

“Data is more valuable
than **oil** and is the
most expensive
asset
in the world.”



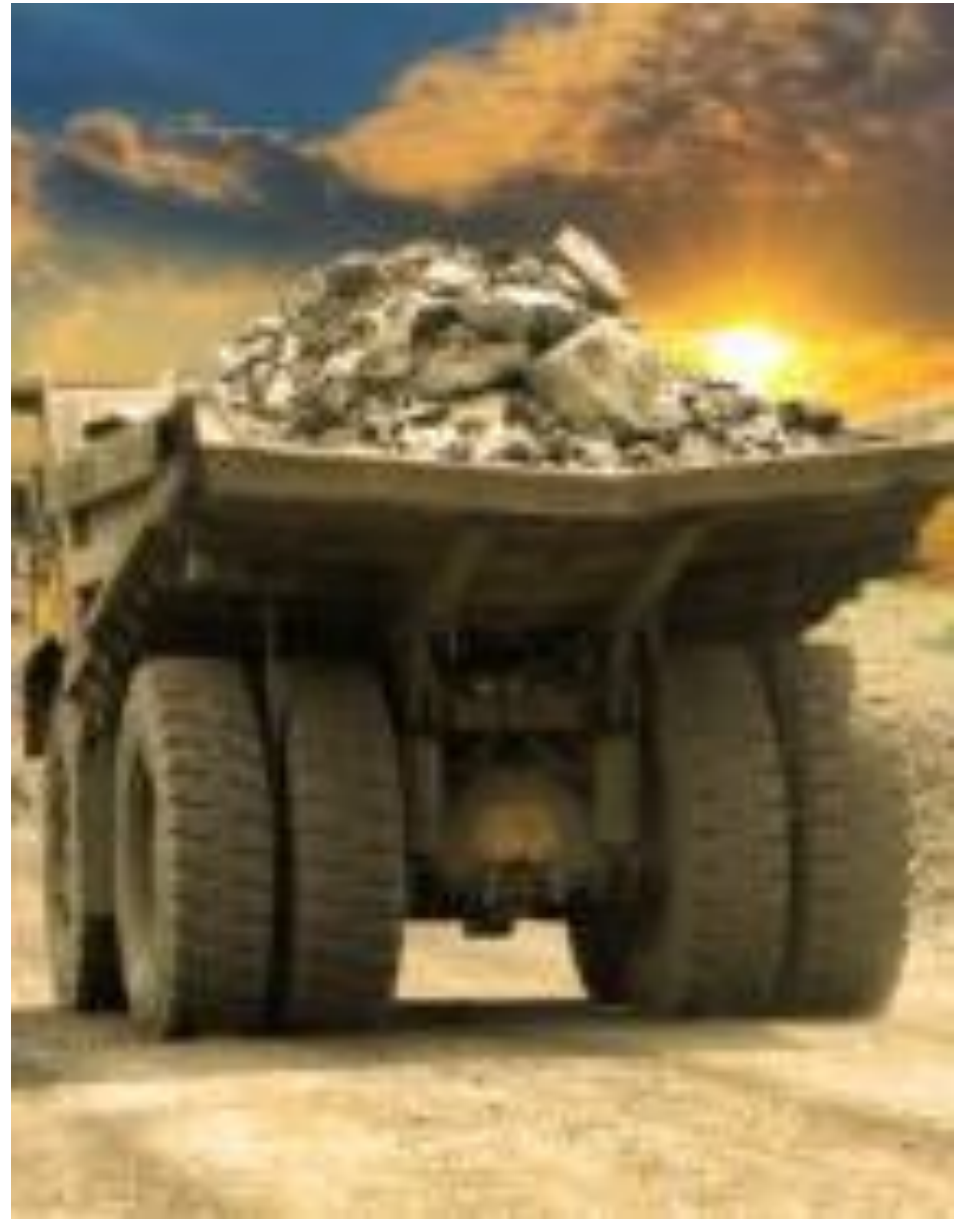
Introduction to Data Mining Methods and Tools



by Michael Hahsler

Agenda

- **What is Data Mining?**
- Data Mining Tasks
- Relationship to Statistics, Optimization, Machine Learning and AI
- Tools
- Data
- Legal, Privacy and Security Issues



Evolution of Database Technology

1960s:

Data collection, database creation, IMS and network DBMS

1970s:

Relational data model, relational DBMS implementation

1980s:

RDBMS, advanced data models (extended-relational, OO, deductive, etc.)

Application-oriented DBMS (spatial, scientific, engineering, etc.)

1990s:

Data mining, data warehousing, multimedia databases, and Web databases

2000s

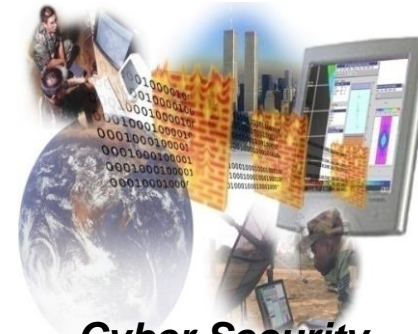
Stream data management and mining

Data mining and its applications

Web technology (XML, data integration) and global information systems

Large-scale Data is Everywhere!

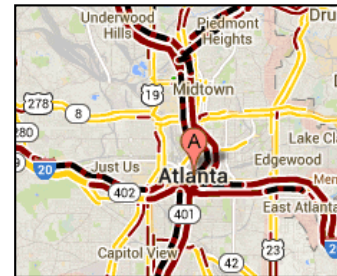
- There has been enormous data growth in both commercial and scientific databases due to advances in data generation and collection technologies
- New mantra
 - Gather whatever data you can whenever and wherever possible.
- Expectations
 - Gathered data will have value either for the purpose collected or for a purpose not envisioned.



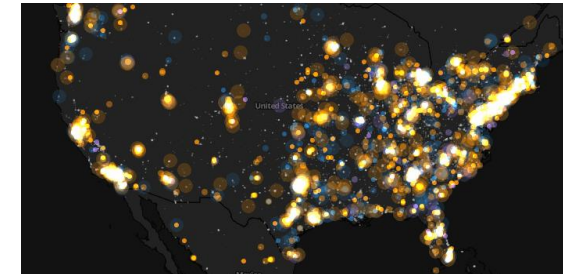
Cyber Security



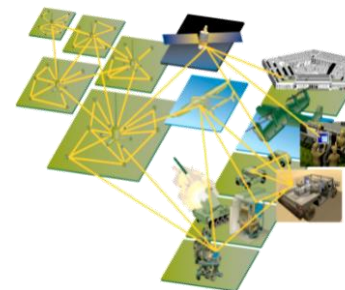
E-Commerce



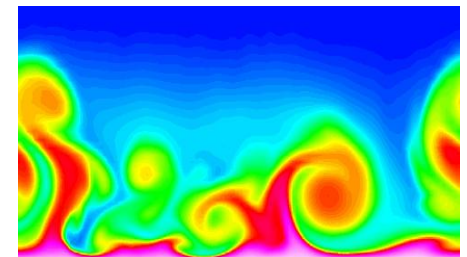
Traffic Patterns



Social Networking: Twitter



Sensor Networks



Computational Simulations

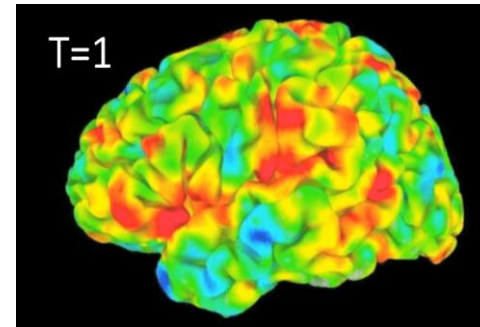
Why Data Mining? Commercial Viewpoint

- Lots of data is being collected and warehoused
 - Web data
 - ◆ Google has Peta Bytes of web data
 - ◆ Facebook has billions of active users
 - purchases at department/grocery stores, e-commerce
 - ◆ Amazon handles millions of visits/day
 - Bank/Credit Card transactions
- Computers have become cheaper and more powerful
- Competitive Pressure is Strong
 - Provide better, customized services for an edge (e.g. in Customer Relationship Management)



Why Data Mining? Scientific Viewpoint

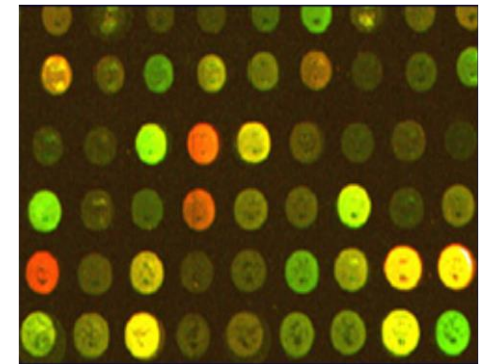
- Data collected and stored at enormous speeds
 - remote sensors on a satellite
 - ◆ NASA EOSDIS archives over petabytes of earth science data / year
 - telescopes scanning the skies
 - ◆ Sky survey data
 - High-throughput biological data
 - scientific simulations
 - ◆ terabytes of data generated in a few hours
- Data mining helps scientists
 - in automated analysis of massive datasets
 - In hypothesis formation



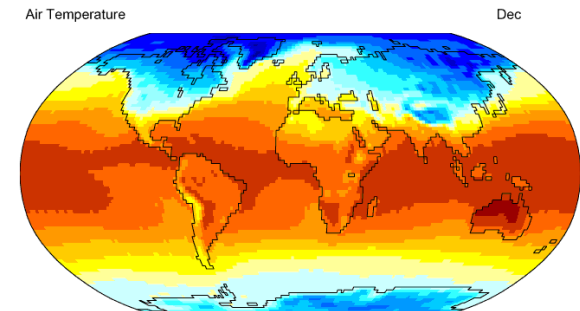
fMRI Data from Brain



Sky Survey Data



Gene Expression Data



Surface Temperature of Earth

Great opportunities to improve productivity in all walks of life

McKinsey Global Institute

Big data: The next frontier for innovation, competition, and productivity

Big data—a growing torrent

\$600 to buy a disk drive that can store all of the world's music

5 billion mobile phones in use in 2010

30 billion pieces of content shared on Facebook every month

40% projected growth in global data generated per year vs. **5%** growth in global IT spending

235 terabytes data collected by the US Library of Congress in April 2011

15 out of 17 sectors in the United States have more data stored per company than the US Library of Congress

Big data—capturing its value

\$300 billion potential annual value to US health care—more than double the total annual health care spending in Spain

€250 billion potential annual value to Europe's public sector administration—more than GDP of Greece

\$600 billion potential annual consumer surplus from using personal location data globally

60% potential increase in retailers' operating margins possible with big data

140,000–190,000 more deep analytical talent positions, and

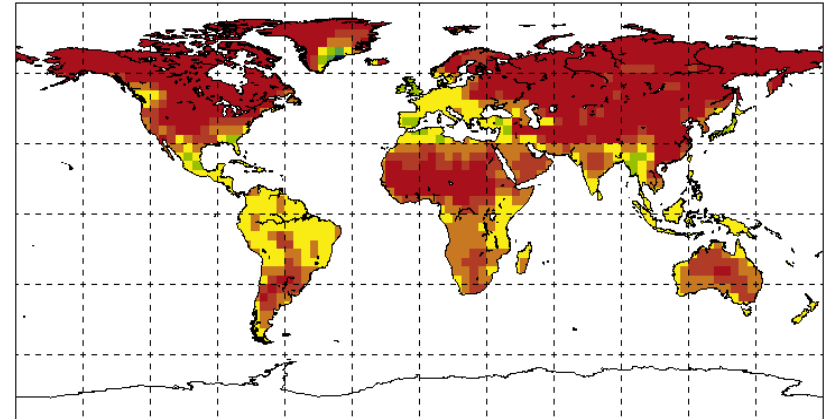
1.5 million more data-savvy managers needed to take full advantage of big data in the United States

Great Opportunities to Solve Society's Major Problems



Improving health care and reducing costs

CCCma/A2a January to January Mean Temperature (degrees C) 2080s relative to 1961-90



Predicting the impact of climate change



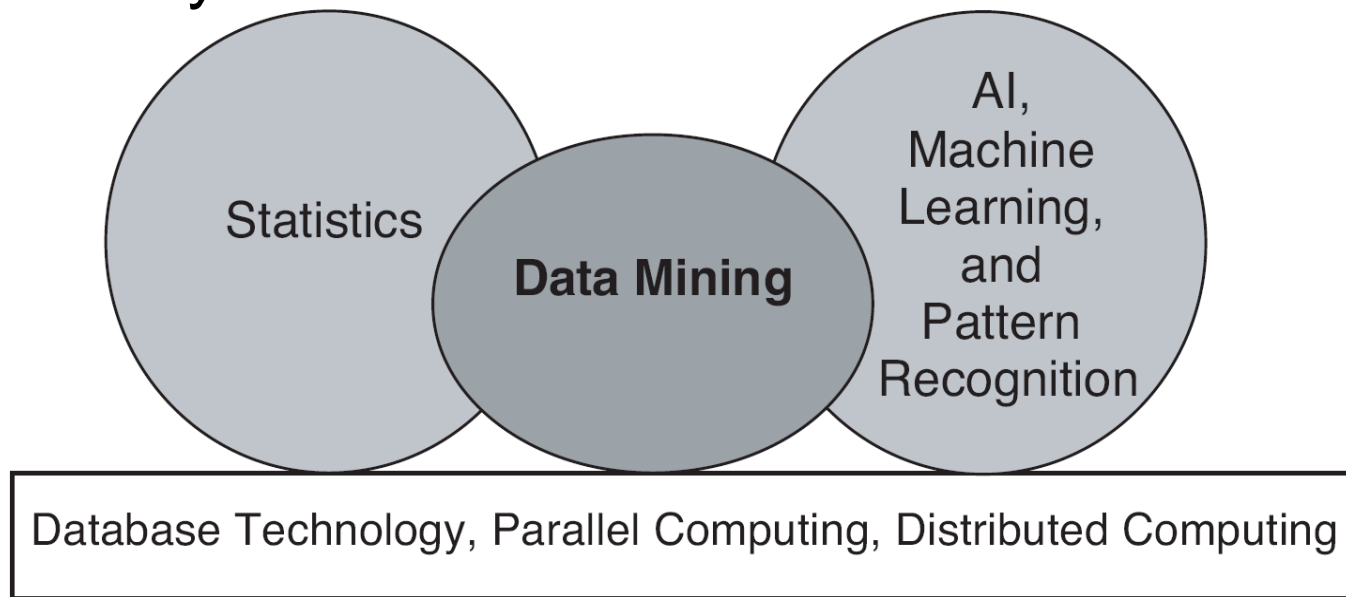
Finding alternative/ green energy sources



Reducing hunger and poverty by increasing agriculture production

Origins of Data Mining

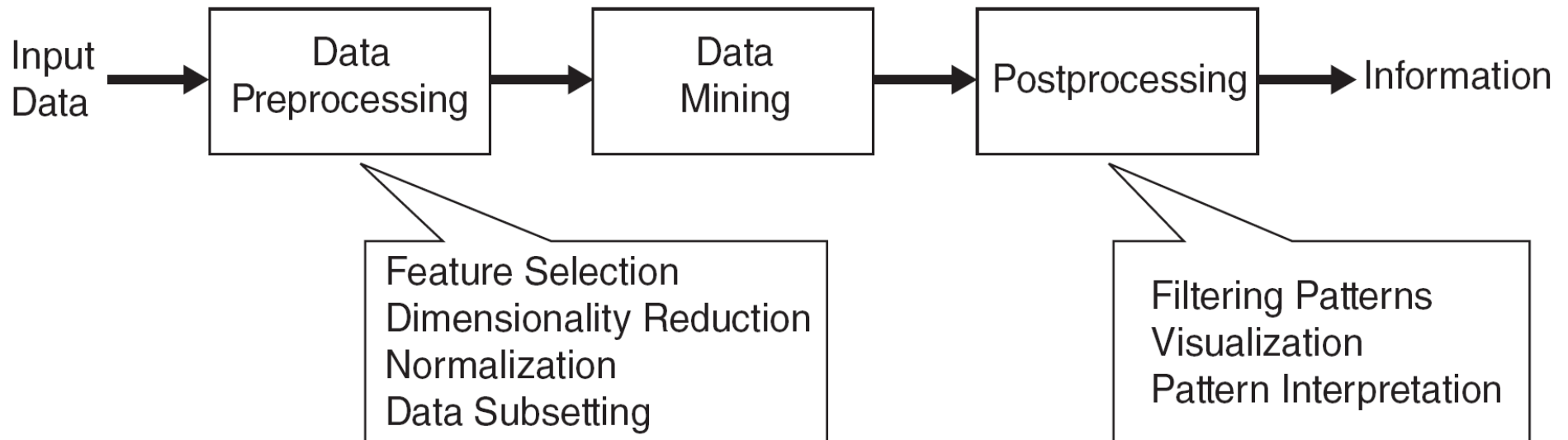
- Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems
- Traditional techniques may be unsuitable due to data that is
 - Large-scale
 - High dimensional
 - Heterogeneous
 - Complex
 - Distributed
- A key component of the emerging field of data science and data-driven discovery



What is Data Mining?

□ Many Definitions

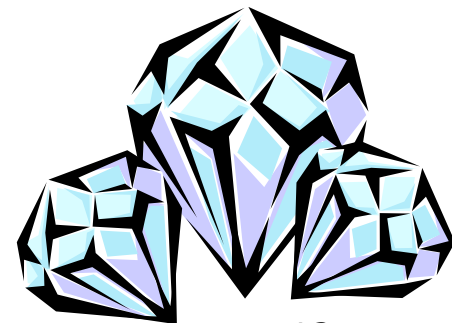
- Non-trivial extraction of implicit, previously unknown and potentially useful information from data
- Exploration & analysis, by automatic or semi-automatic means, of large quantities of data in order to discover meaningful patterns



What Is Data Mining?

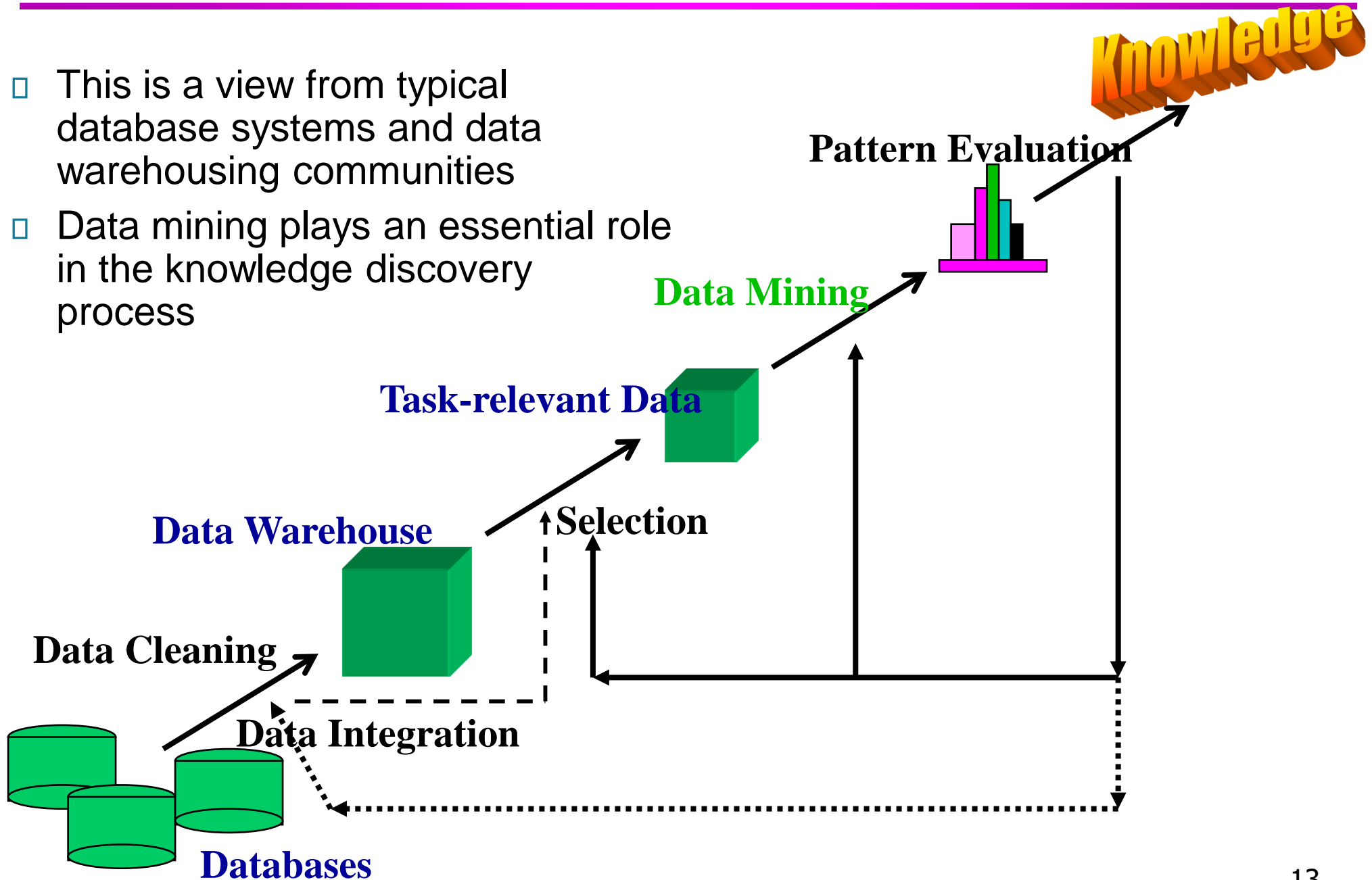


- Data mining (knowledge discovery from data)
 - Extraction of interesting (non-trivial, implicit, previously unknown and potentially useful) patterns or knowledge from huge amount of data
 - Data mining: a misnomer?
- Alternative names
 - Knowledge discovery (mining) in databases (KDD), knowledge extraction, data/pattern analysis, data archeology, data dredging, information harvesting, business intelligence, etc.
- Watch out: Is everything “data mining”?
 - Simple search and query processing
 - (Deductive) expert systems



