Introduction to Data Mining

Chapter 1 Introduction

by Michael Hahsler

Based on slides by Tan, Steinbach, Karpatne, Kumar

Agenda

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

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

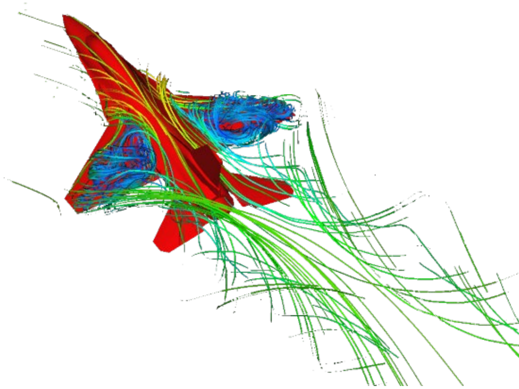
http://www.kdd.org/curriculum

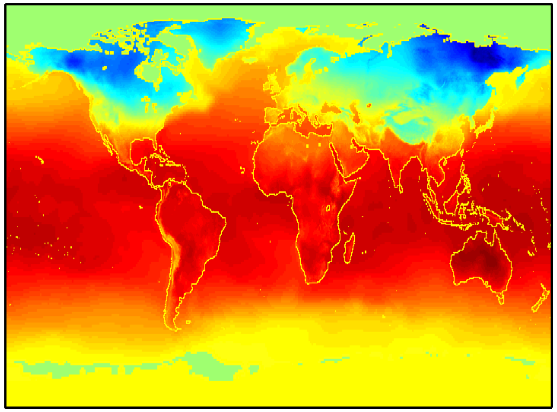
Why Data Mining? Commercial Viewpoint

- Businesses collect and warehouse lots of data.
  - —Purchases at department/grocery stores
  - —Bank/credit card transactions
  - —Web and social media data
  - —Mobile and IOT
- Computers are cheaper and more powerful.
- Competition to provide better services.
  - —Mass customization and recommendation systems
  - —Targeted advertising
  - —Improved logistics

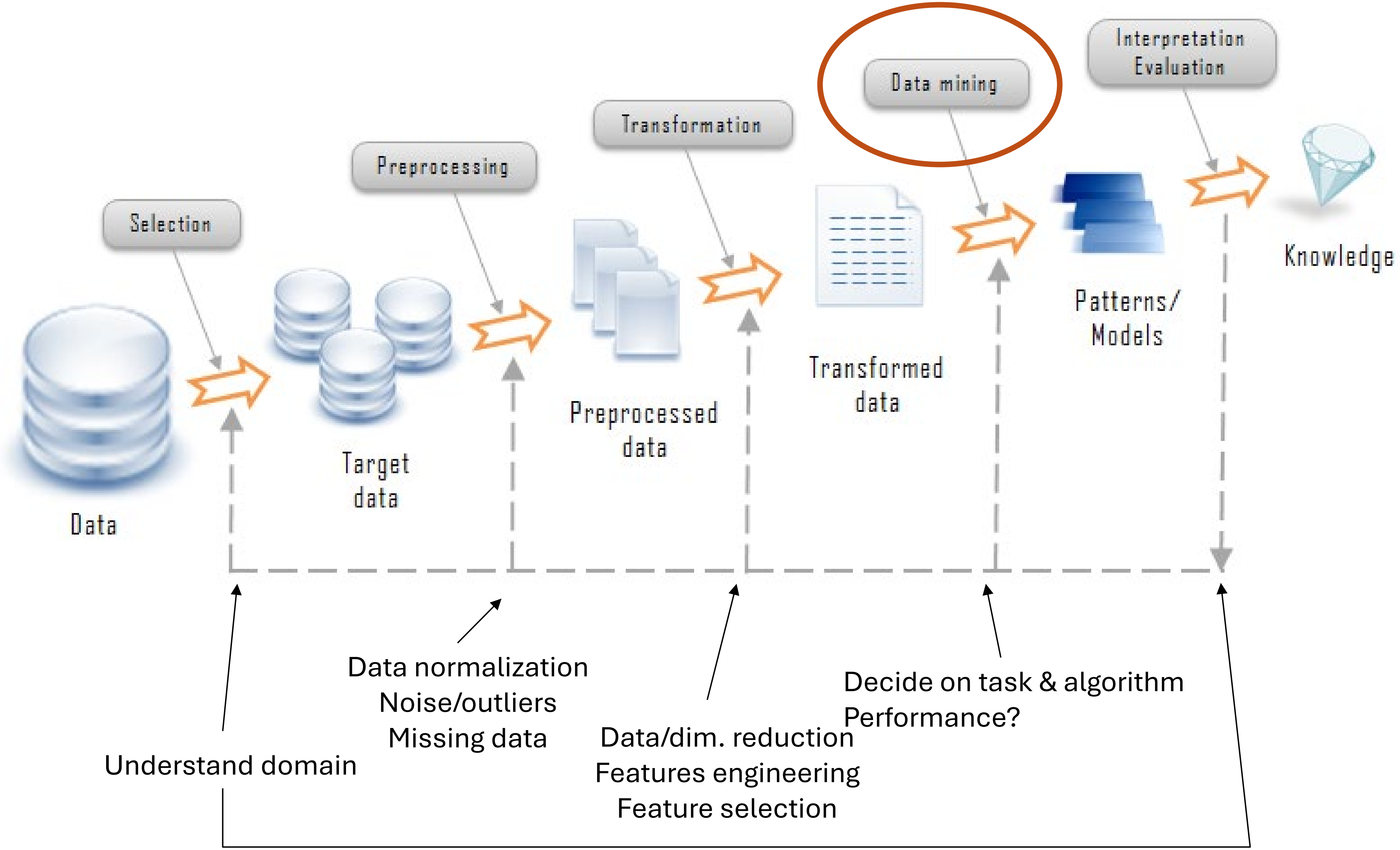
Why Mine Data? Scientific Viewpoint

- Data collected and stored at enormous speeds (GB/hour)
  - —remote sensors on a satellite
  - —telescopes scanning the skies
  - —microarrays generating gene expression data
  - —scientific simulations generating terabytes of data
- Data mining may help scientists
  - —identify patterns and relationships
  - —to classify and segment data
  - —formulate hypotheses





