose if an electrocardiogram is associated to a health problem
  - Input data: time series, possibly multi-dimensional
  - Output: binary label or risk score
  - Algorithms: outlier detection or classification

Example scenario 4

- Help a sysadmin determine if an intruder is trying or has accessed the network
  - Input data: time series of event records
  - Output: binary label or risk score
  - Algorithms: event detection

Are these data mining tasks?

A) Dividing the customers of a company by gender

B) Finding credit card scammers among customers of a company

C) Computing the total sales of a company

D) Sorting a student database by student identification number

E) Predicting the future stock price of a company using past records

F) Determine when a complex machine needs to be repaired

G) Extracting the frequencies of a sound wave

Major challenges

Methodological challenges

- Mining new kinds of knowledge
- Mining multidimensional data
- Fully utilizing the expertise of domain experts who know the data better
- Handling uncertainty, noise, incompleteness

User interaction challenges

- Allowing users to ask the questions that matter to them
- Performing interactive mining
- Presenting and visualizing data mining results

Efficiency and scalability

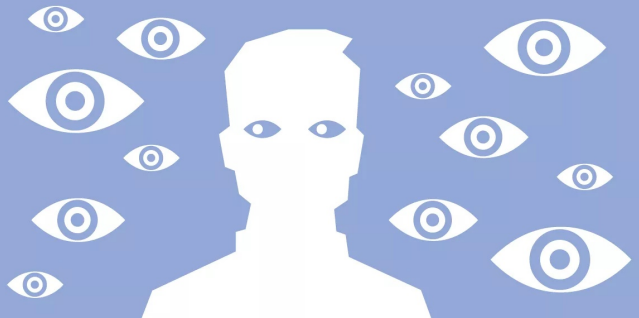
- Data cannot be stored in a single machine
  - Processing time of an algorithm might be exponential in input … or even polynomial, even with small degree: a process can become unreasonably slow very quickly
  - Streaming algorithms
  - Parallel/distributed mining algorithms

Diversity of database types

- Real databases are a complex mixture of very rich and diverse data types
- Mining dynamic, networked, global data repositories
  - Integrating from complementary sources

Data mining can be harmful

- Social impacts of data mining
  - Who wins? And more importantly, who loses?
- Privacy-preserving data mining
  - Avoid invisible, pervasive, invasive data mining



Summary

Things to remember

- Prototypical data mining scenarios
- Types of data mining methods
- Data types
- Data mining challenges

Exercises for this topic

- **Section 1.9 of Data Mining, The Textbook (2015) by Charu Aggarwal**
- Exercises 1.7 of Introduction to Data Mining, Second Edition (2019) by Tan et al.