Knowledge Discovery (KDD) Process

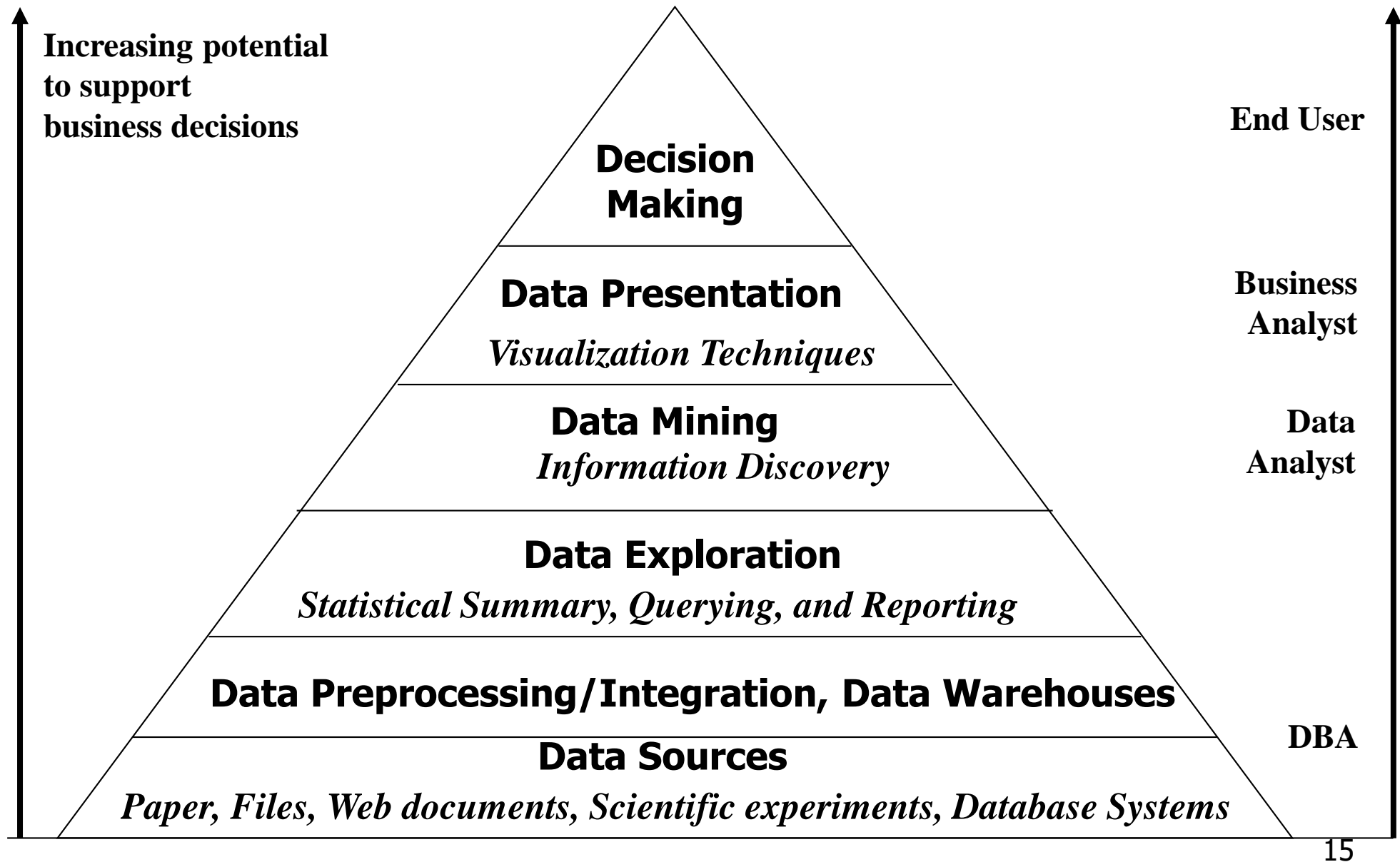
- This is a view from typical database systems and data warehousing communities
- Data mining plays an essential role in the knowledge discovery process



Example: A Web Mining Framework

- Web mining usually involves
 - Data cleaning
 - Data integration from multiple sources
 - Warehousing the data
 - Data cube construction
 - Data selection for data mining
 - Data mining
 - Presentation of the mining results
 - Patterns and knowledge to be used or stored into knowledge-base

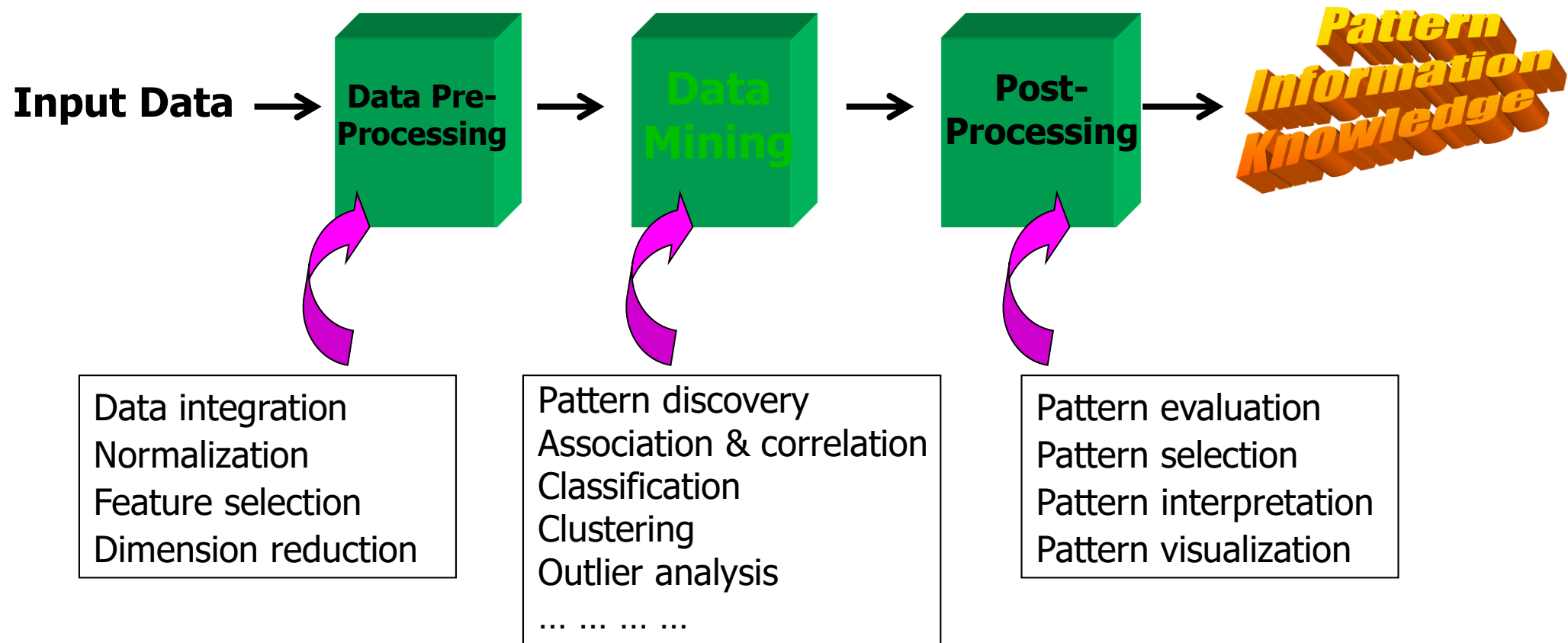
Data Mining in Business Intelligence



Example: Mining vs. Data Exploration

- Business intelligence view
 - Warehouse, data cube, reporting but not much mining
- Business objects vs. data mining tools
- Supply chain example: tools
- Data presentation
- Exploration

KDD Process: A Typical View from ML and Statistics



- This is a view from typical machine learning and statistics communities

Example: Medical Data Mining

- Health care & medical data mining – often adopted such a view in statistics and machine learning
- Preprocessing of the data (including feature extraction and dimension reduction)
- Classification or/and clustering processes
- Post-processing for presentation

What is Data Mining?

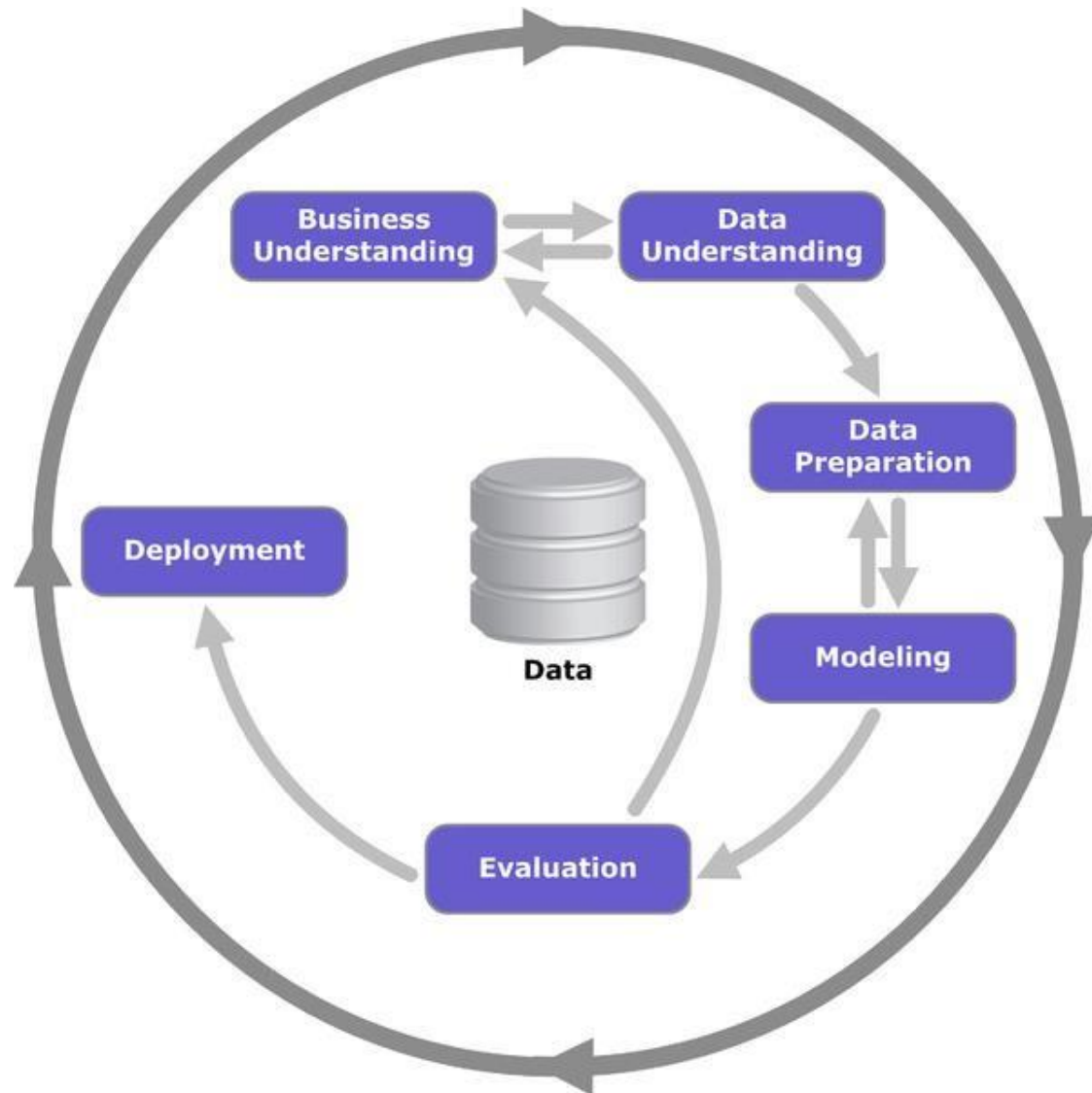
One of many definitions:

*"Data mining is the science **of extracting useful knowledge** from huge data repositories."*

ACM SIGKDD, Data Mining Curriculum: A Proposal

CRISP-DM Reference Model

- Cross Industry Standard Process for Data Mining
- Open standard process model
- Industry, tool and application neutral
- Defines tasks and outputs.
- Now developed by IBM as the Analytics Solutions Unified Method for Data Mining/Predictive Analytics (ASUM-DM).
- SAS has SEMMA and most consulting companies use their own similar process.



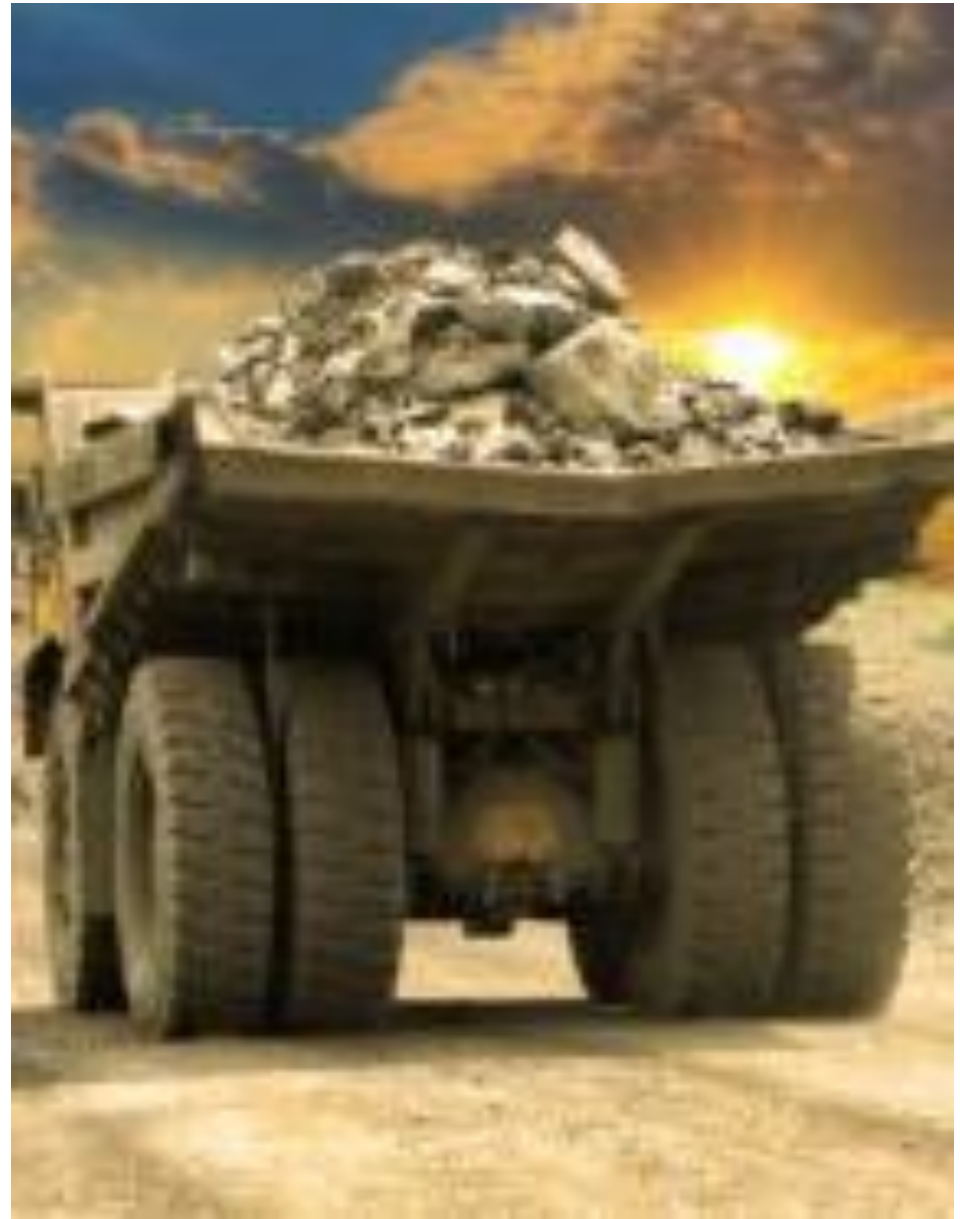
Tasks in the CRISP-DM Model

Business Understanding	Data Understanding	Data Preparation	Modeling	Evaluation	Deployment
Determine Business Objectives <i>Background</i> <i>Business Objectives</i> <i>Business Success Criteria</i>	Collect Initial Data <i>Initial Data Collection Report</i>	Select Data <i>Rationale for Inclusion/Exclusion</i>	Select Modeling Techniques <i>Modeling Technique</i> <i>Modeling Assumptions</i>	Evaluate Results <i>Assessment of Data Mining Results w.r.t. Business Success Criteria</i> <i>Approved Models</i>	Plan Deployment <i>Deployment Plan</i>
Assess Situation <i>Inventory of Resources</i> <i>Requirements, Assumptions, and Constraints</i> <i>Risks and Contingencies</i> <i>Terminology</i> <i>Costs and Benefits</i>	Describe Data <i>Data Description Report</i>	Clean Data <i>Data Cleaning Report</i>	Generate Test Design <i>Test Design</i>	Review Process <i>Review of Process</i>	Plan Monitoring and Maintenance <i>Monitoring and Maintenance Plan</i>
Determine Data Mining Goals <i>Data Mining Goals</i> <i>Data Mining Success Criteria</i>	Explore Data <i>Data Exploration Report</i>	Construct Data <i>Derived Attributes</i> <i>Generated Records</i>	Build Model <i>Parameter Settings</i> <i>Models</i> <i>Model Descriptions</i>	Determine Next Steps <i>List of Possible Actions</i> <i>Decision</i>	Produce Final Report <i>Final Report</i> <i>Final Presentation</i>
Produce Project Plan <i>Project Plan</i> <i>Initial Assessment of Tools and Techniques</i>	Verify Data Quality <i>Data Quality Report</i>	Integrate Data <i>Merged Data</i>	Assess Model <i>Model Assessment</i> <i>Revised Parameter Settings</i>		Review Project Experience <i>Documentation</i>
		Format Data <i>Reformatted Data</i> <i>Dataset</i> <i>Dataset Description</i>			

Figure 3: Generic tasks (bold) and outputs (italic) of the CRISP-DM reference model

Agenda

- What is Data Mining?
- **Data Mining Tasks**
- Relationship to Statistics, Optimization, Machine Learning and AI
- Tools
- Data
- Legal, Privacy and Security Issues



Data Mining Tasks

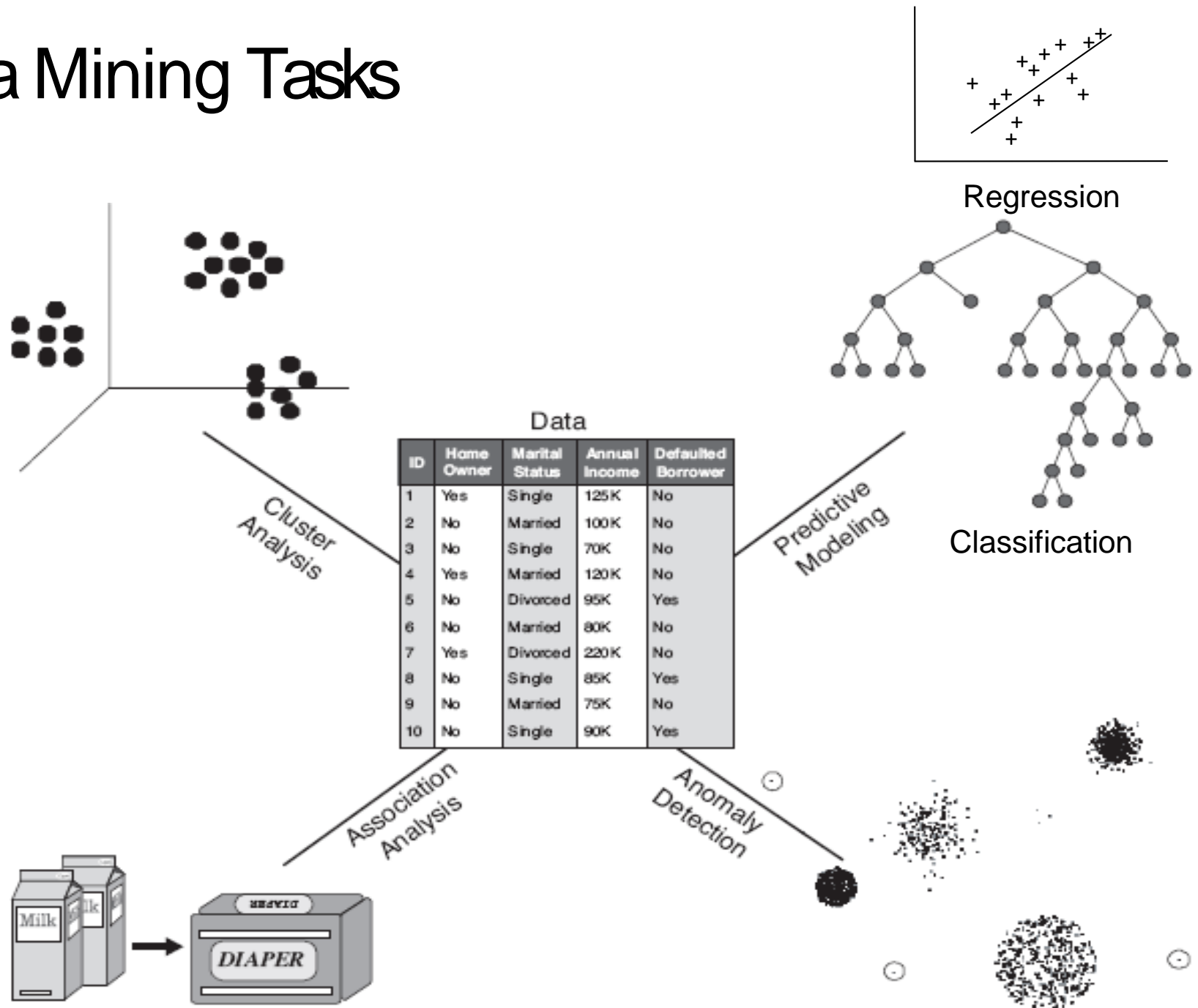
Descriptive Methods

Find human-interpretable patterns that describe the data.