Knowledge Discovery in Databases (KDD) Process



Understand domain

Data normalization
Noise/outliers
Missing data

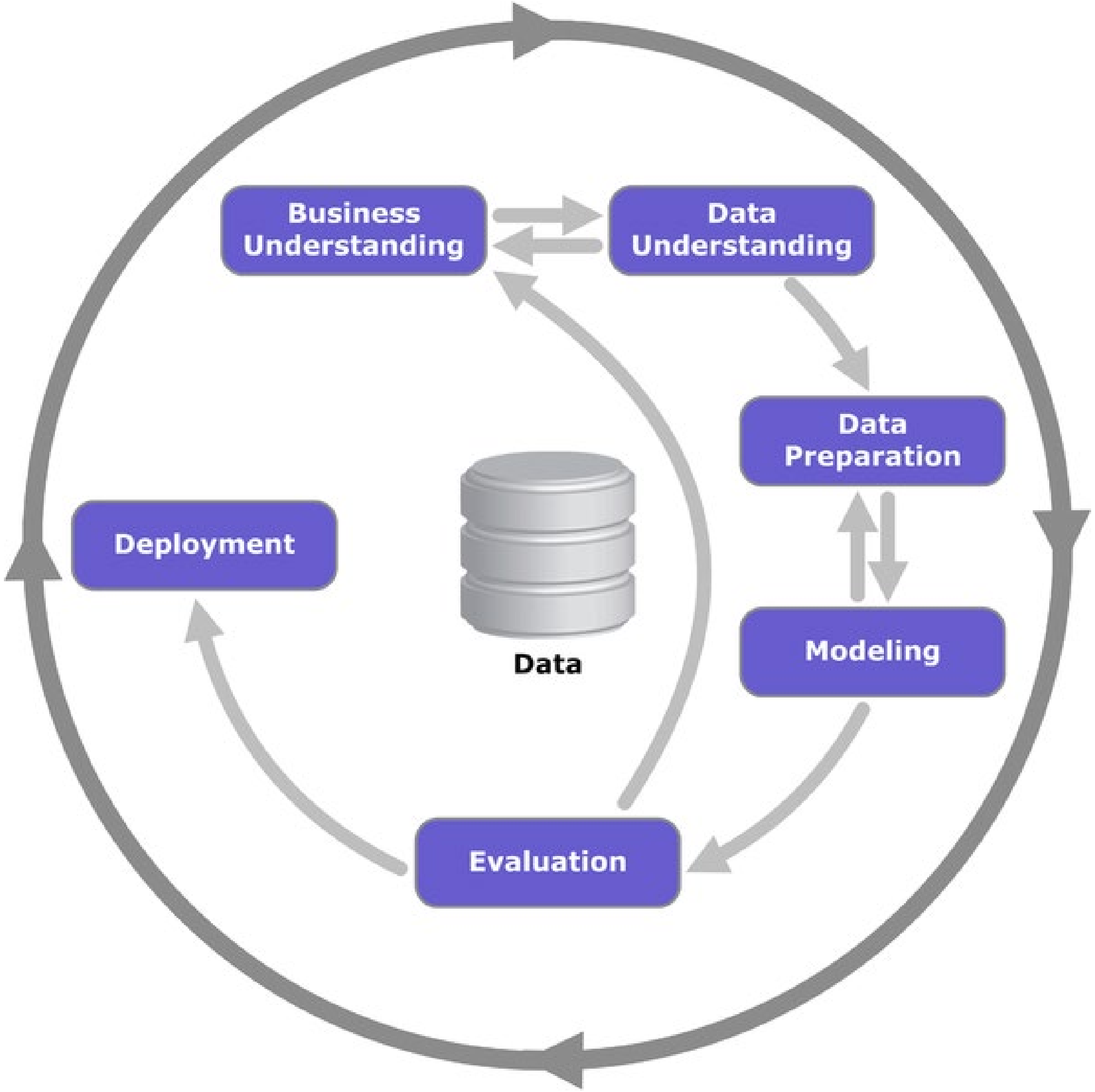
Data/dim. reduction
Features engineering
Feature selection

Decide on task & algorithm
Performance?

Usama M. Fayyad, Gregory Piatetsky-Shapiro, and Padhraic Smyth. 1996. From data mining to knowledge discovery: an overview.