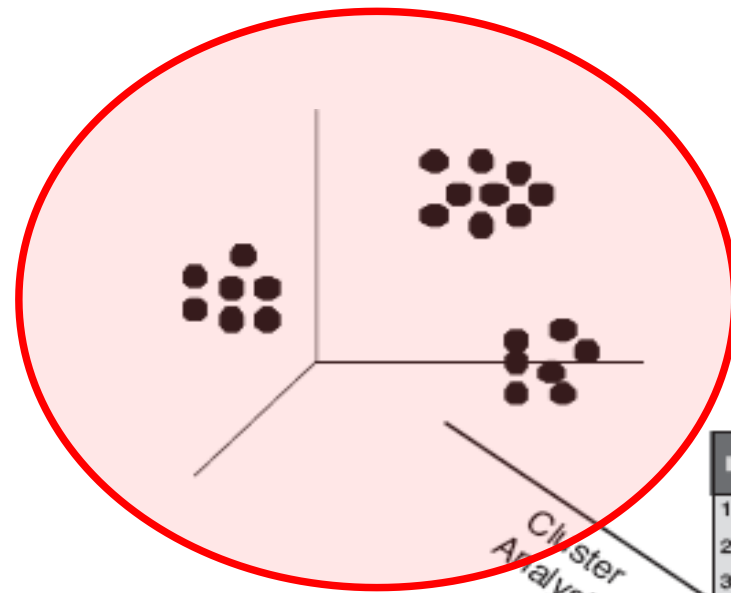
Predictive Methods

Use some features (variables) to predict unknown or future value of other variable.

Data Mining Tasks



Data Mining Tasks



Cluster Analysis

Data

ID	Home Owner	Marital Status	Annual Income	Defaulted Borrower
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	80K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

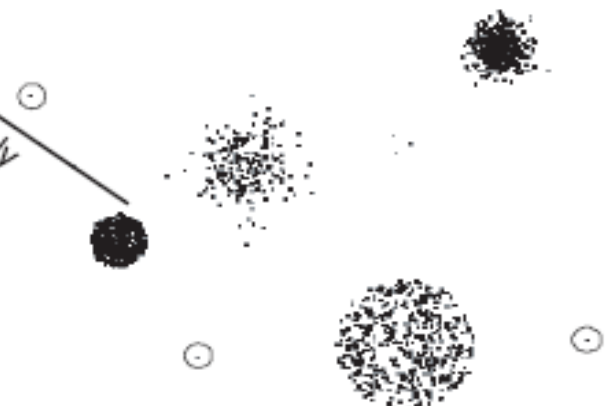
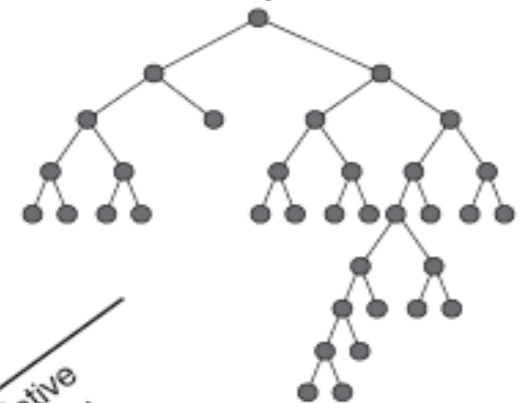
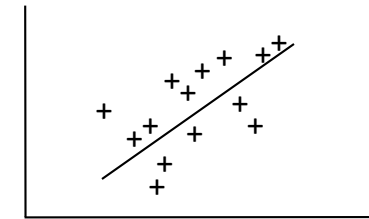
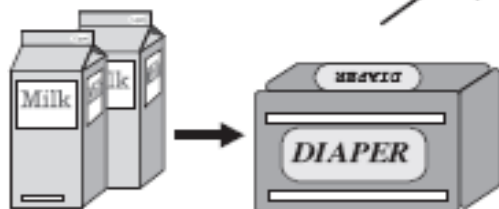
Predictive Modeling

Regression

Classification

Association Analysis

Anomaly Detection

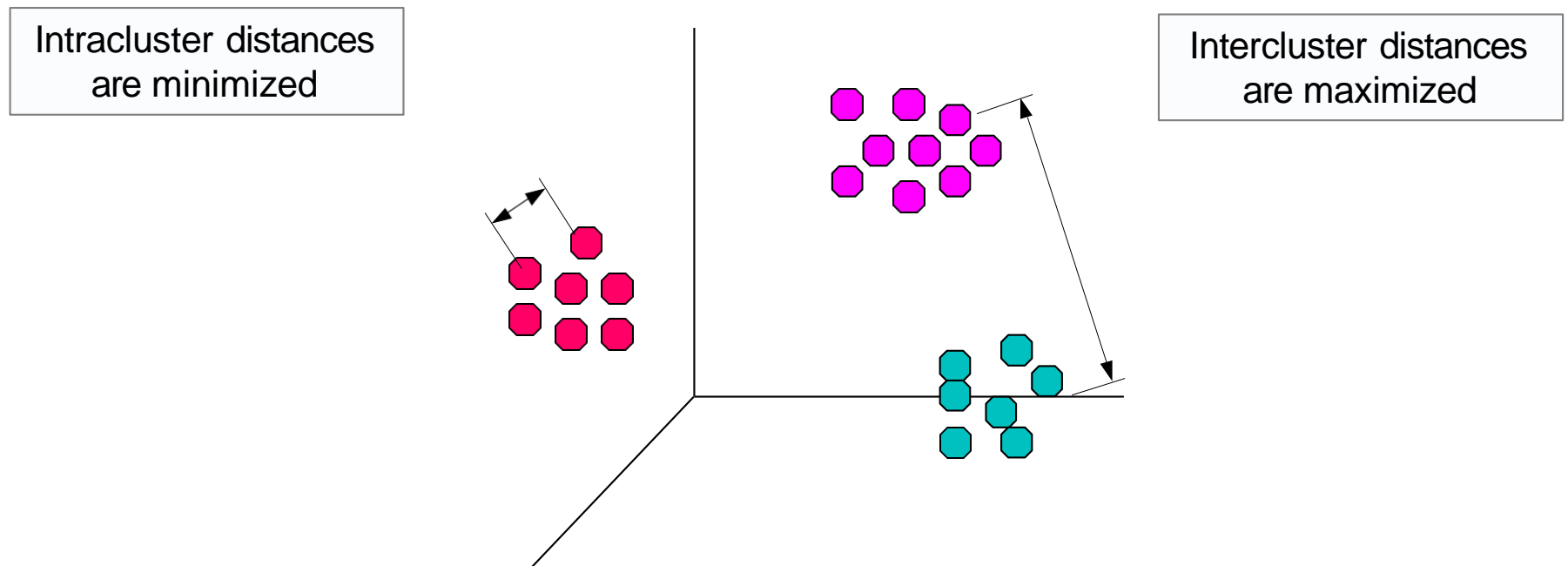


Clustering

Group points such that

- Data points in one cluster are more similar to one another.
- Data points in separate clusters are less similar to one another.

Ideal grouping is not known → Unsupervised Learning



Euclidean distance based clustering in 3-D space.

Clustering: Market Segmentation



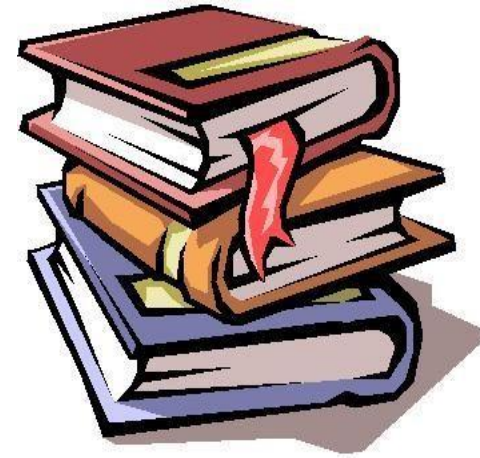
Goal: subdivide a market into distinct subsets of customers. Use a different marketing mix for each segment.



Approach:

1. Collect different attributes of customers based on their geographical and lifestyle related information and observed buying patterns.
2. Find clusters of similar customers.

Clustering Documents



Goal: Find groups of documents that are similar to each.



Approach: Identify frequently occurring terms in each document. Define a similarity measure based on term co-occurrences. Use it to cluster.

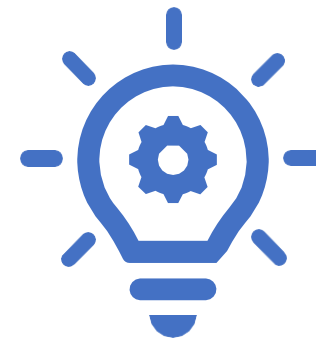


Gain: Can be used to organize documents or to create recommendations.

Clustering: Data Reduction

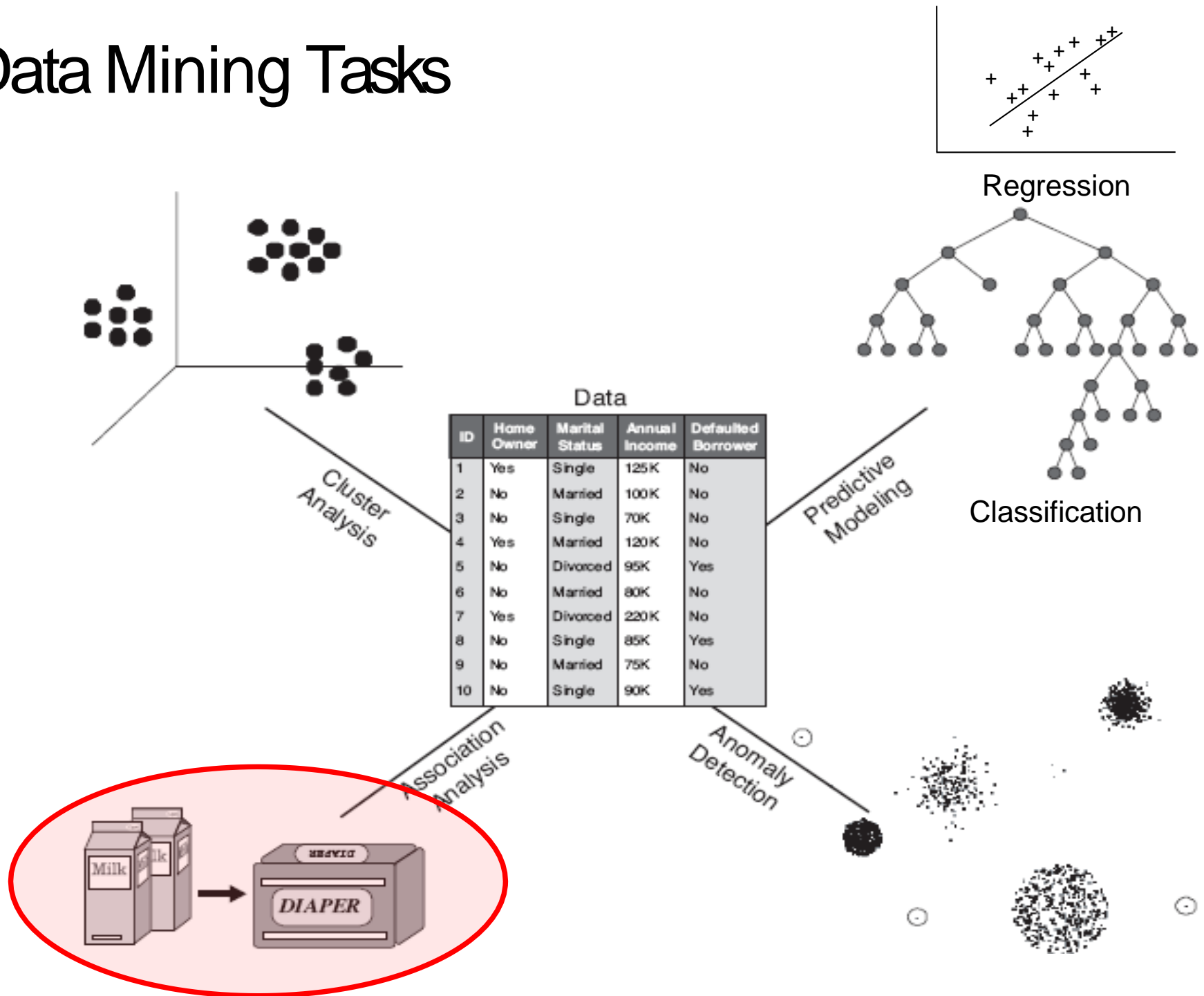


Goal: Reduce the data size for predictive models.



Approach: Group data given a subset of the available information and then use the group label instead of the original data as input for predictive models.

Data Mining Tasks



Association Rule Discovery

- Given is a set of transactions. Each contains a number of items.
- Produce dependency rules of the form
$$\text{LHS} \rightarrow \text{RHS}$$
- which indicate that if the set of items in the LHS are in a transaction, then the transaction likely will also contain the RHS item.



TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Transaction data



$\{\text{Milk}\} \rightarrow \{\text{Coke}\}$

$\{\text{Diaper, Milk}\} \rightarrow \{\text{Beer}\}$

Discovered Rules

Association Rule Discovery Marketing and Sales Promotion

- Let the rule discovered be

$\{\text{Potato Chips, ...}\} \rightarrow \{\text{Soft drink}\}$

- **Soft drink as RHS:** What should be done to boost sales? Discount Potato Chips?
- **Potato Chips in LHS:** Shows which products would be affected if the store discontinues selling Potato Chips.
- **Potato Chips in LHS and Soft drink in RHS:** What products should be sold with Potato Chips to promote sales of Soft drinks!





Association Rule Discovery Supermarket shelf management

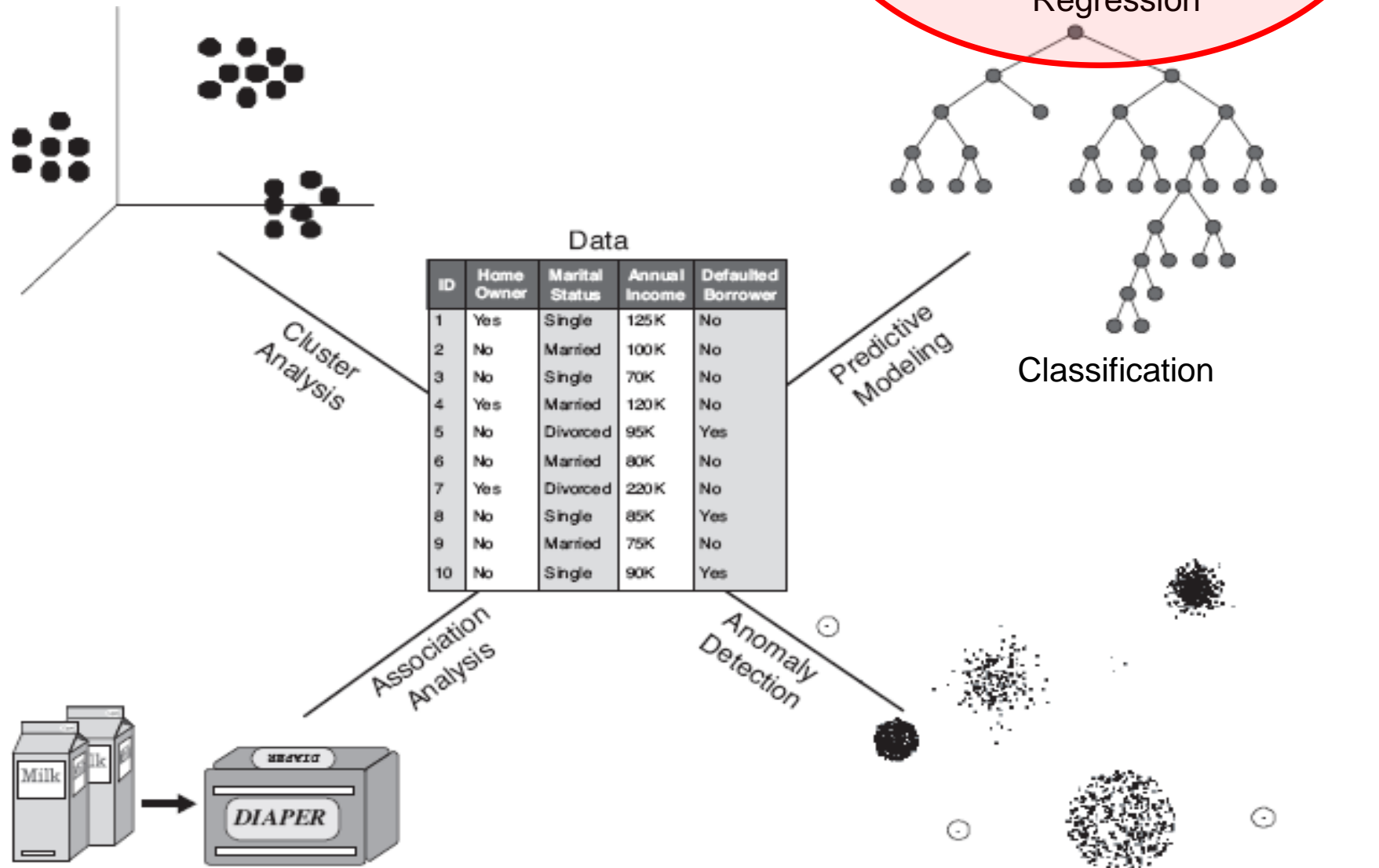
- **Goal:** To identify items that are bought together by sufficiently many customers.
- **Approach:**
 - Process the point-of-sale data to find dependencies among items.
 - Place dependent items
 - close to each other (convenience).
 - far from each other to expose the customer to the maximum number of products in the store.



Association Rule Discovery Inventory Management

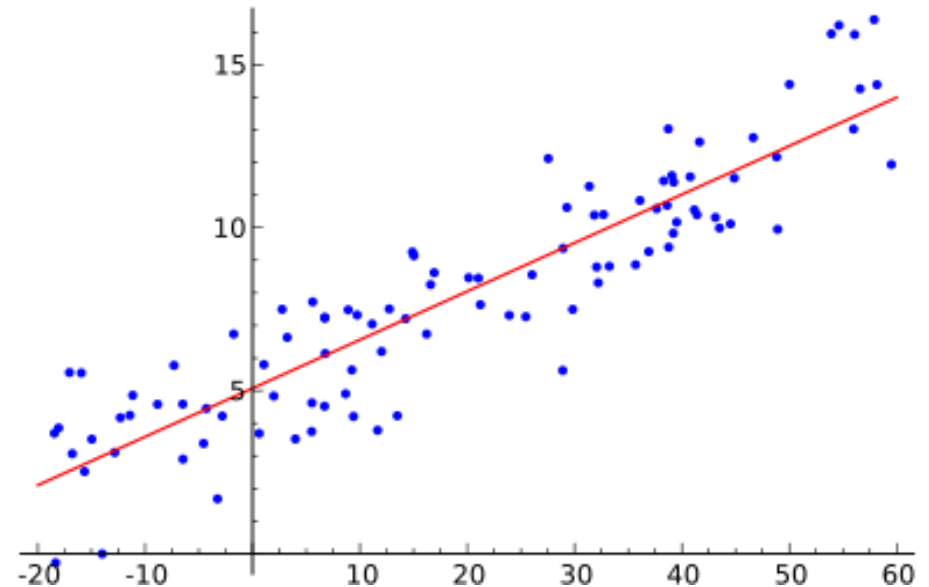
- **Goal:** Anticipate the nature of repairs to keep the service vehicles equipped with right parts to speed up repair time.
- **Approach:** Process the data on tools and parts required in previous repairs at different consumer locations and discover co-occurrence patterns.