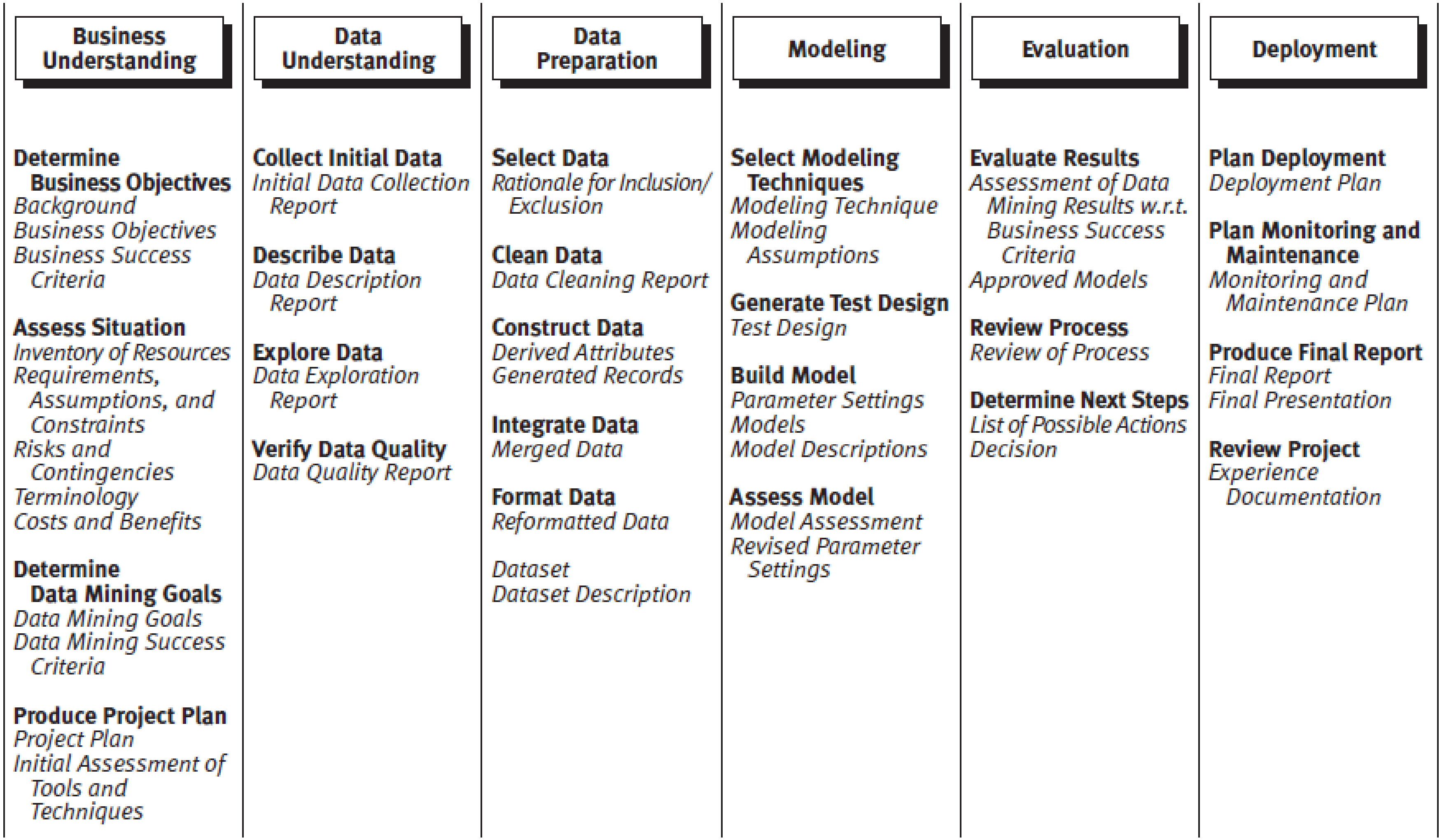
CRISP-DM Reference Model

- 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.



https://en.wikipedia.org/wiki/Cross_Industry_Standard_Process_for_Data_Mining

Tasks in the CRISP-DM Model



Business Understanding

Determine Business Objectives
Background
Business Objectives
Business Success Criteria

Assess Situation
Inventory of Resources
Requirements, Assumptions, and Constraints
Risks and Contingencies
Terminology
Costs and Benefits

Determine Data Mining Goals
Data Mining Goals
Data Mining Success Criteria

Produce Project Plan
Project Plan
Initial Assessment of Tools and Techniques

Data Understanding

Collect Initial Data
Initial Data Collection Report

Describe Data
Data Description Report

Explore Data
Data Exploration Report

Verify Data Quality
Data Quality Report

Data Preparation

Select Data
Rationale for Inclusion/ Exclusion

Clean Data
Data Cleaning Report

Construct Data
Derived Attributes
Generated Records

Integrate Data
Merged Data

Format Data
Reformatted Data

Dataset
Dataset Description

Modeling

Select Modeling Techniques
Modeling Technique
Modeling Assumptions

Generate Test Design
Test Design

Build Model
Parameter Settings
Models
Model Descriptions

Assess Model
Model Assessment
Revised Parameter Settings

Evaluation

Evaluate Results
Assessment of Data Mining Results w.r.t. Business Success Criteria
Approved Models

Review Process
Review of Process

Determine Next Steps
List of Possible Actions
Decision

Deployment

Plan Deployment
Deployment Plan

Plan Monitoring and Maintenance
Monitoring and Maintenance Plan

Produce Final Report
Final Report
Final Presentation

Review Project
Experience Documentation

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

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- **Data Mining Tasks**
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- Tools
- Data
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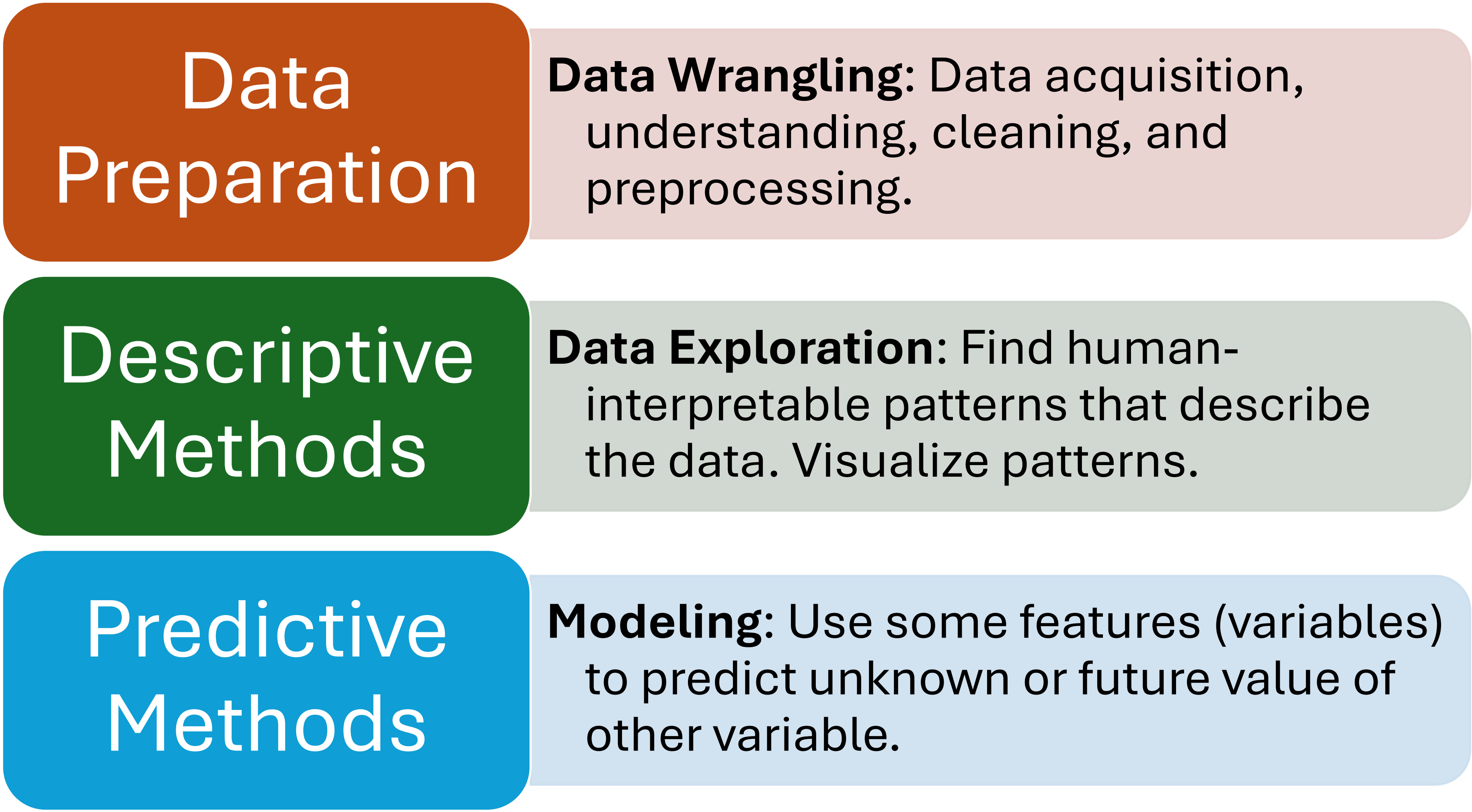
Data Mining Tasks



Data Preparation

Data Wrangling: Data acquisition, understanding, cleaning, and preprocessing.

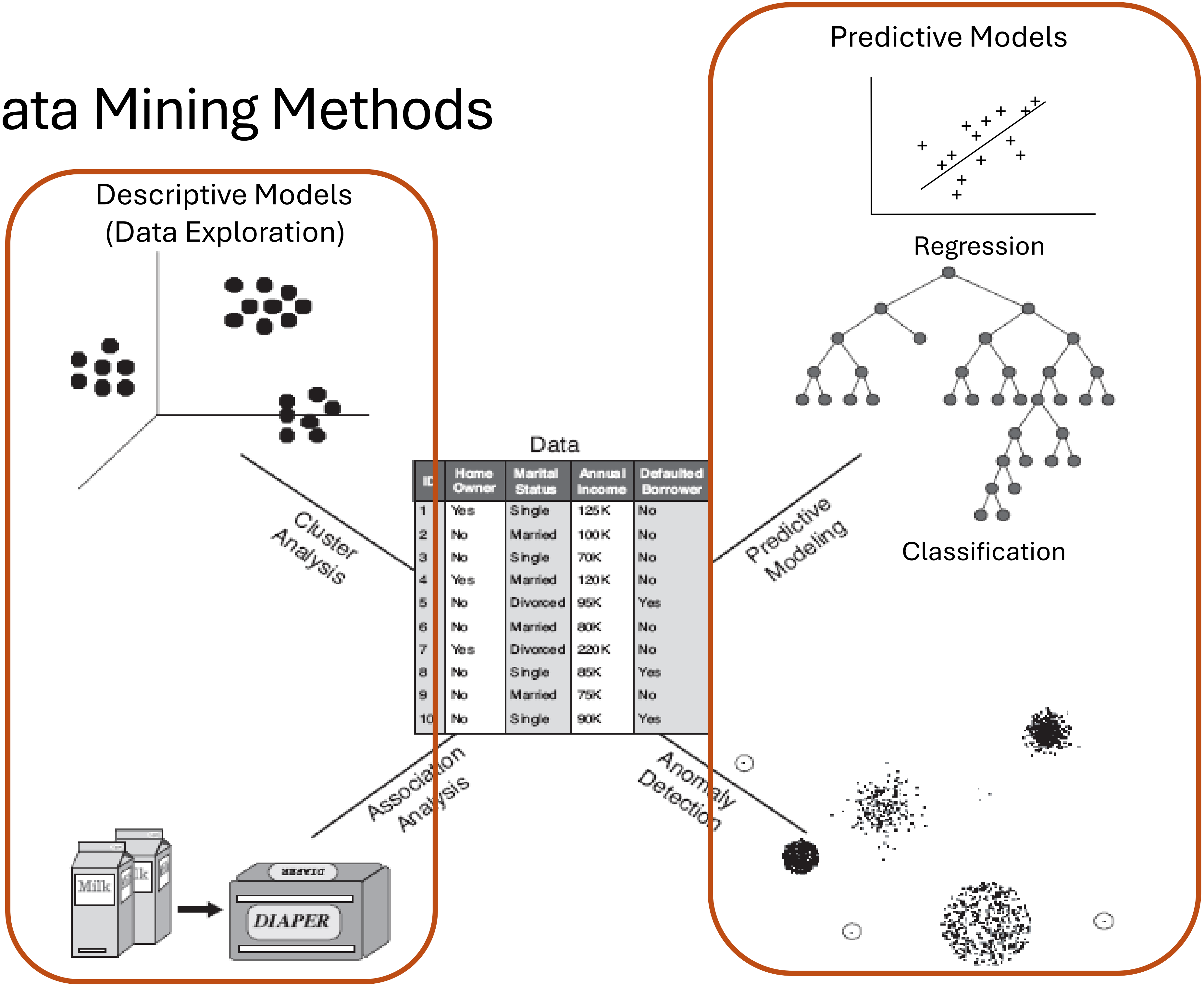
Descriptive Methods

Data Exploration: Find human-interpretable patterns that describe the data. Visualize patterns.

Predictive Methods

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

Data Mining Methods



Predictive Models

Regression

Classification

Descriptive Models
(Data Exploration)

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	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Introduction to Data Mining by Pang-Ning Tan, Michael Steinbach and Vipin Kumar, Addison Wesley, 2006