Data Mining Tasks



Regression

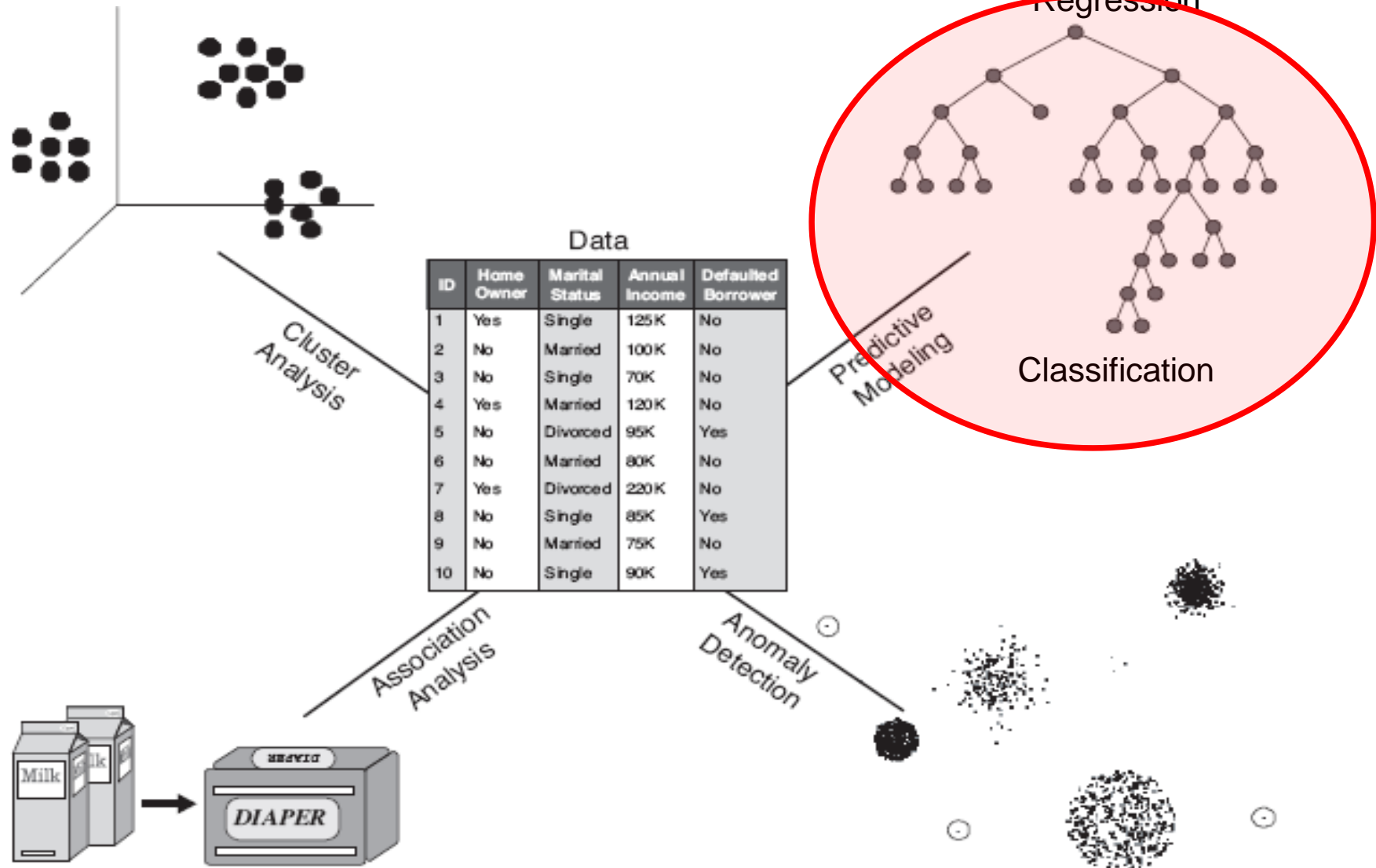
- Predict a value of a given continuous valued variable based on the values of other variables, assuming a linear or nonlinear model of dependency.
- Studied in statistics and econometrics.



Applications:

- Predicting sales amounts of new product based on advertising expenditure.
- Predicting wind velocities as a function of temperature, humidity, air pressure, etc.
- Time series prediction of stock market indices (autoregressive models).

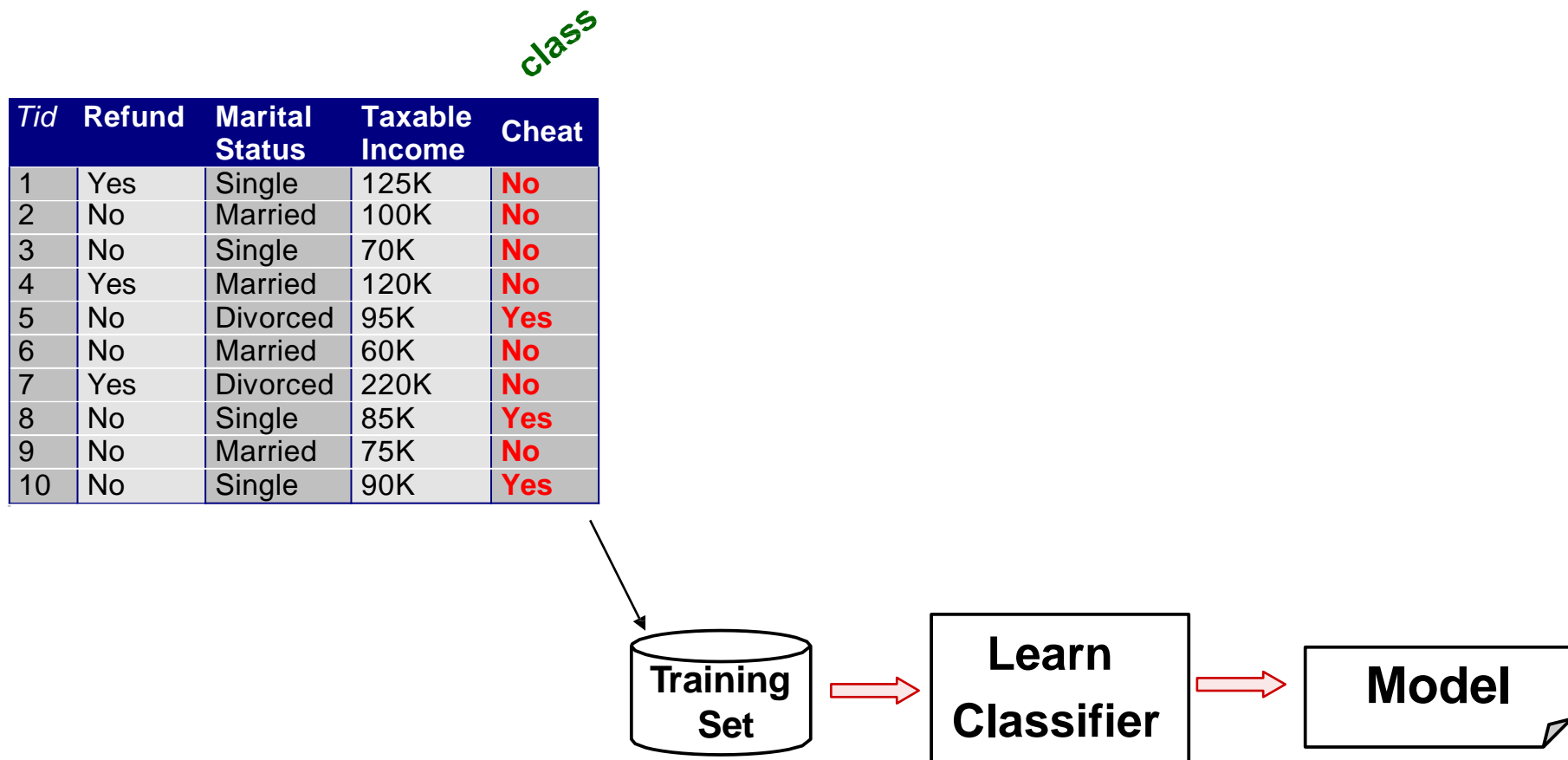
Data Mining Tasks



Classification

Find a **model** for the class attribute as a function of the values of other attributes/features.

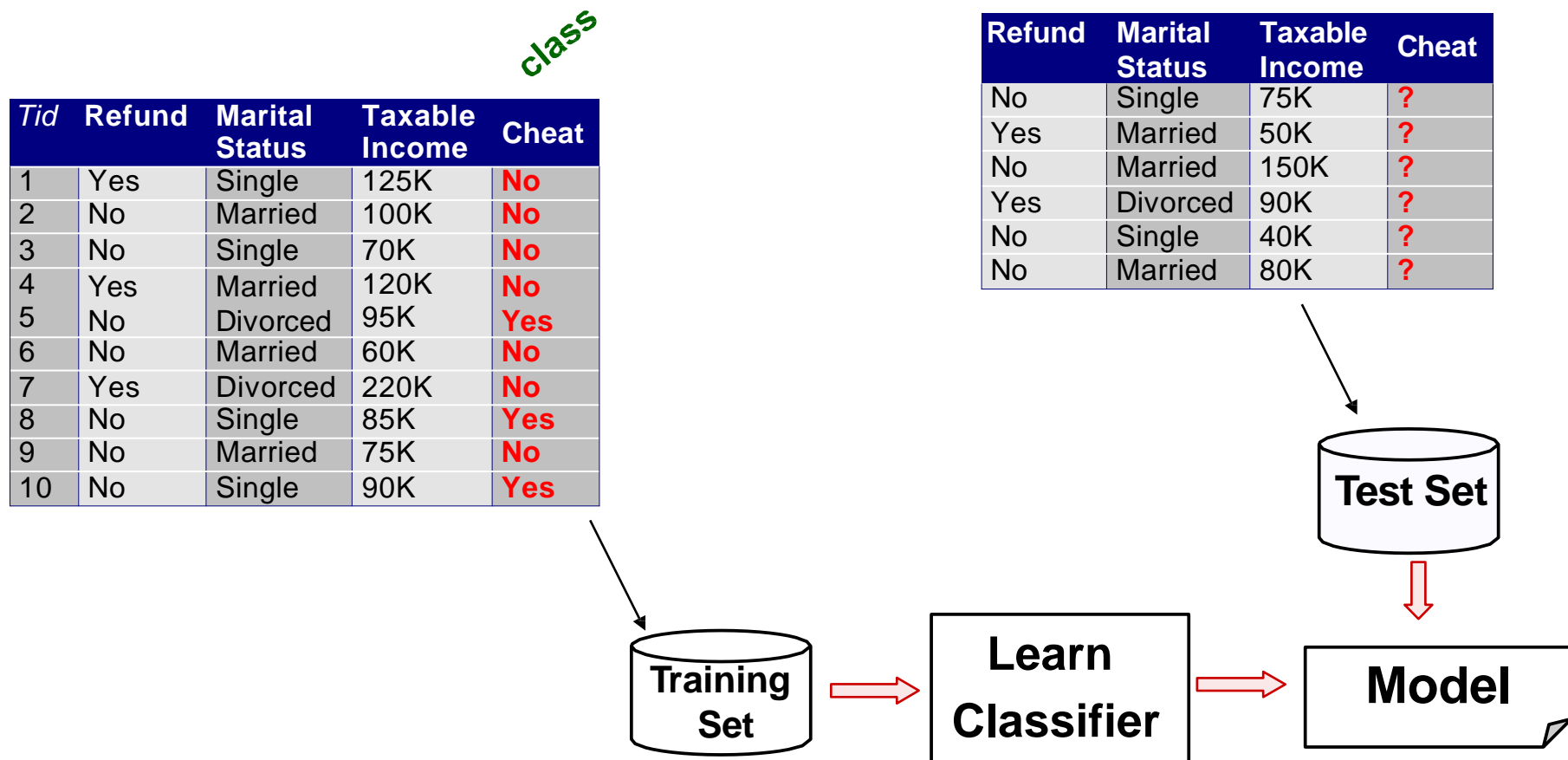
Class information is available → **Supervised Learning**

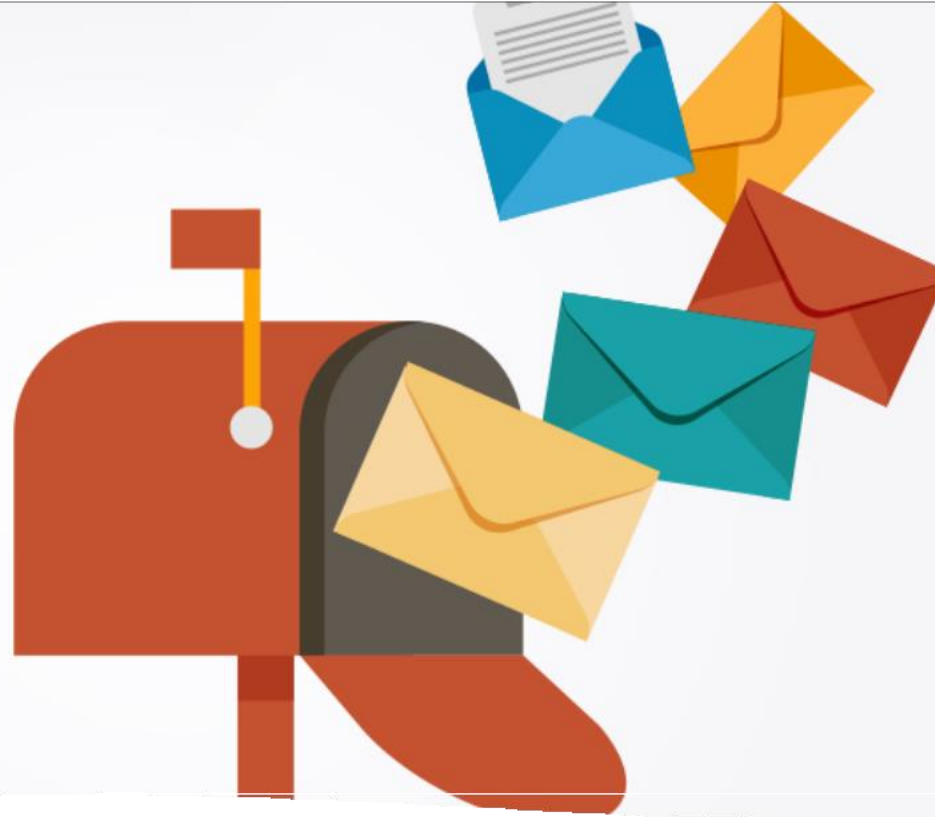


Classification

Find a **model** for the class attribute as a function of the values of other attributes/features.

Goal: assign new records to a class as accurately as possible.





Classification: Direct Marketing

- Goal: Reduce cost of mailing by targeting a set of consumers likely to buy a new product.
- Approach:
 - Use the data for a similar product introduced before or from a focus group. We have customer information (e.g., demographics, lifestyle, previous purchases) and know which customers decided to buy and which decided otherwise. This buy/don't buy decision forms the class attribute.
 - Use this information as input attributes to learn a classifier model.
 - Apply the model to new customers to predict if they will buy the product.

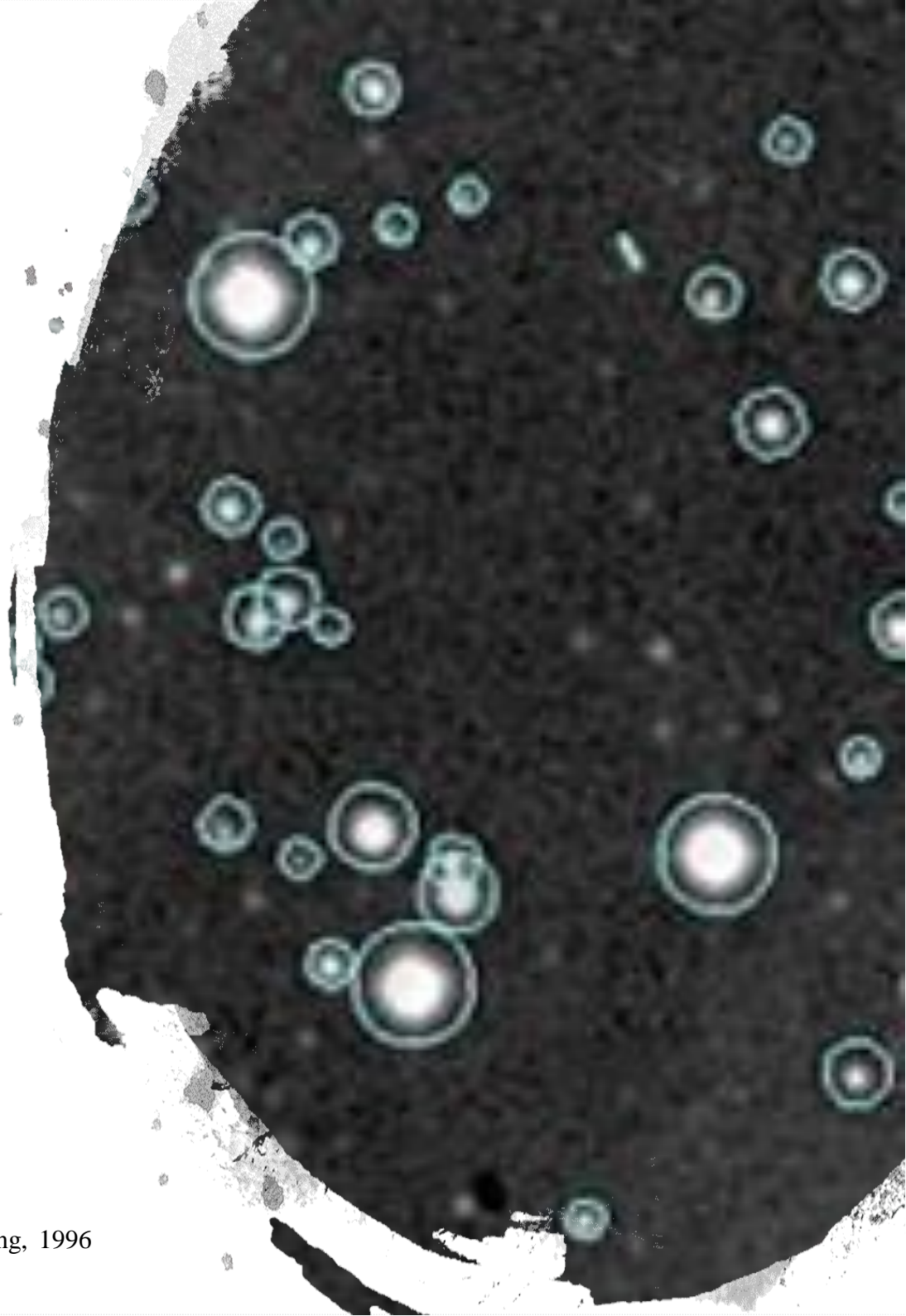


Classification: Customer Attrition/Churn

- Goal: To predict whether a customer is likely to be lost to a competitor.
- Approach:
 - Use detailed record of transactions with each of the past and present customers, to find attributes (frequency, recency, complaints, demographics, etc.).
 - Label the customers as loyal or disloyal.
 - Find a model for disloyalty.
 - Rank each customer on a loyal/disloyal scale (e.g., churn probability).

Classification: Sky Survey Cataloging

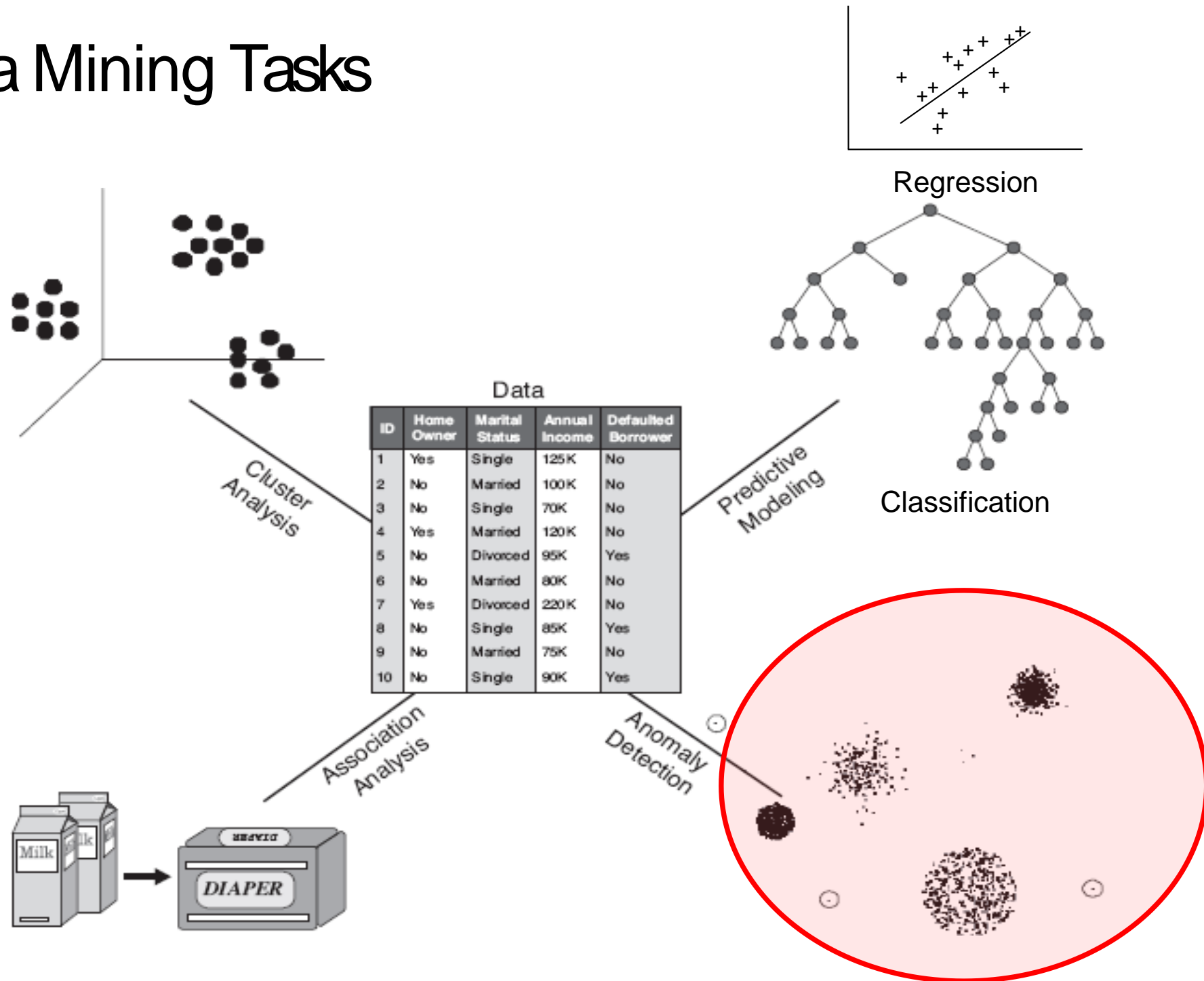
- Goal: To predict class (star or galaxy) of sky objects, especially visually faint ones, based on the telescopic survey images (from Palomar Observatory).
- Approach:
 - Segment the image to identify objects.
 - Derive features per object (40).
 - Use known objects to model the class based on these features.
- Result: Found 16 new high red-shift quasars.