Figure 1.3 Four of the core data mining tasks

Data Mining Methods

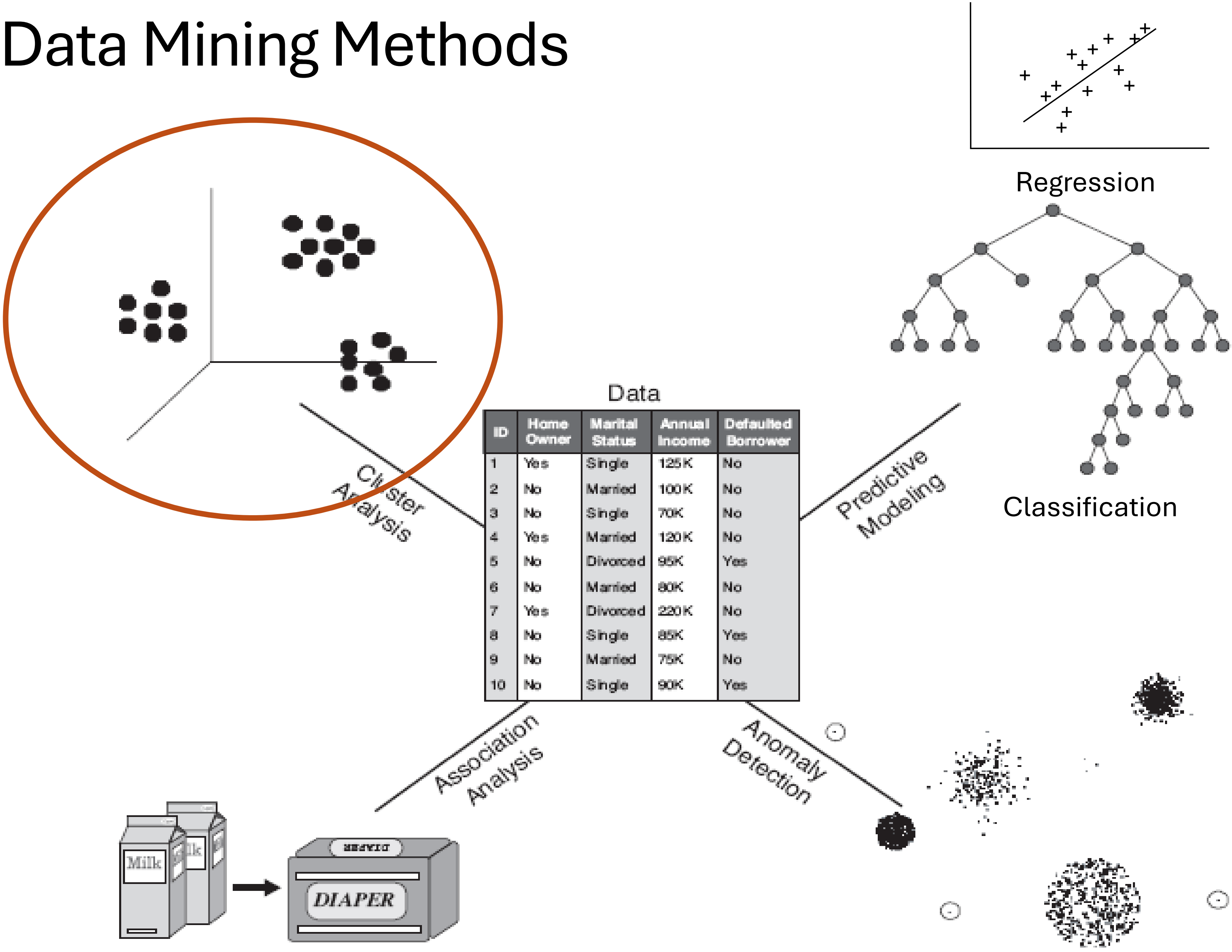


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Figure 1.3 Four of the core data mining tasks

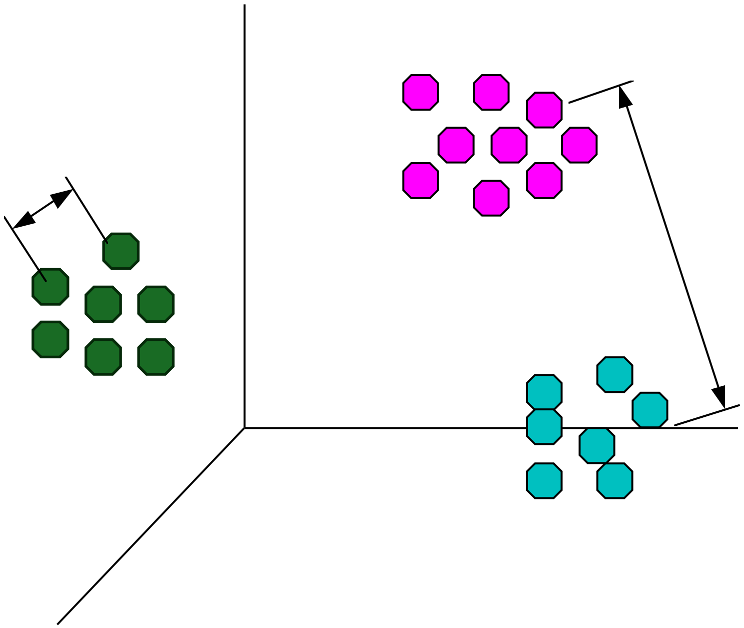
Clustering

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

Intracluster distances are minimized



Intercluster distances are maximized

Euclidean distance based clustering in 3-D space.

Concepts:

- similarity $dist(x_1, x_2)$
- density

Clustering: Market Segmentation

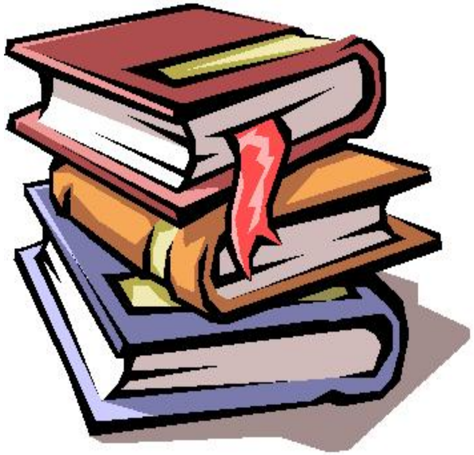
Goal: subdivide a market into distinct subsets of customers. Use a different marketing mix for each segment.