Classification vs



Data Mining Tasks



Deviation/Anomaly Detection

- Detect significant deviations from normal behavior.

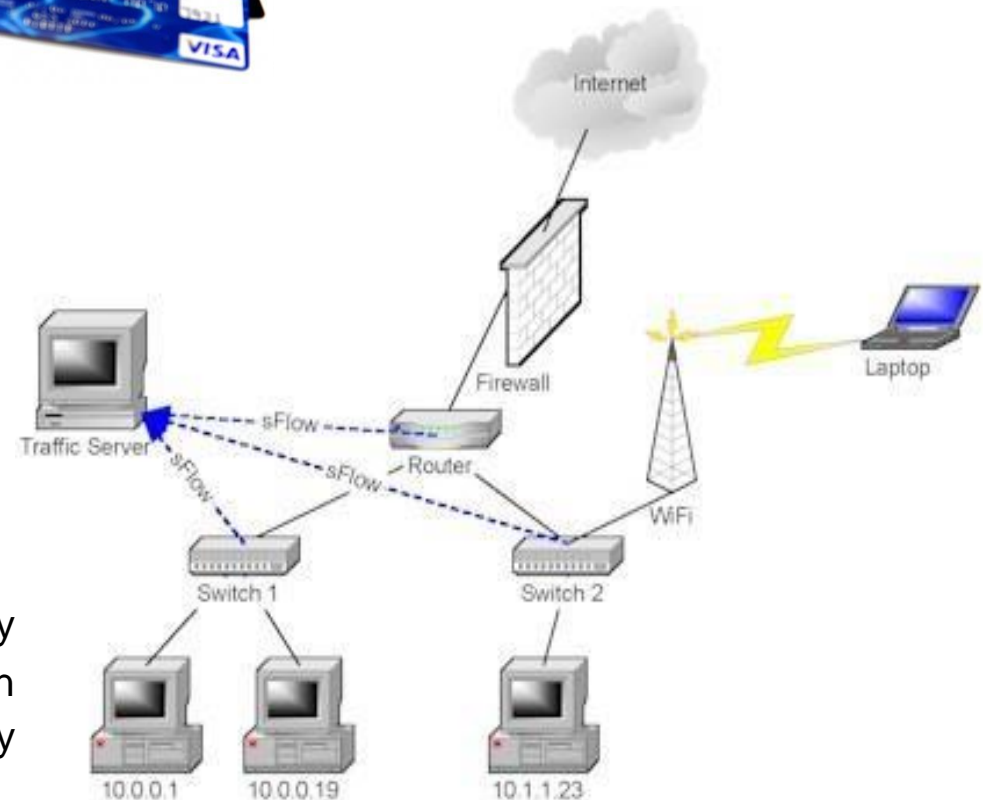
- Applications:

- Credit Card Fraud Detection



- Network Intrusion Detection

Typical network traffic at University level may reach over 100 million connections per day



Other Data Mining Tasks

Text mining –
document
clustering, topic
models

Graph mining –
social networks

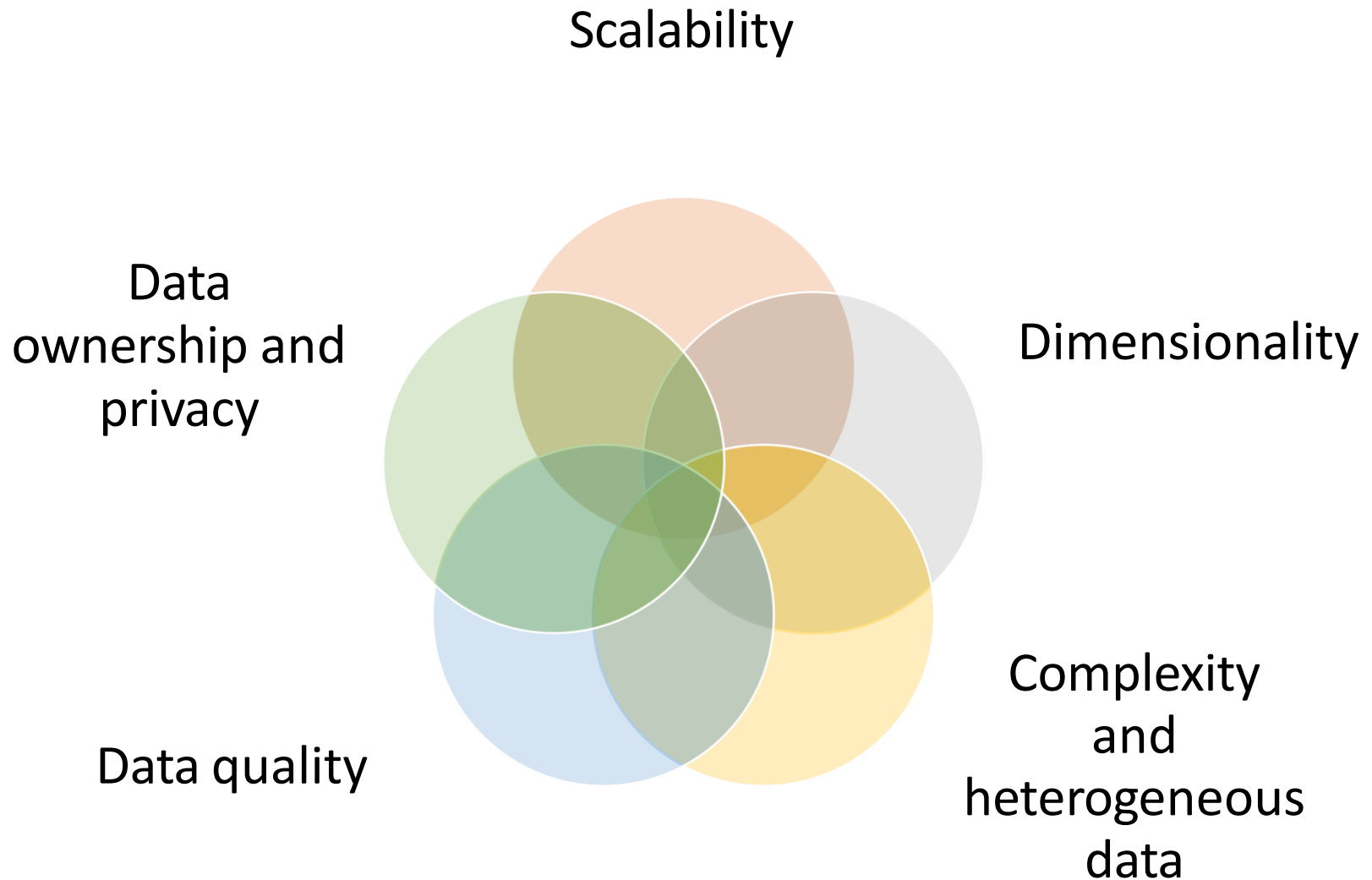
Data stream
mining/real time
data mining

Mining
spatiotemporal
data (e.g., moving
objects)

Visual data mining

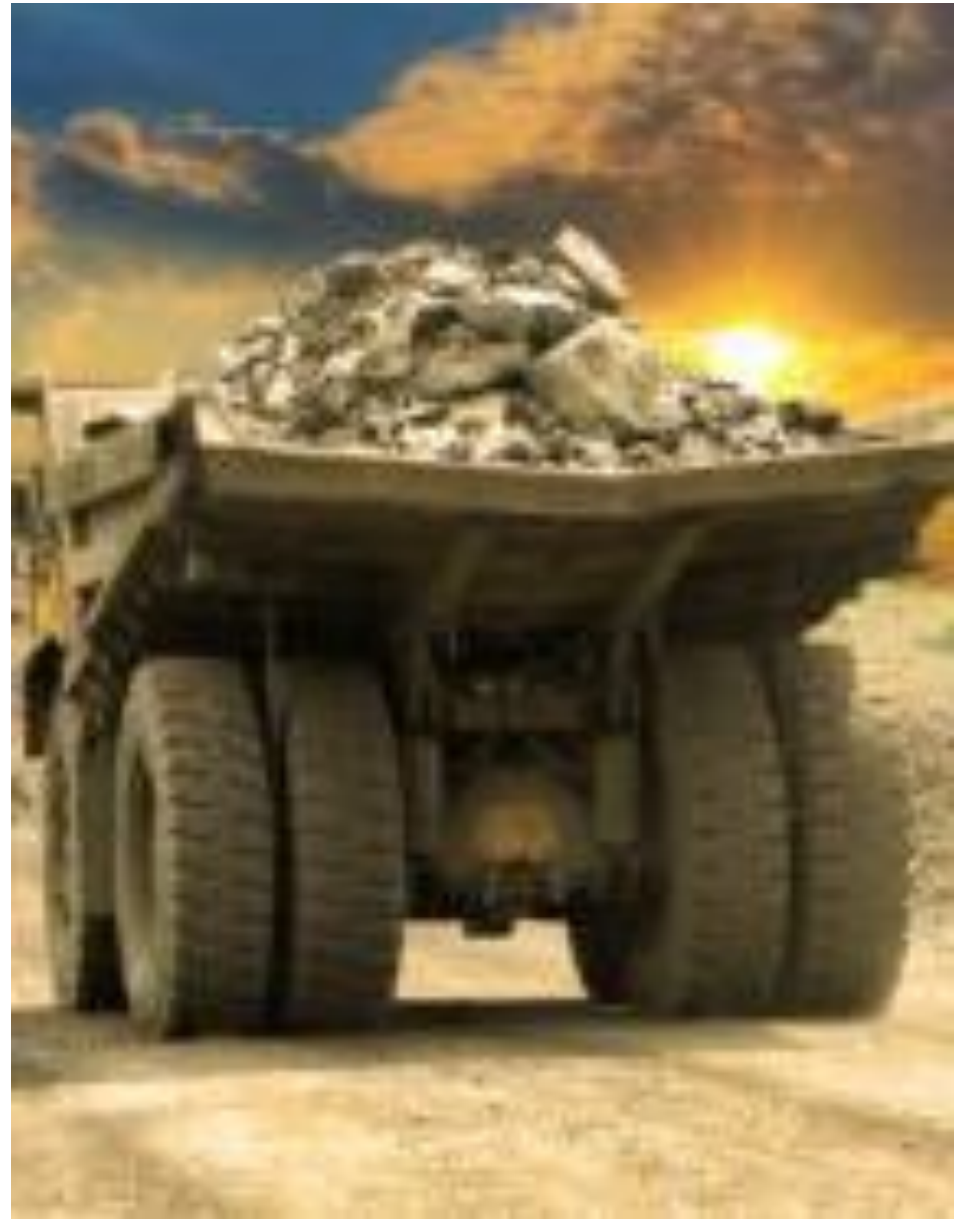
Distributed data
mining

Challenges of Data Mining



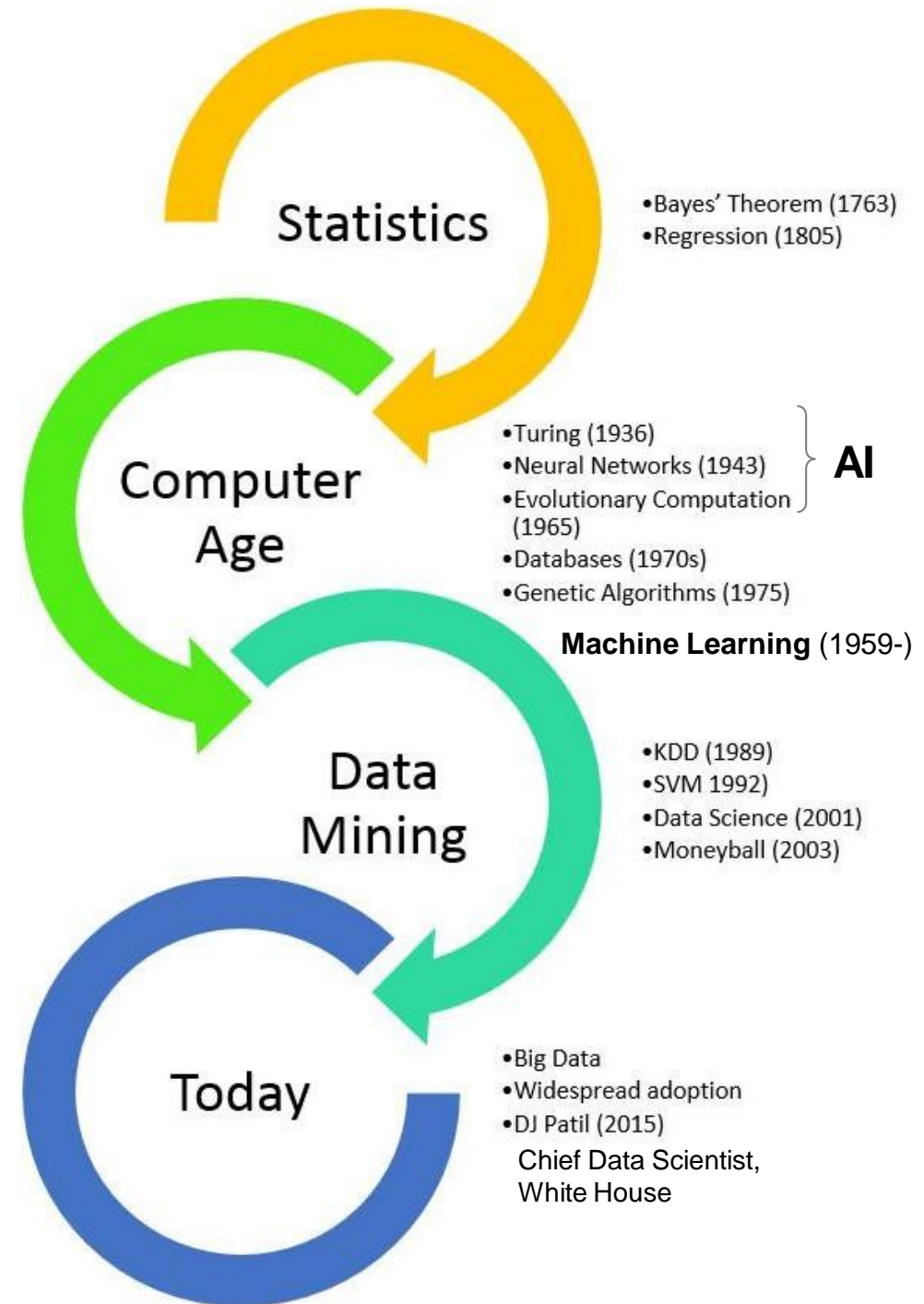
Agenda

- What is Data Mining?
- Data Mining Tasks
- **Relationship to Statistics, Optimization, Machine Learning and AI**
- Tools
- Data
- Legal, Privacy and Security Issues

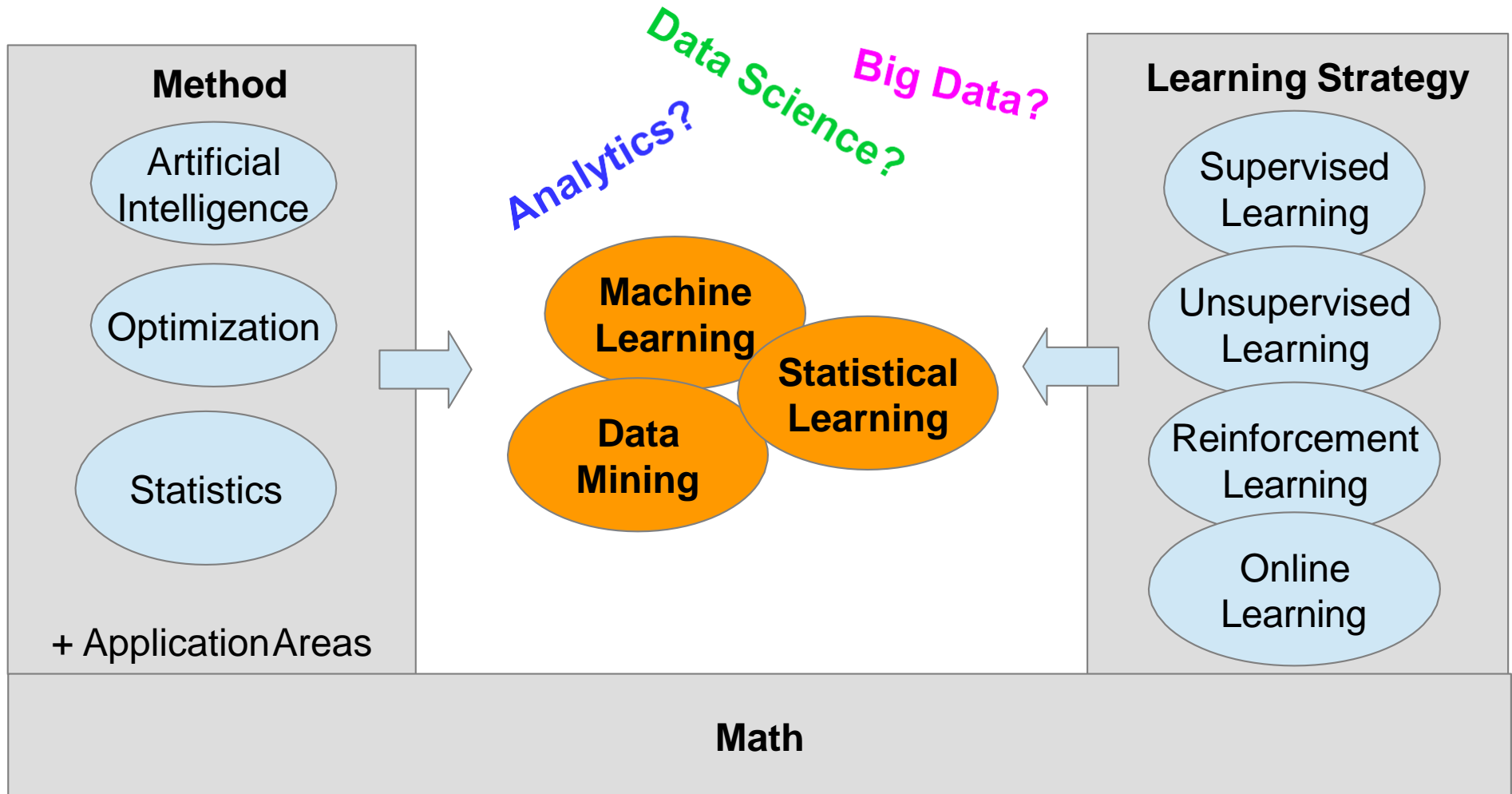


Origins of Data Mining

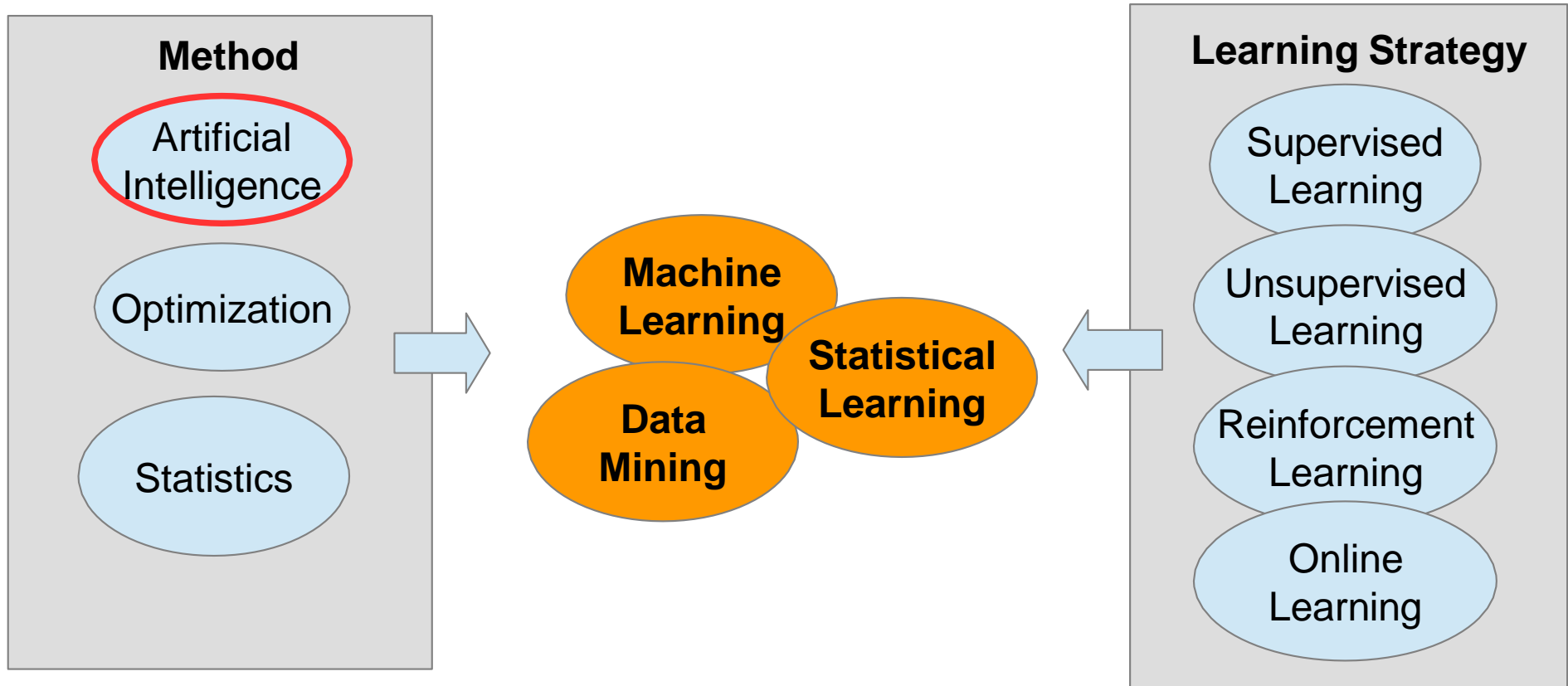
- Draws ideas from AI, machine learning, pattern recognition, statistics, and database systems.
- There are differences in terms of
 - used data and
 - the goals.