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 Methods

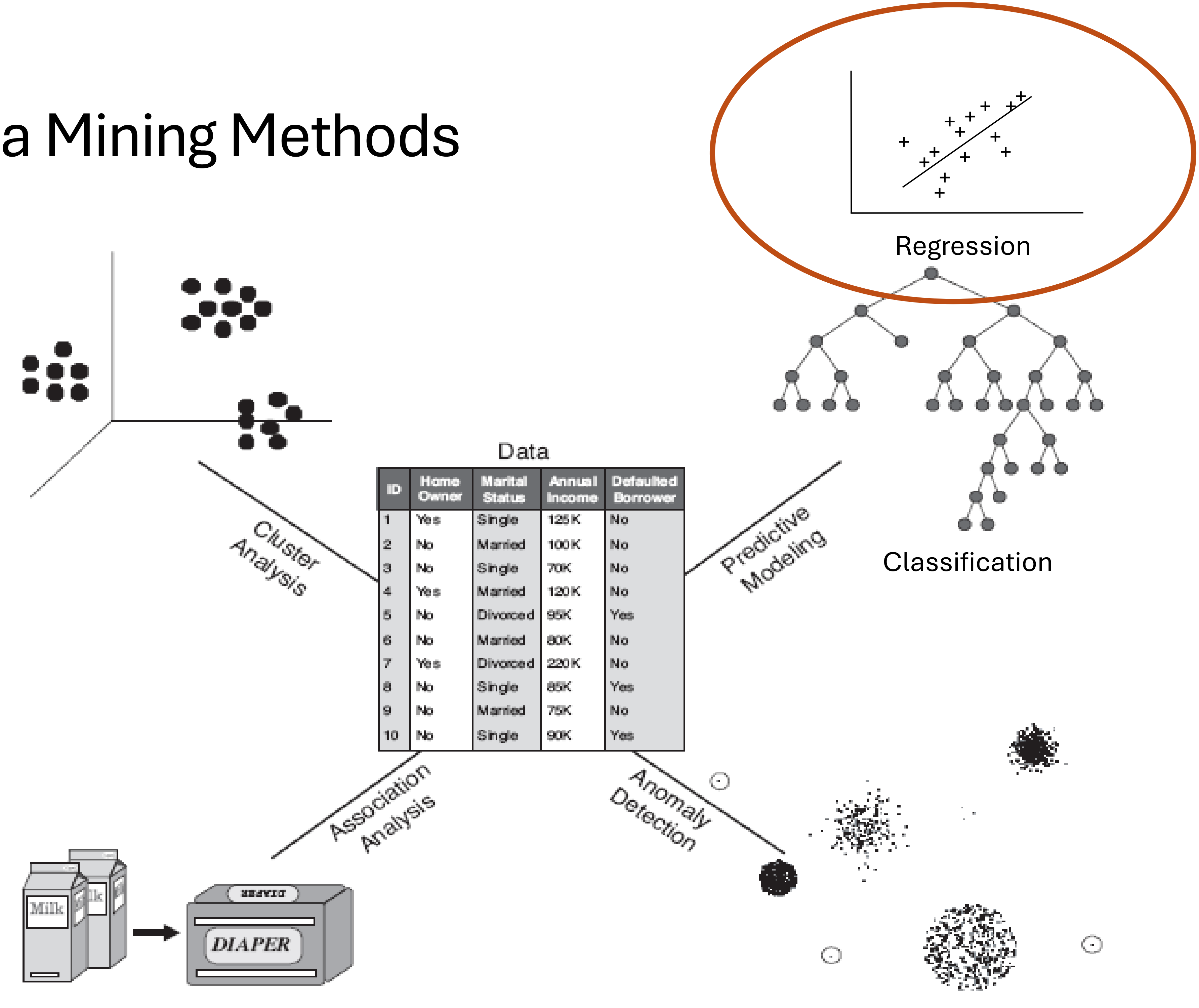


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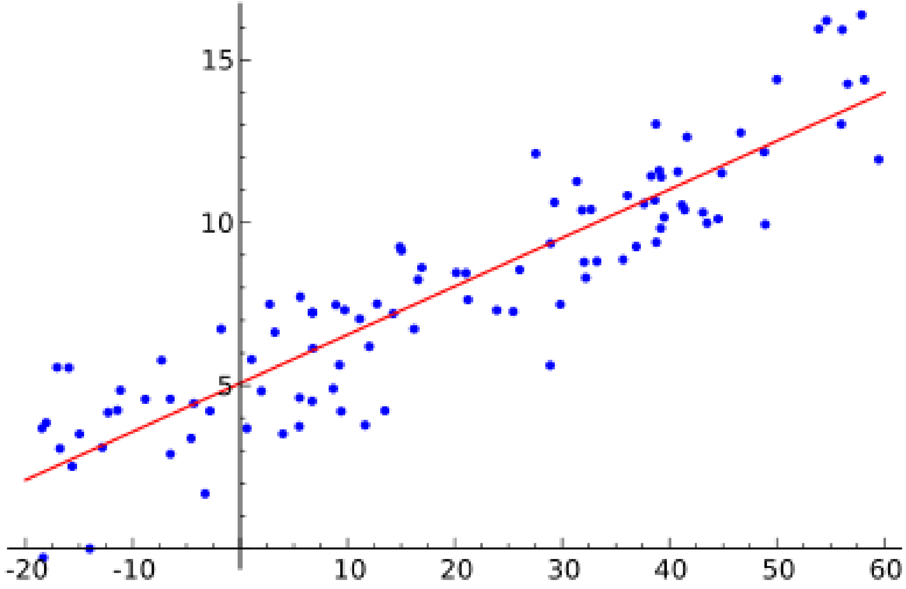
Figure 1.3 Four of the core data mining tasks

Concept:

- Function fitting: $y = f(X)$

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 Methods

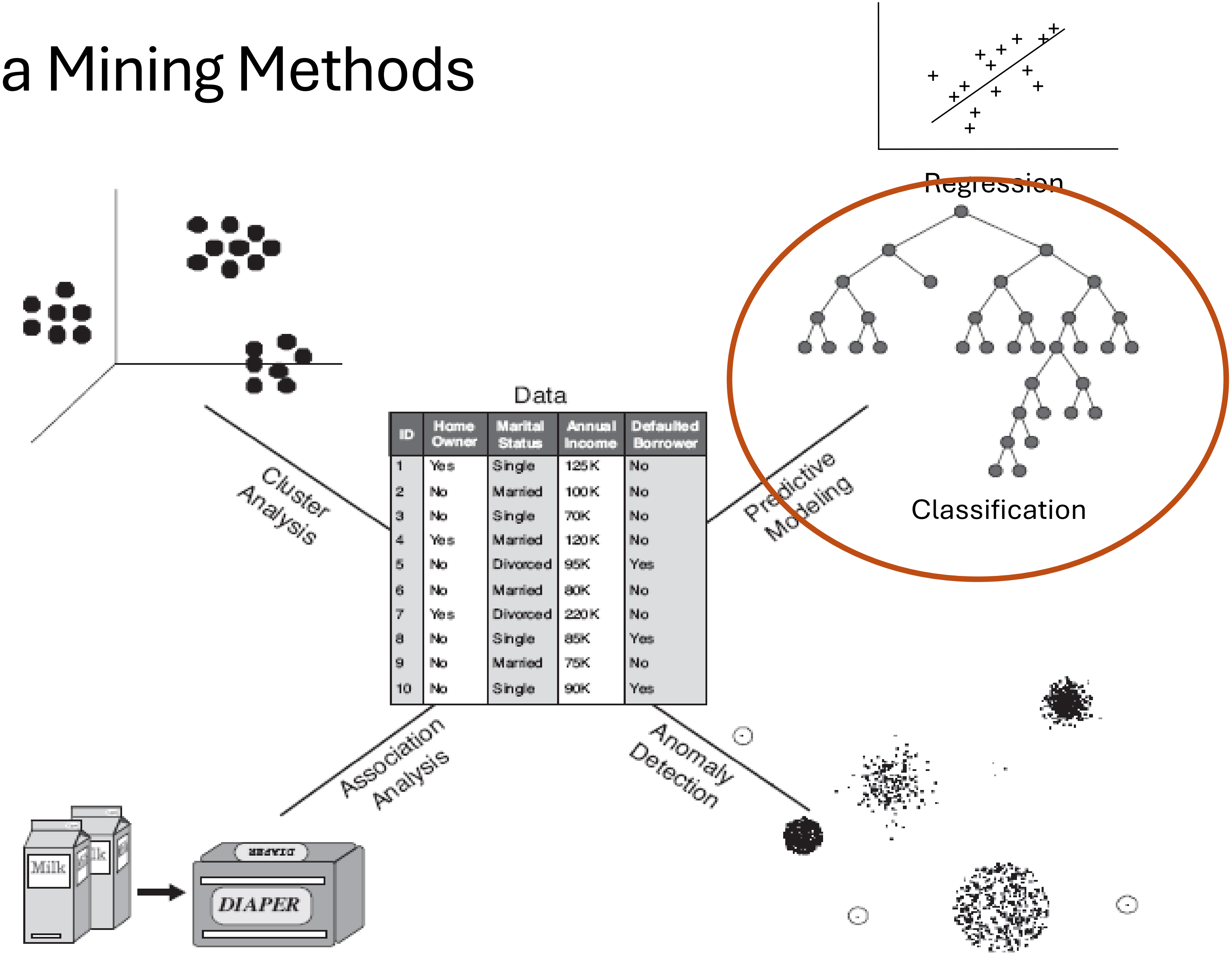


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Figure 1.3 Four of the core data mining tasks

Classification

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

Class information is available → **Supervised Learning**

class

Tid	**Refund**	**Marital Status**	**Taxable Income**	**Cheat**
1	Yes	Single	125K	**No**
2	No	Married	100K	**No**
3	No	Single	70K	**No**
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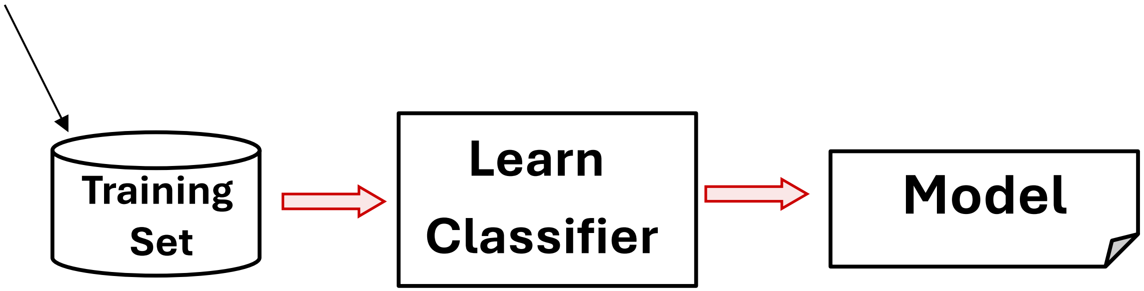
Concept:

- Probability estimation $\mathrm{P}(y\,|X)$



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.

class

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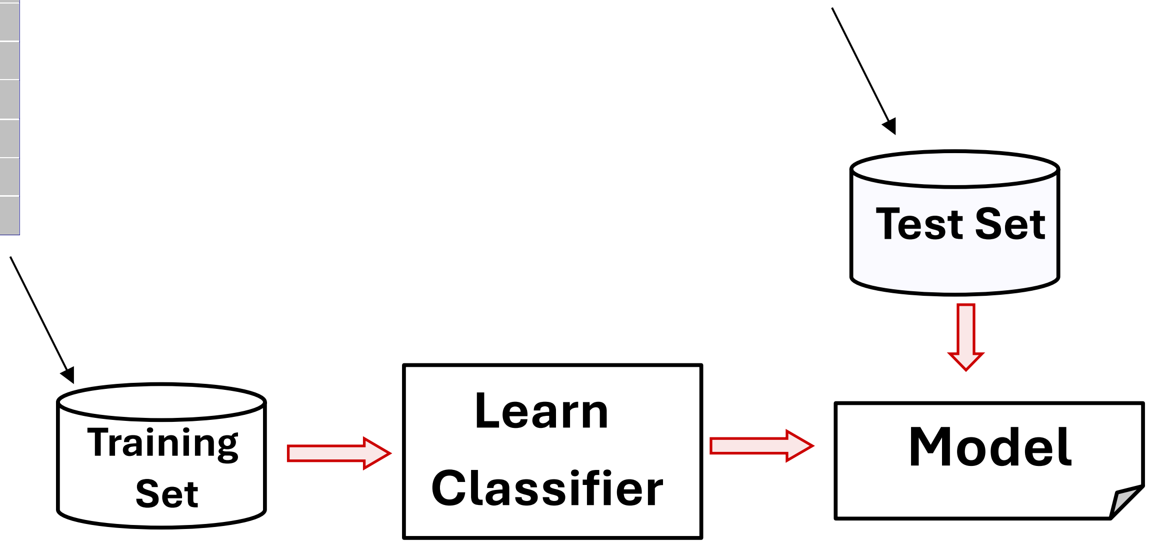
Refund	Marital Status	Taxable Income	Cheat
No	Single	75K	?
Yes	Married	50K	?
No	Married	150K	?
Yes	Divorced	90K	?
No	Single	40K	?
No	Married	80K	?