Relationship to other Fields



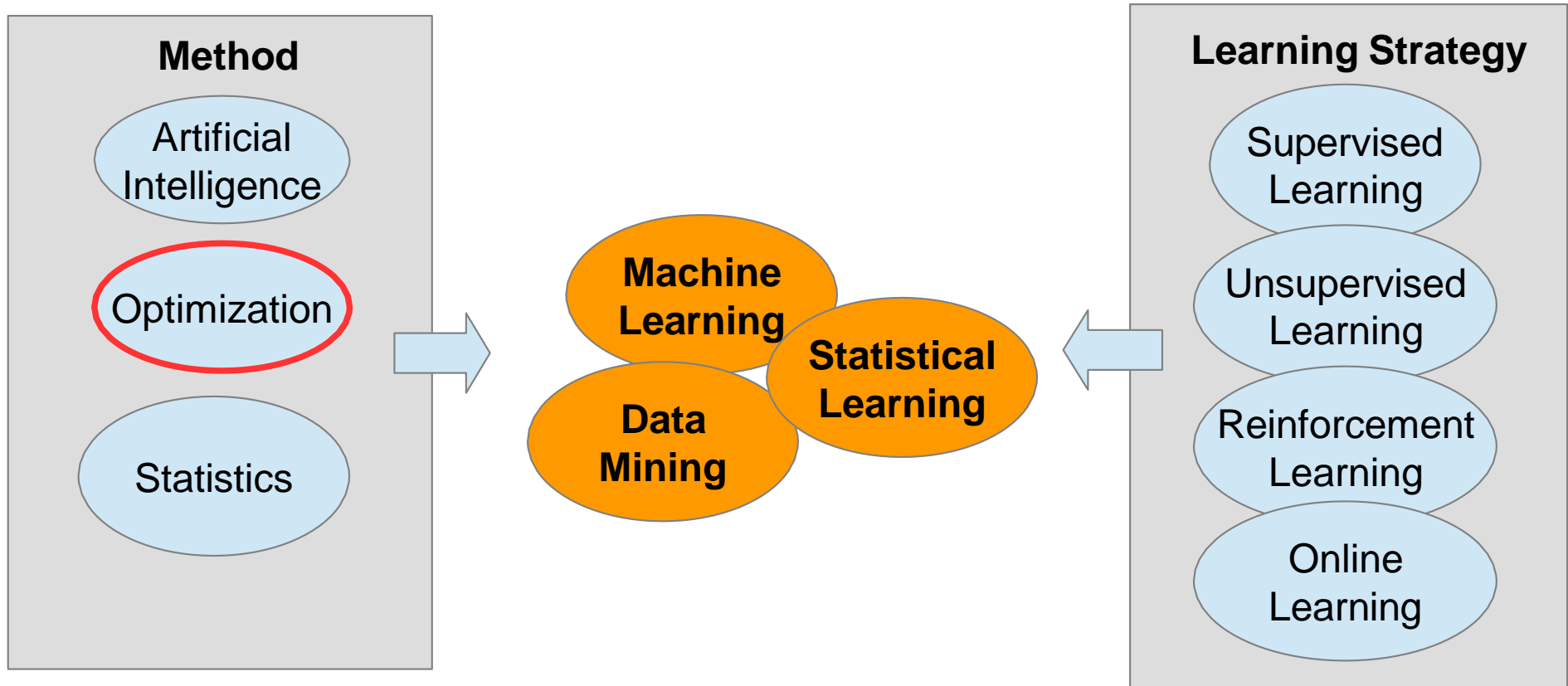
Relationship to other Fields



Artificial Intelligence: Create an **autonomous agent** that perceives its environment and takes actions that maximize its chance of reaching some goal.

Areas: reasoning, knowledge representation, planning, learning, natural language processing, and vision.

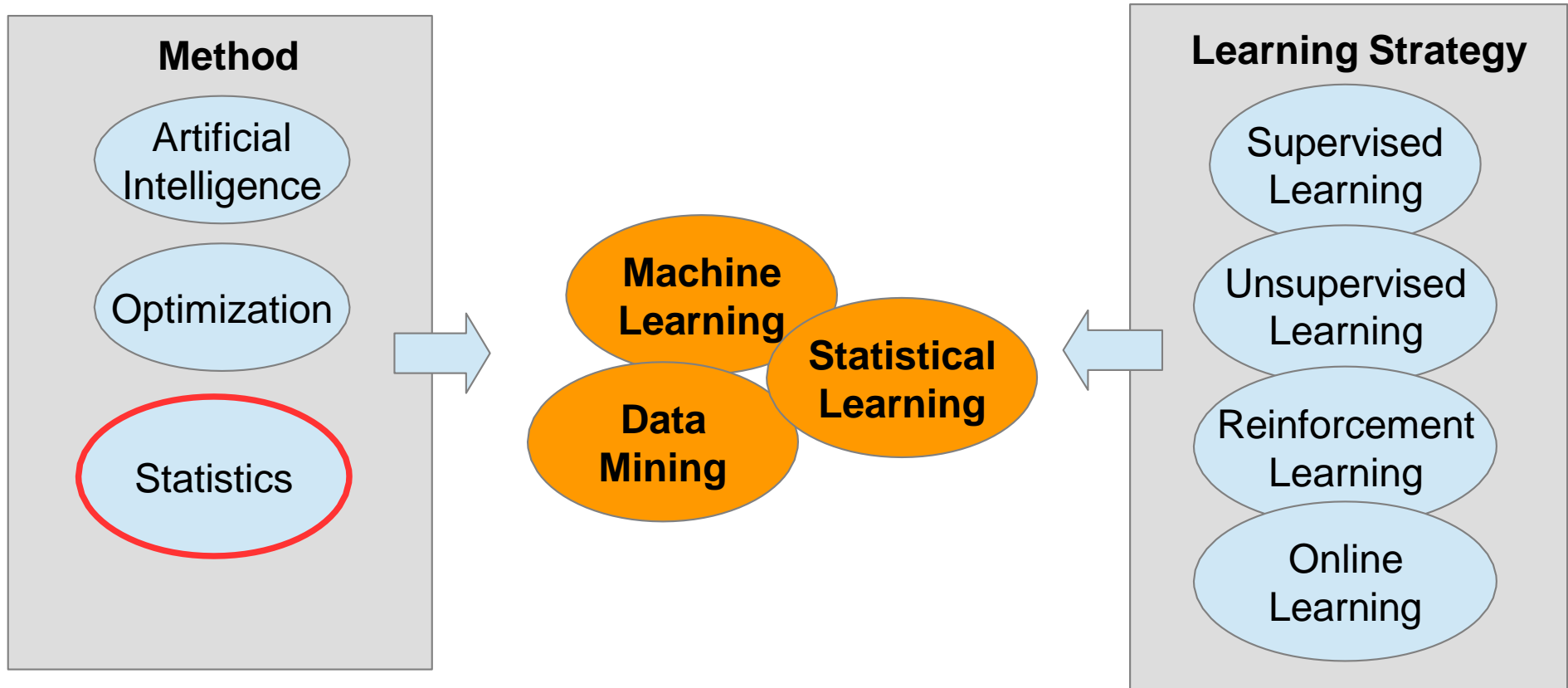
Relationship to other Fields



Optimization: Selection of a best alternative from some set of available alternatives with regard to some criterion.

Techniques: Linear programming, integer programming, nonlinear programming, stochastic and robust optimization, heuristics, etc.

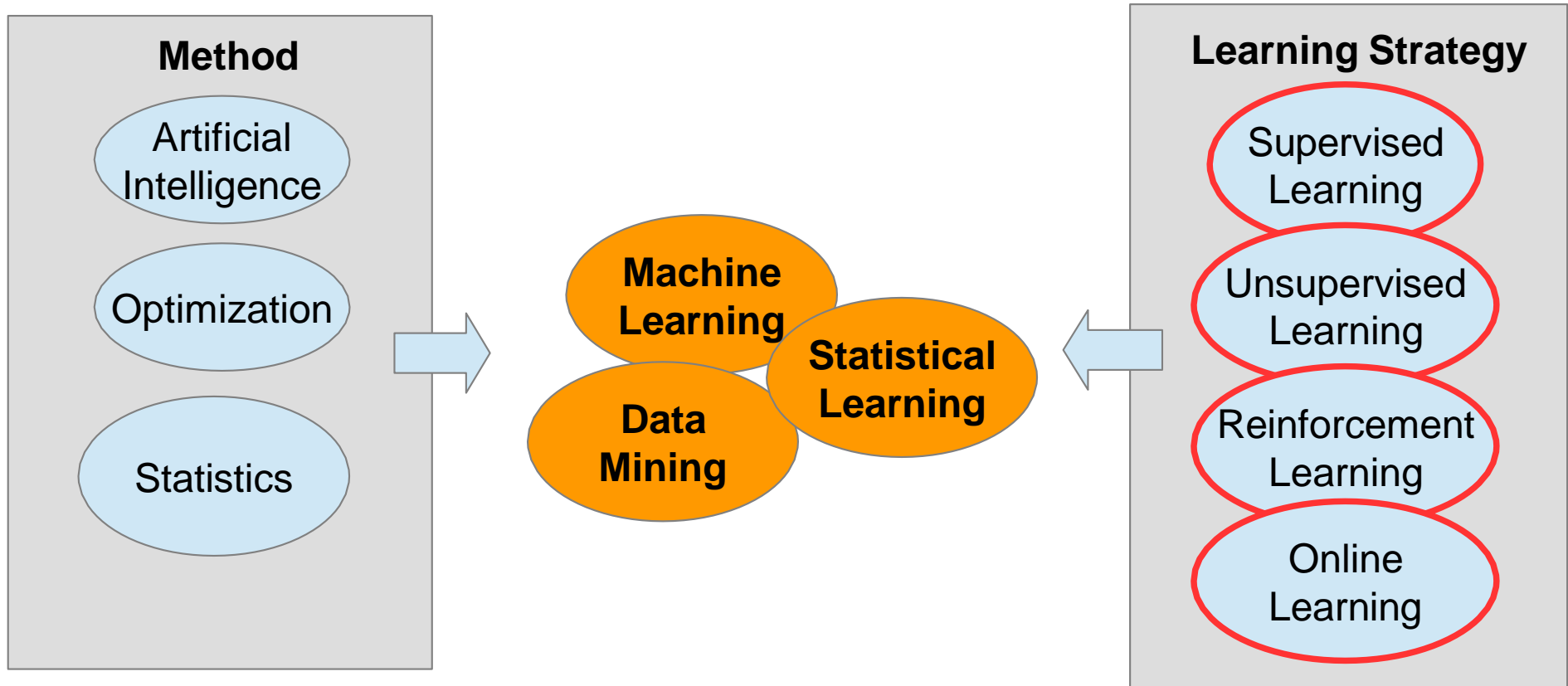
Relationship to other Fields



Statistics: Study of the collection, analysis, interpretation, presentation, and organization of data.

Techniques: Descriptive statistics, statistical inference (estimation, testing), design of experiments.

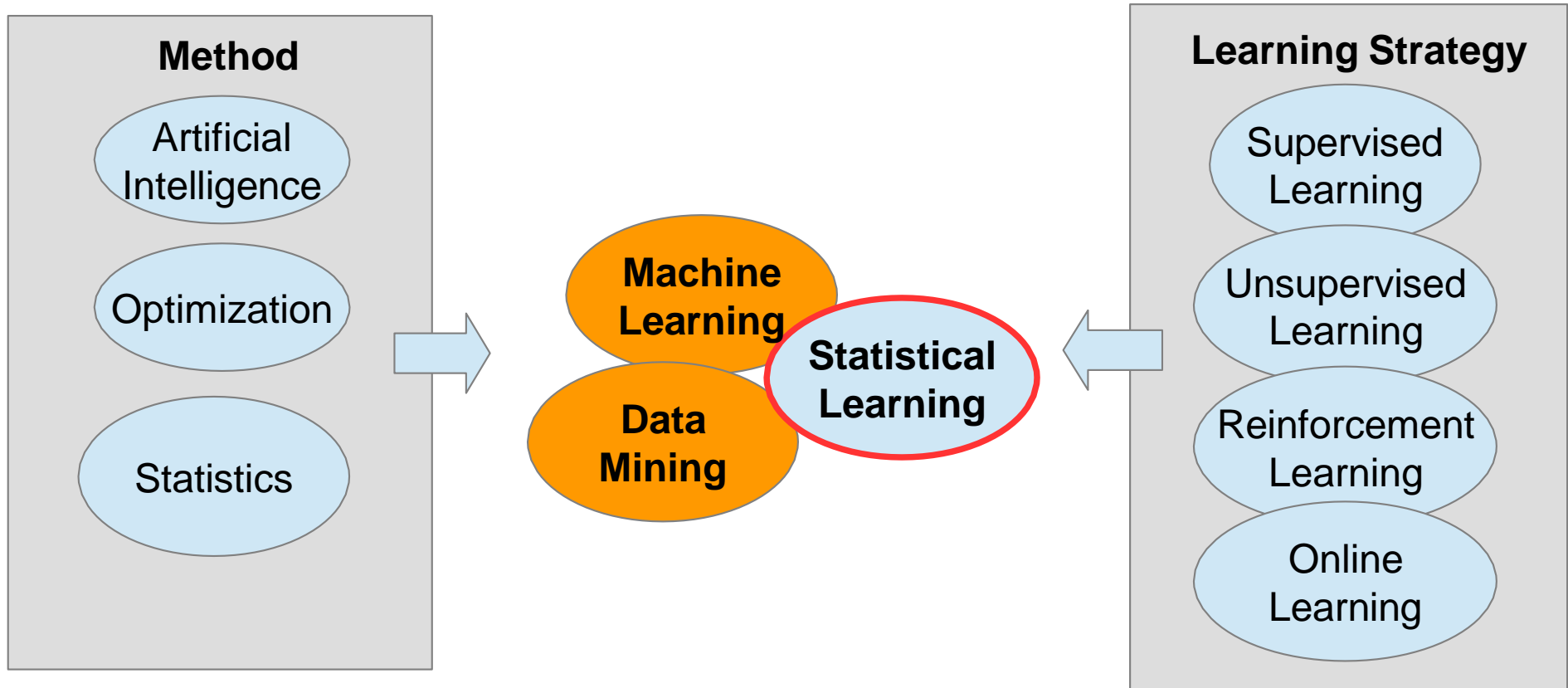
Relationship to other Fields



Learning Strategy: From what data do we learn?

- ★ Is a training set with correct answers available? → Supervised learning
- ★ Long-term structure of rewards? → Reinforcement learning
- ★ No answer and no reward structure? → Unsupervised learning
- ★ Do we have to update the model regularly? → Online learning

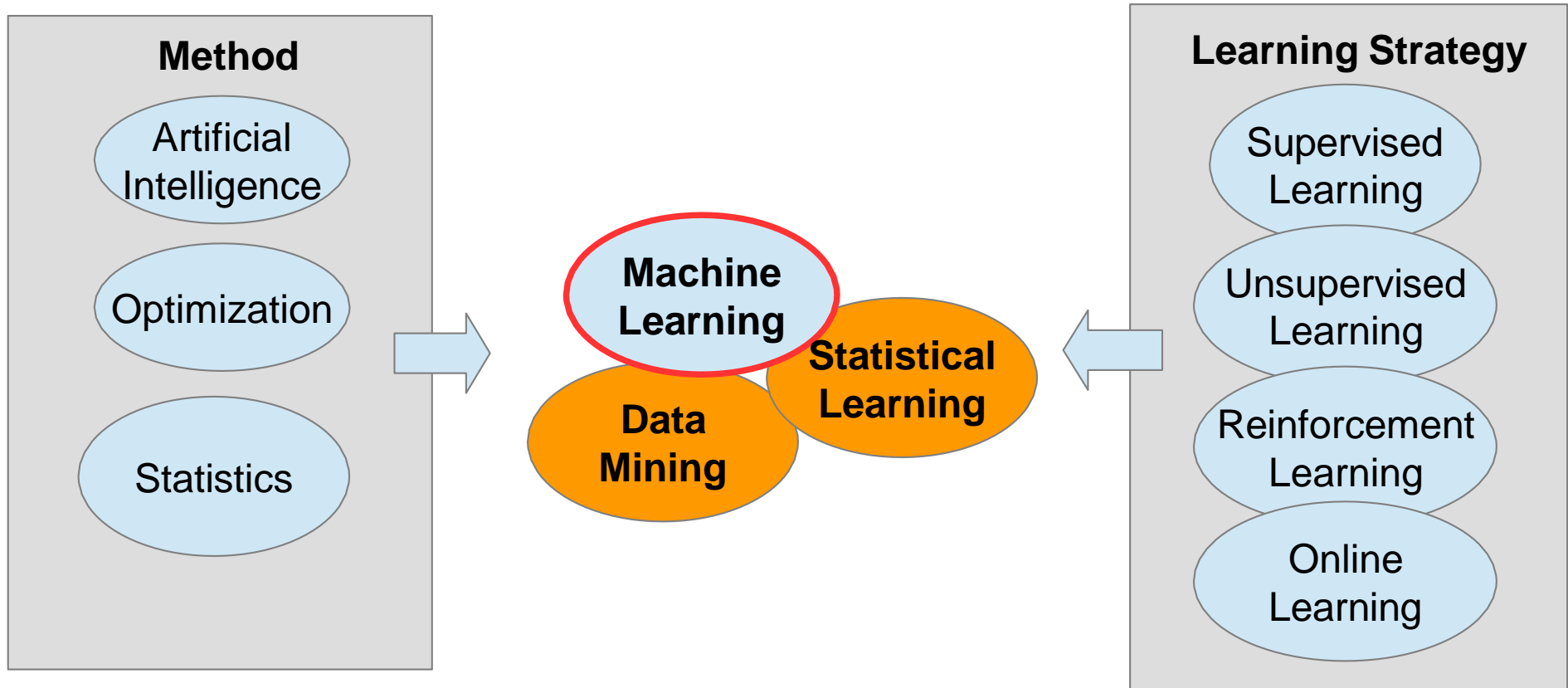
Relationship to other Fields



Statistical learning: deals with the problem of finding a **predictive function** based on data.

Tools: (Linear) classifiers, regression and regularization.

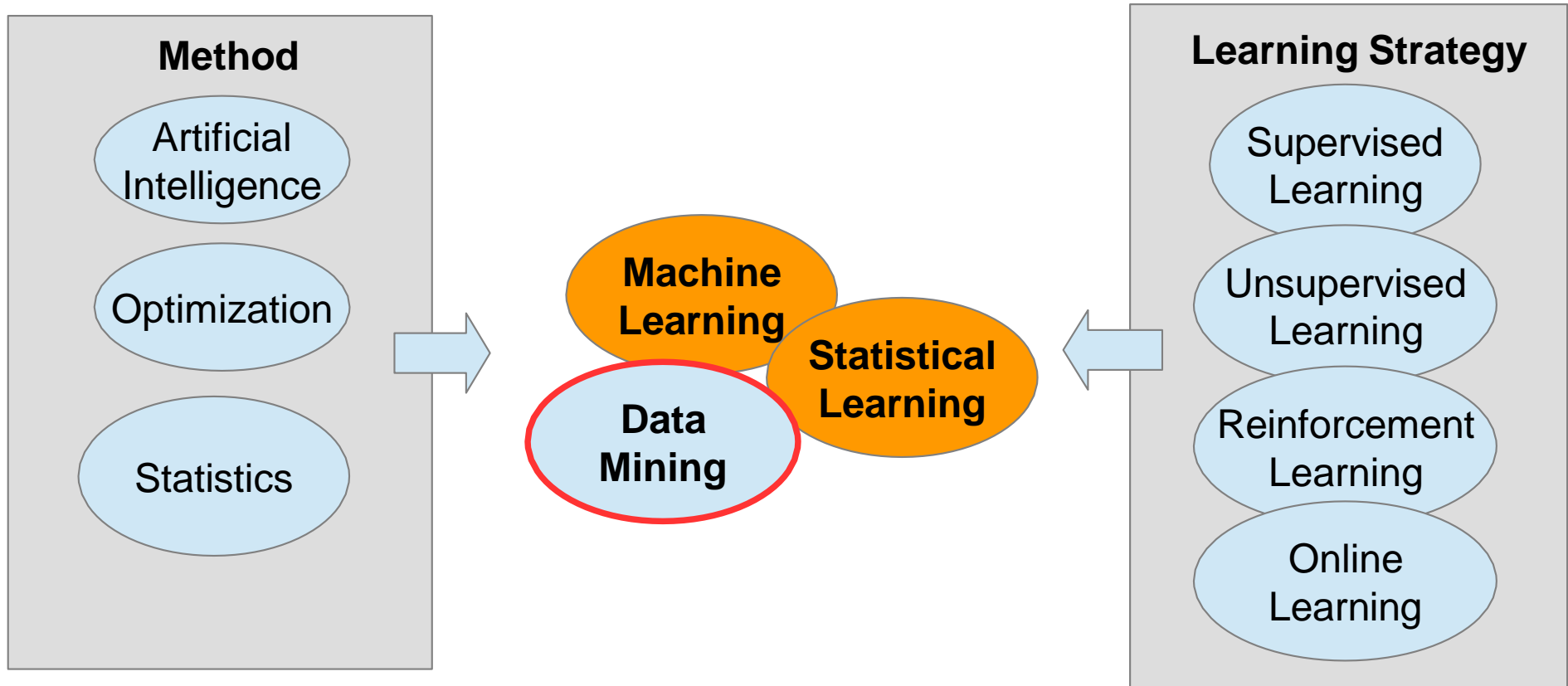
Relationship to other Fields



Machine Learning involves the study of algorithms that can extract information **automatically**, i.e., without on-line human guidance.

Techniques: Focus on supervised learning.

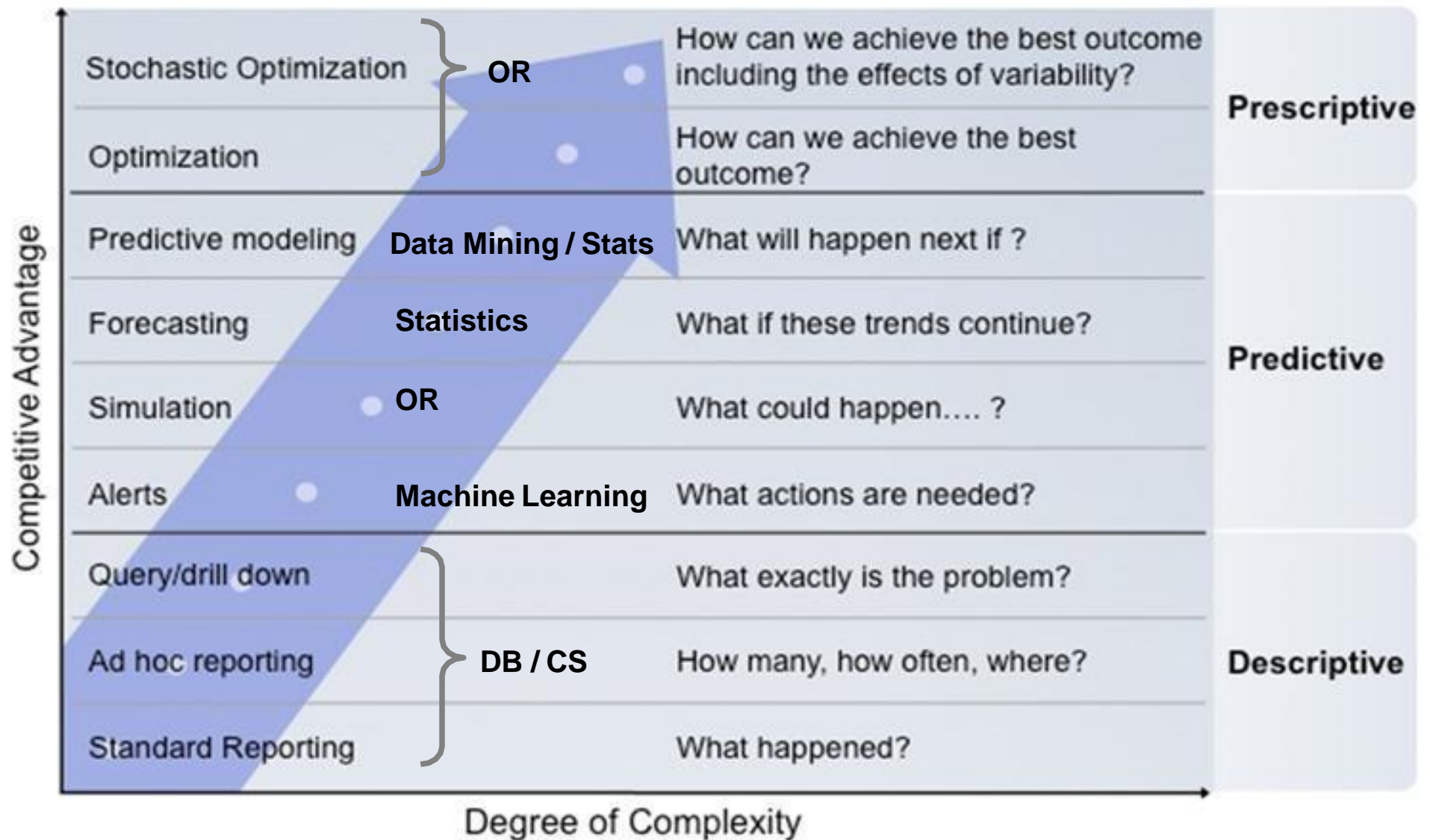
Relationship to other Fields



Data Mining: Manually analyze a given dataset to gain insights and predict potential outcomes.

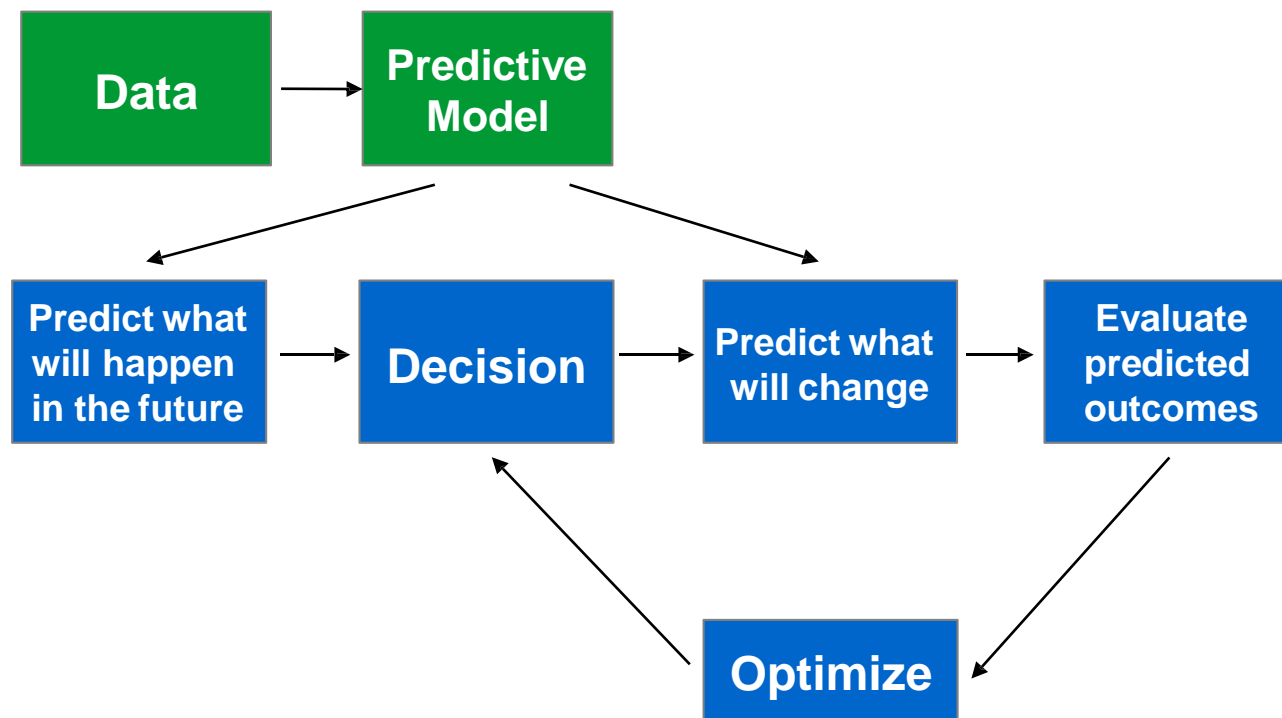
Techniques: Any applicable technique from databases, statistics, machine/statistical learning. New methods were developed by the Data Mining community.

Data Mining & Analytics



Prescriptive Analytics

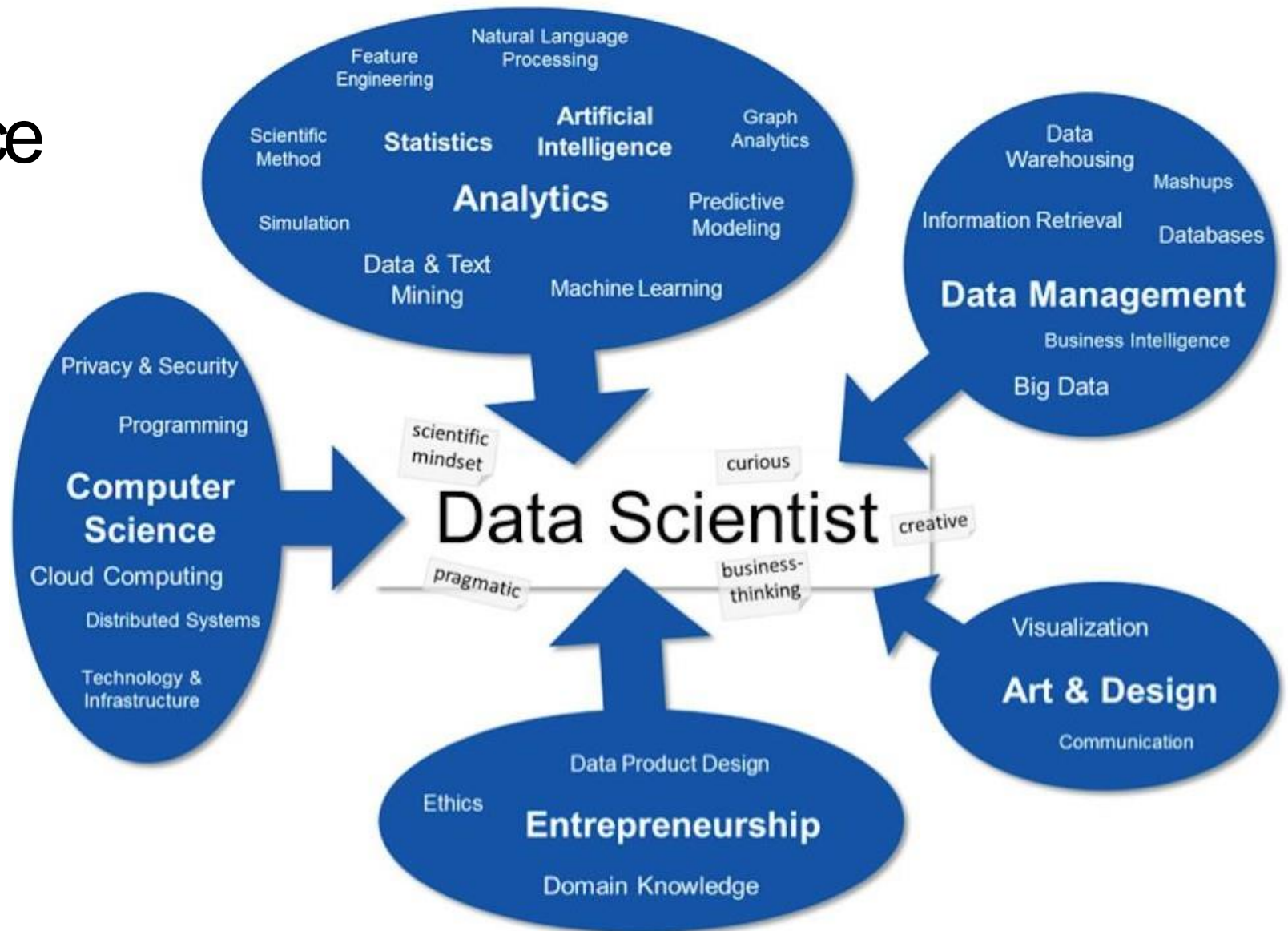
What decisions should we make now to achieve the best future outcome?



Issues:

- What are the decision variables? Causality?
- Relationship can be non-linear. Convex?
- Uncertainty about quality and reliability of the predictive model.

Data Science

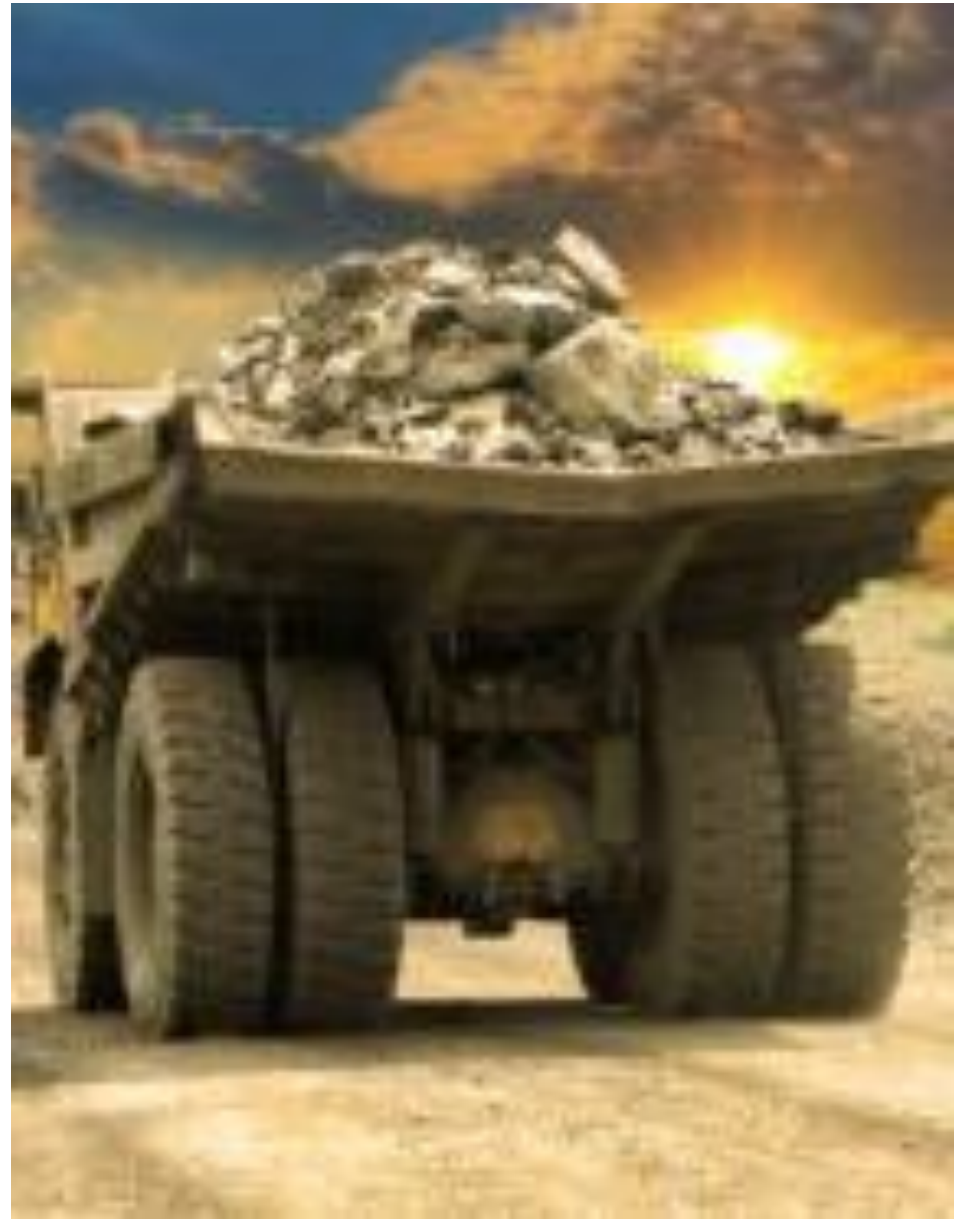


Source: T. Stadelmann, et al., Applied Data Science in Europe

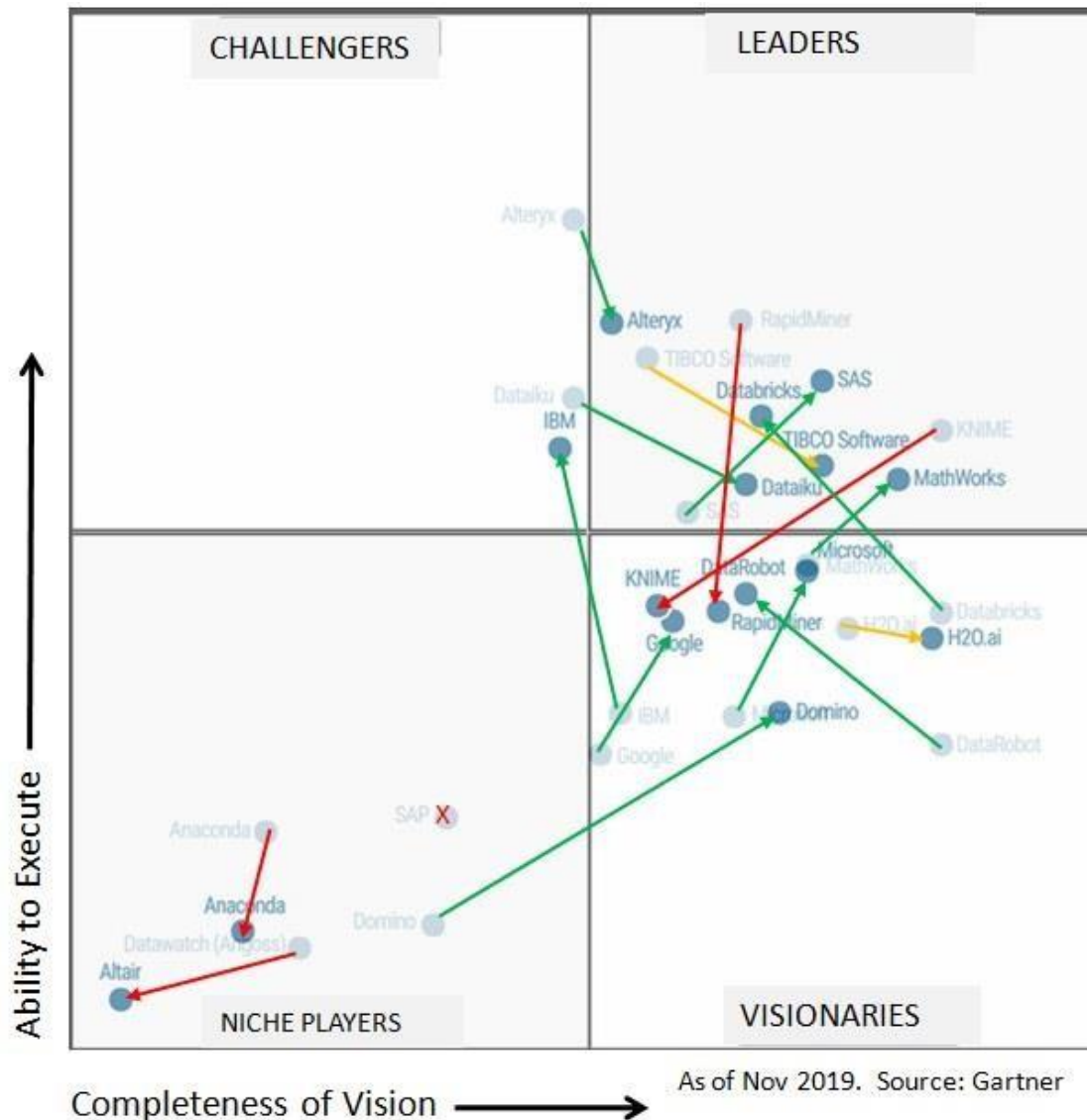
Good luck finding this person!
Probably a team effort!

Agenda

- What is Data Mining?
- Data Mining Tasks
- Relationship to Statistics, Optimization, Machine Learning and AI
- **Tools**
- Data
- Legal, Privacy and Security Issues



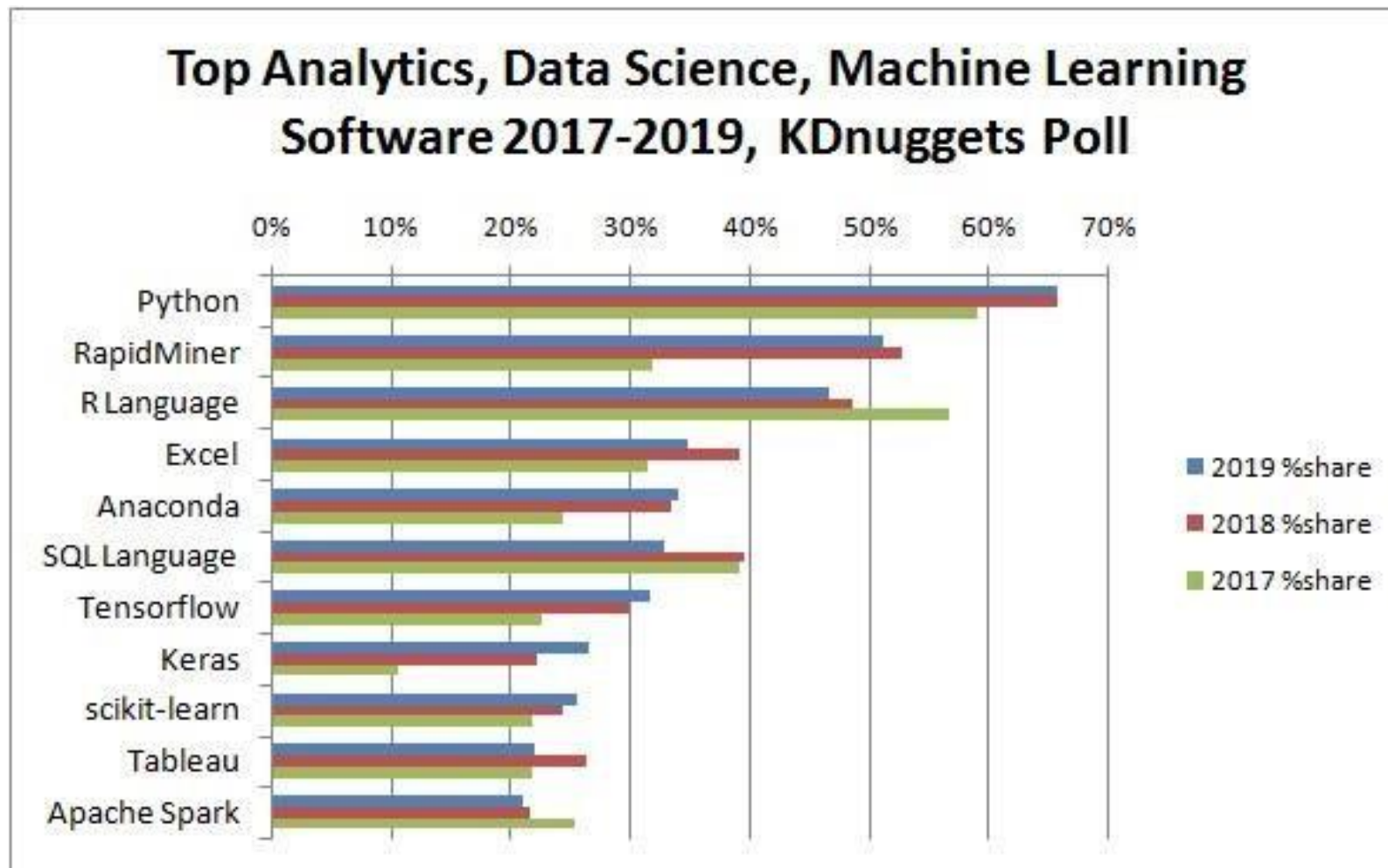
Tools: Commercial Players



Gartner®

Gartner MQ for Data Science and Machine Learning Platforms, 2020 vs 2019 changes.

Tools: Popularity



<https://www.kdnuggets.com/polls/>

Tools: Types

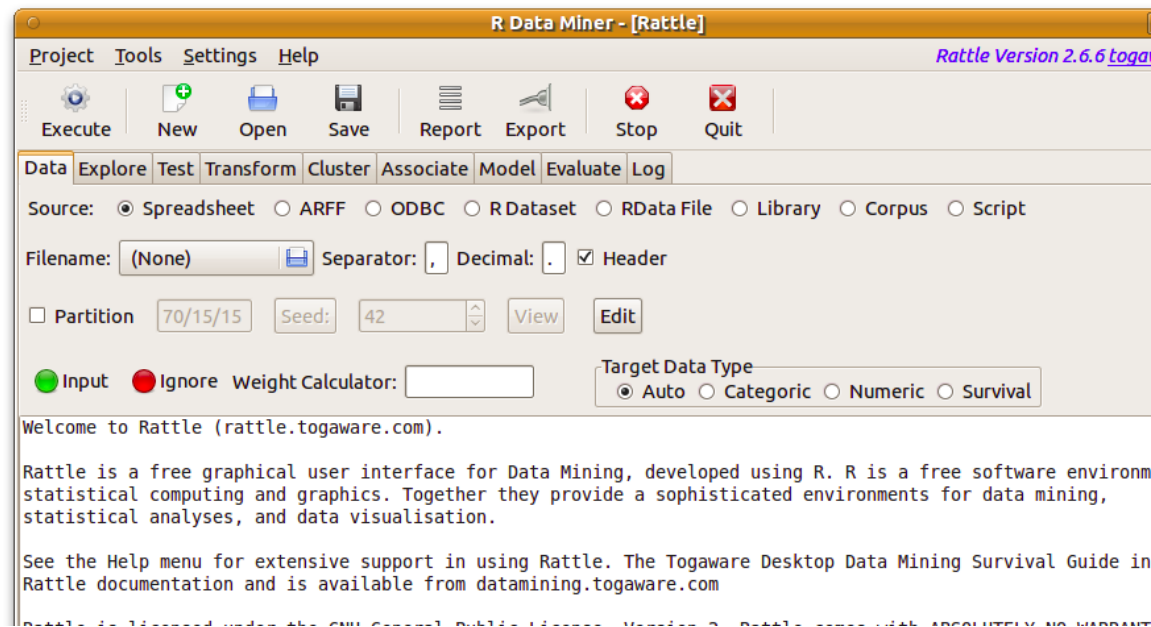
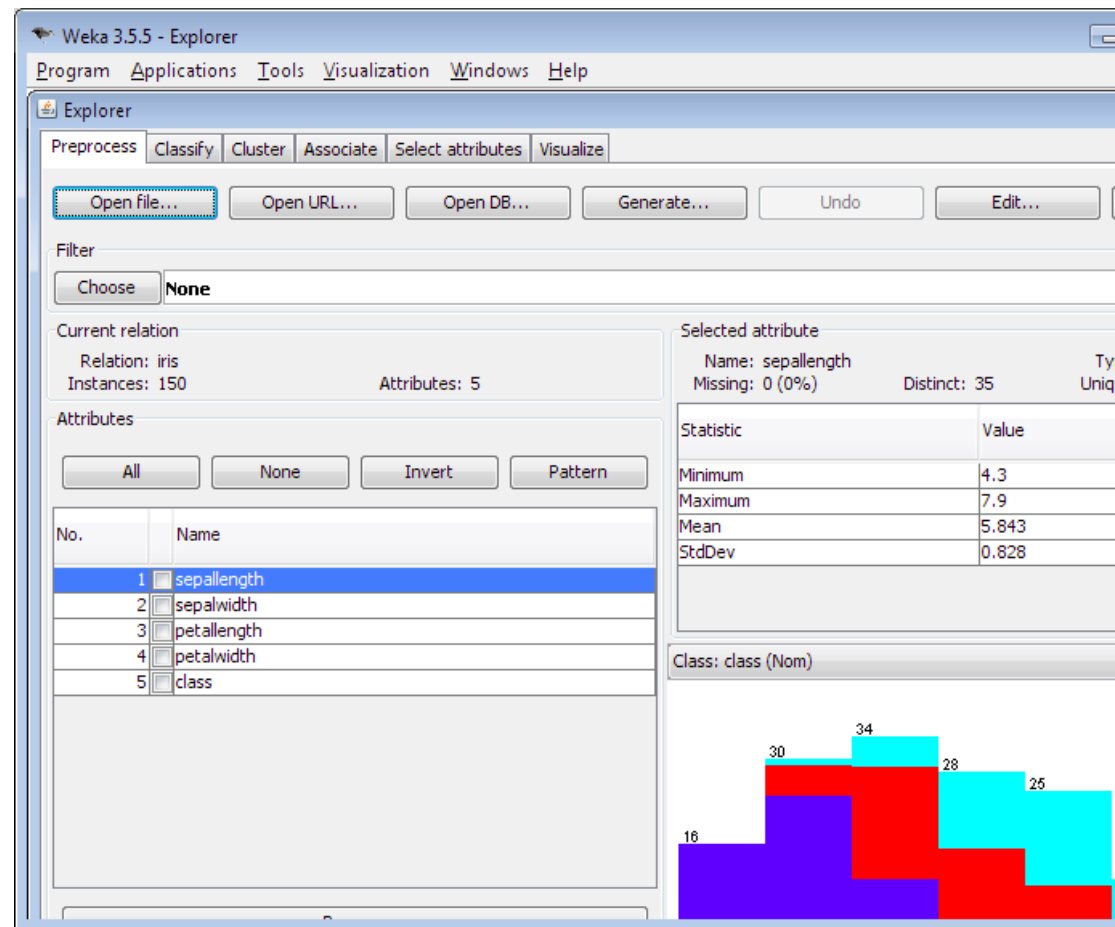
Simple
graphical user
interface

Process
oriented

Programming
oriented

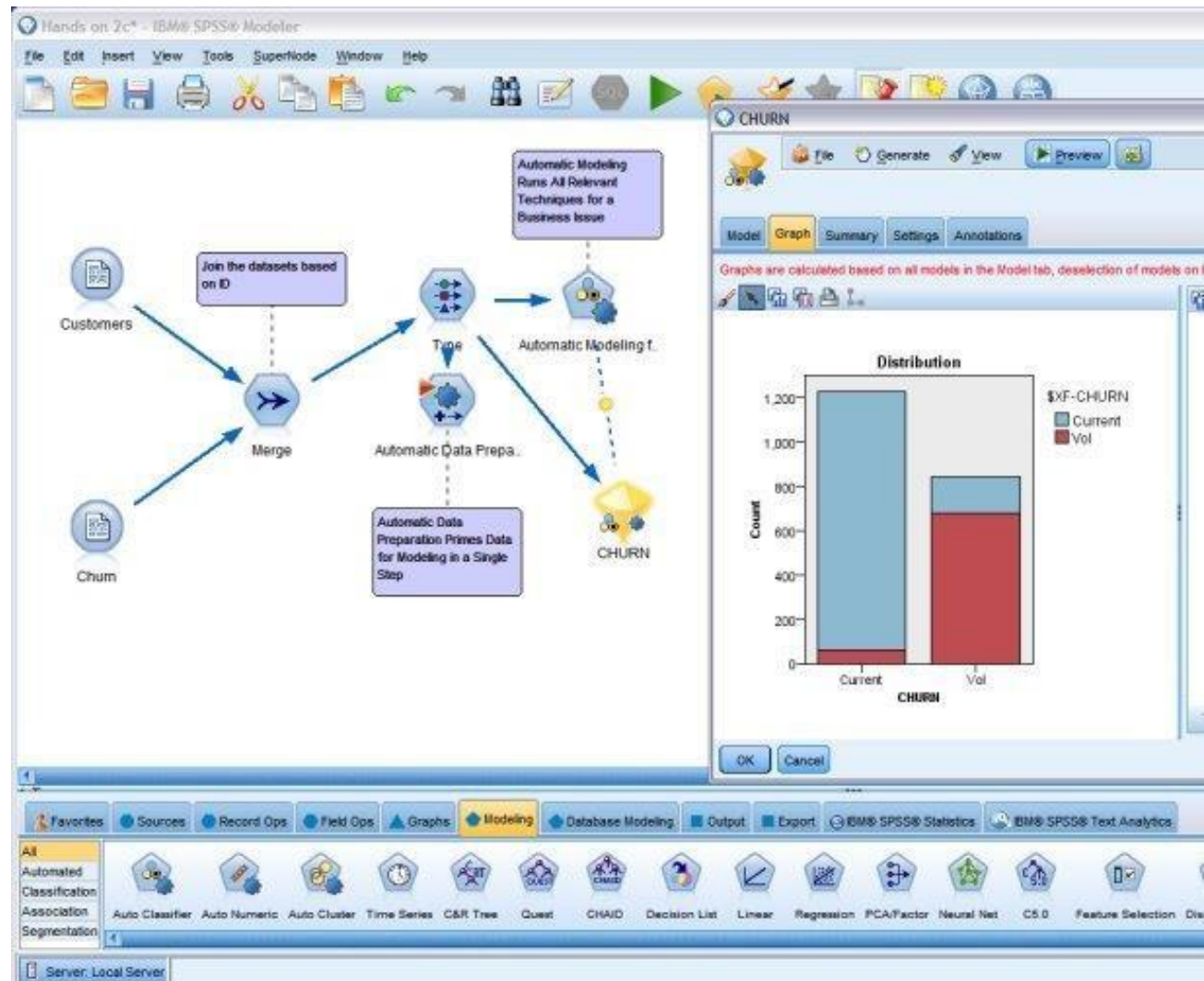
Tools: Simple GUI

- Weka: Waikato Environment for Knowledge Analysis (Java API)
- Rattle: GUI for Data Mining using R



Tools: Process oriented

- SAS Enterprise Miner
- IBM SPSS Modeler
- RapidMiner
- Knime
- Orange



Tools: Programming oriented

■ R

- Rattle for beginners
- RStudio IDE, markdown, shiny
- Microsoft Open R



■ Python

- Numpy, scikit-learn, pandas
- Jupyter notebook

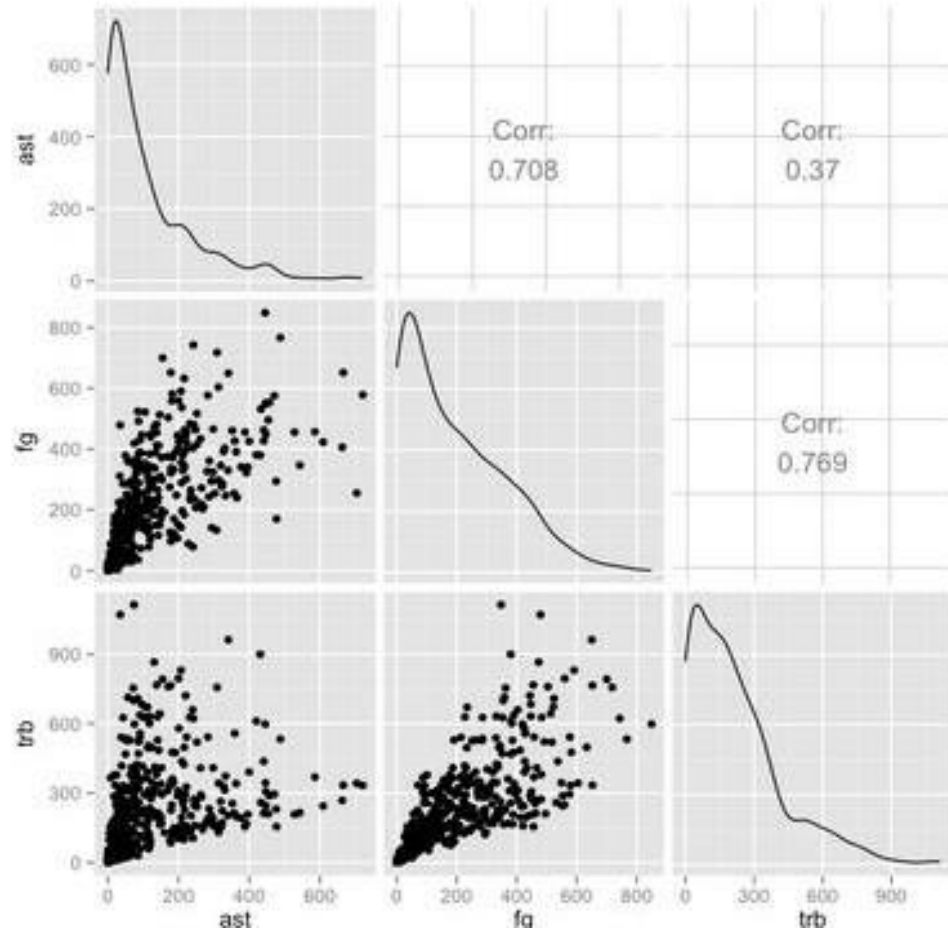


→ Both have similar capabilities. Slightly different focus:

- R: statistical computing and visualization
- Python: Scripting, big data
- Interoperability via rpy2 and rediculate

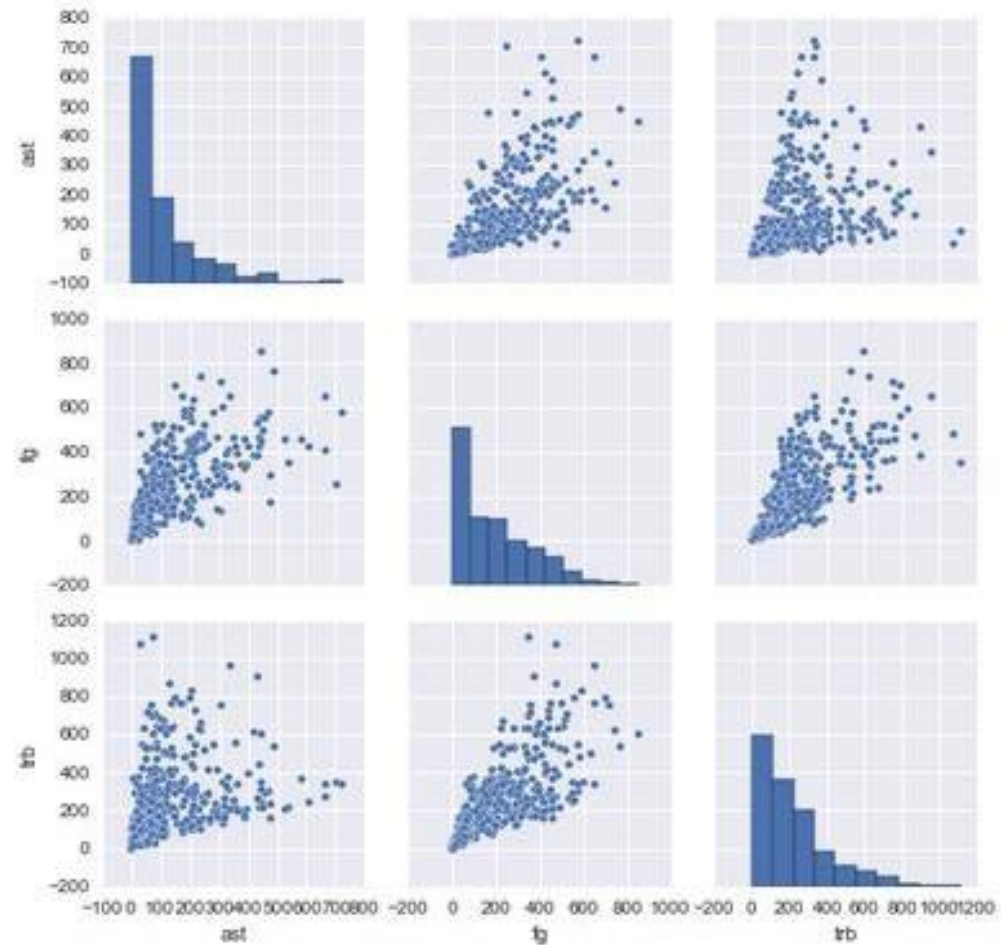
R

```
library(GGally)
ggpairs(nba[,c("ast", "fg", "trb")])
```



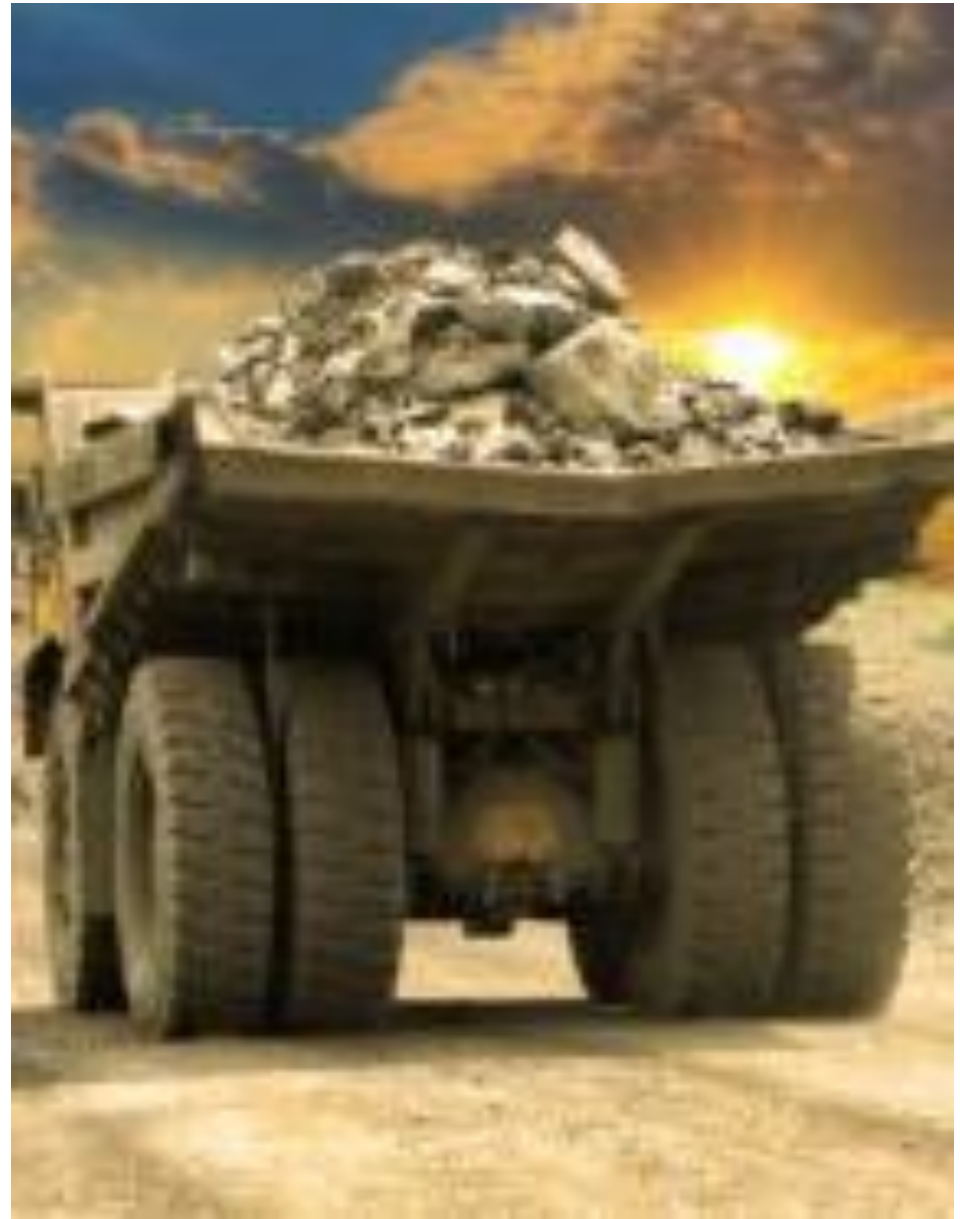
Python

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.pairplot(nba[["ast", "fg", "trb"]])
plt.show()
```



Agenda

- What is Data Mining?
- Data Mining Tasks
- Relationship to Statistics, Optimization, Machine Learning and AI
- Tools
- **Data**
- Legal, Privacy and Security Issues



References

Tan, P., Steinbach, M., Karpatne, A., & Kumar, V. (2020). Introduction to Data Mining. New York, NY: Pearson.

Hahsler, Michael. (2021). An R Companion for Introduction to Data Mining.
Online Book.

https://mhahsler.github.io/Introduction_to_Data_Mining_R_Examples/book/