Classification: Direct Marketing

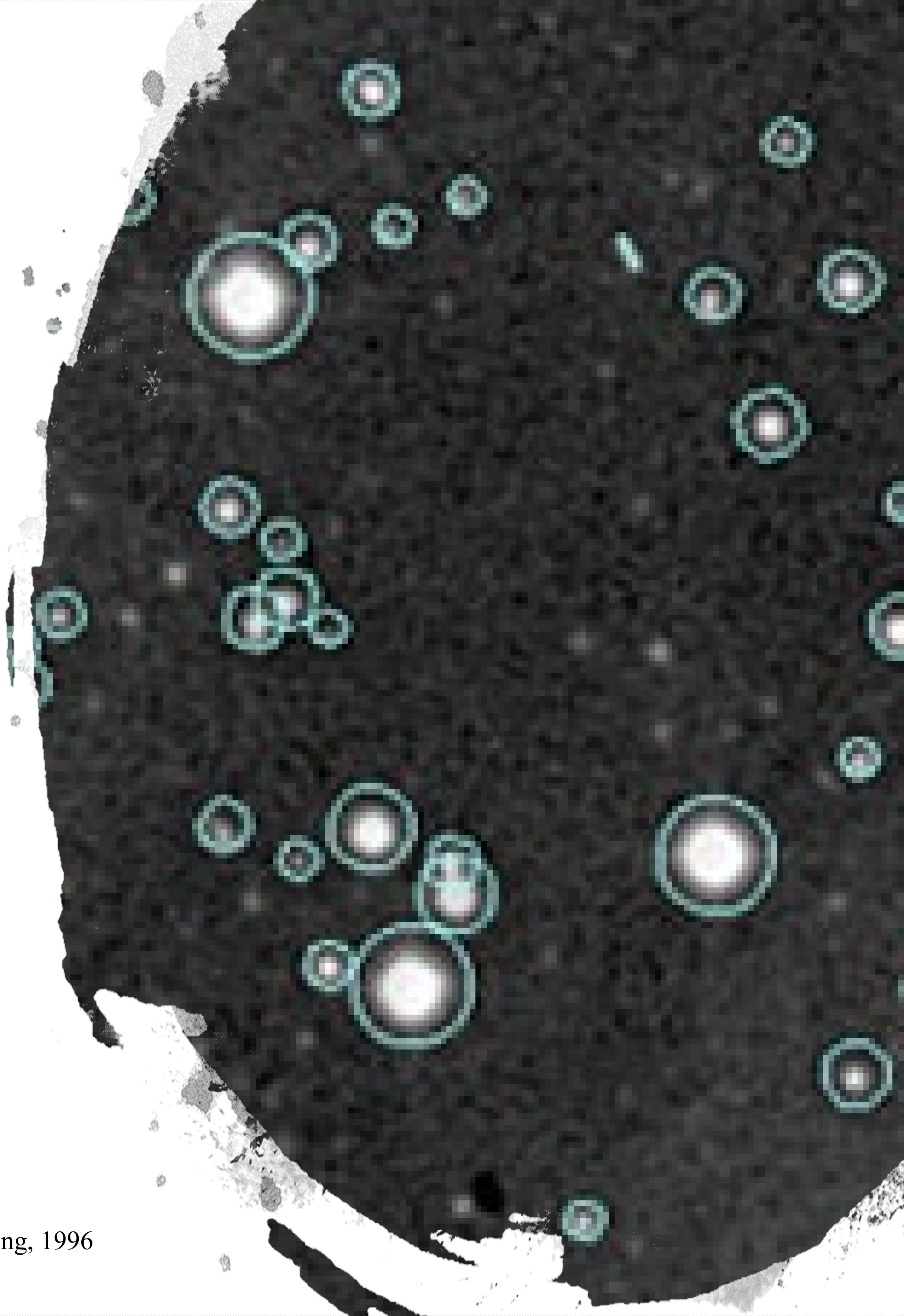
- Goal: Reduce cost of mailing by targeting a set of consumers likely to buy a new product.
- Approach:
  - Use the data for a similar product introduced before or from a focus group. We have customer information (e.g., demographics, lifestyle, previous purchases) and know which customers decided to 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.



From [Fayyad, et.al.] Advances in Knowledge Discovery and Data Mining, 1996

Data Mining Methods

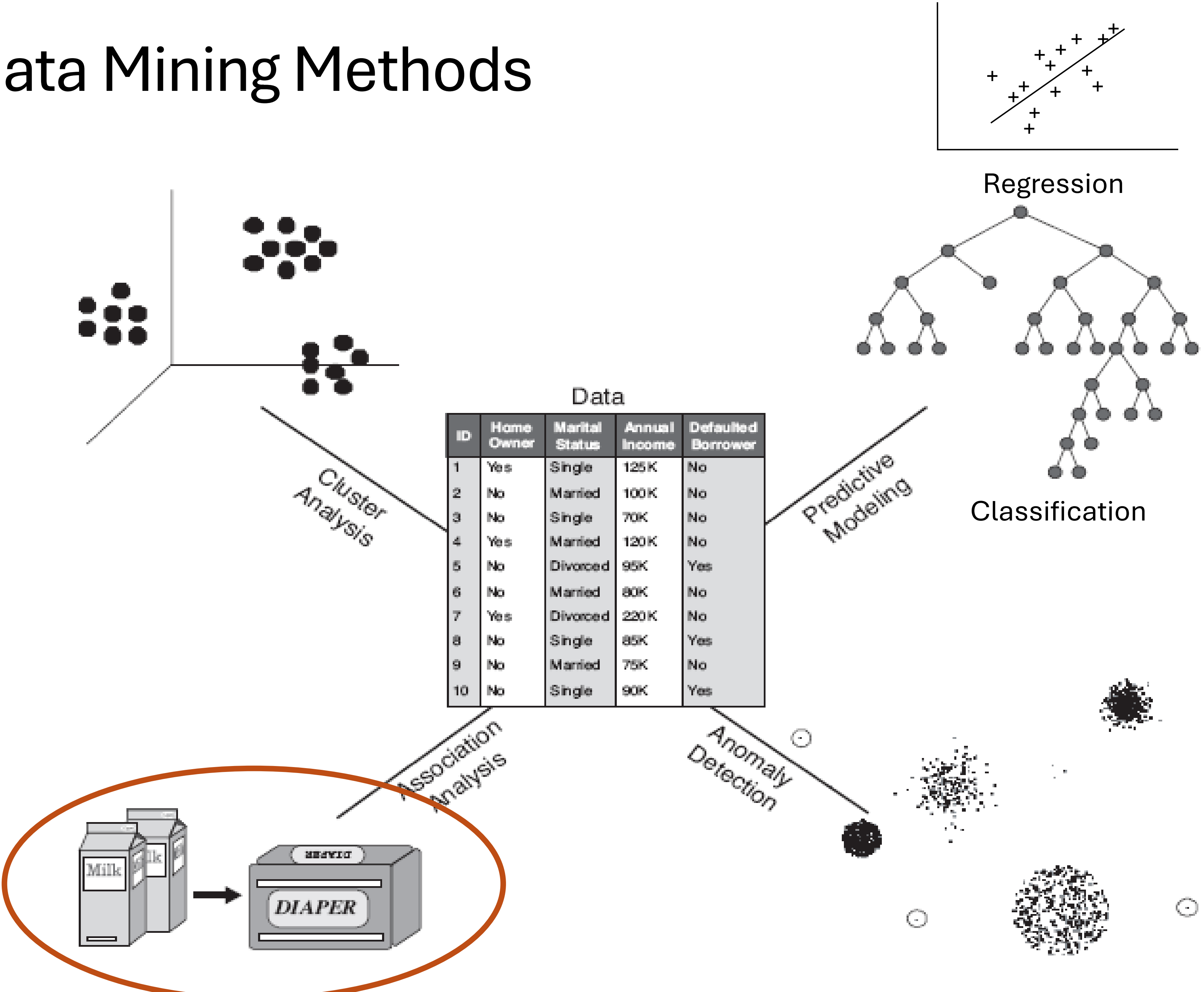


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Figure 1.3 Four of the core data mining tasks

Association Rule Discovery

- Given is a set of transactions. Each contains a number of items.
- Produce dependency rules of the form
  LHS → 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

Discovered Rules

{Milk} → {Coke}

{Diaper, Milk} → {Beer}

Concept:

- Probability estimation $\mathrm{P}(X \rightarrow y)$

Association Rule Discovery Marketing and Sales Promotion

- Let the rule discovered be

  {Potato Chips, … } → {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 Methods

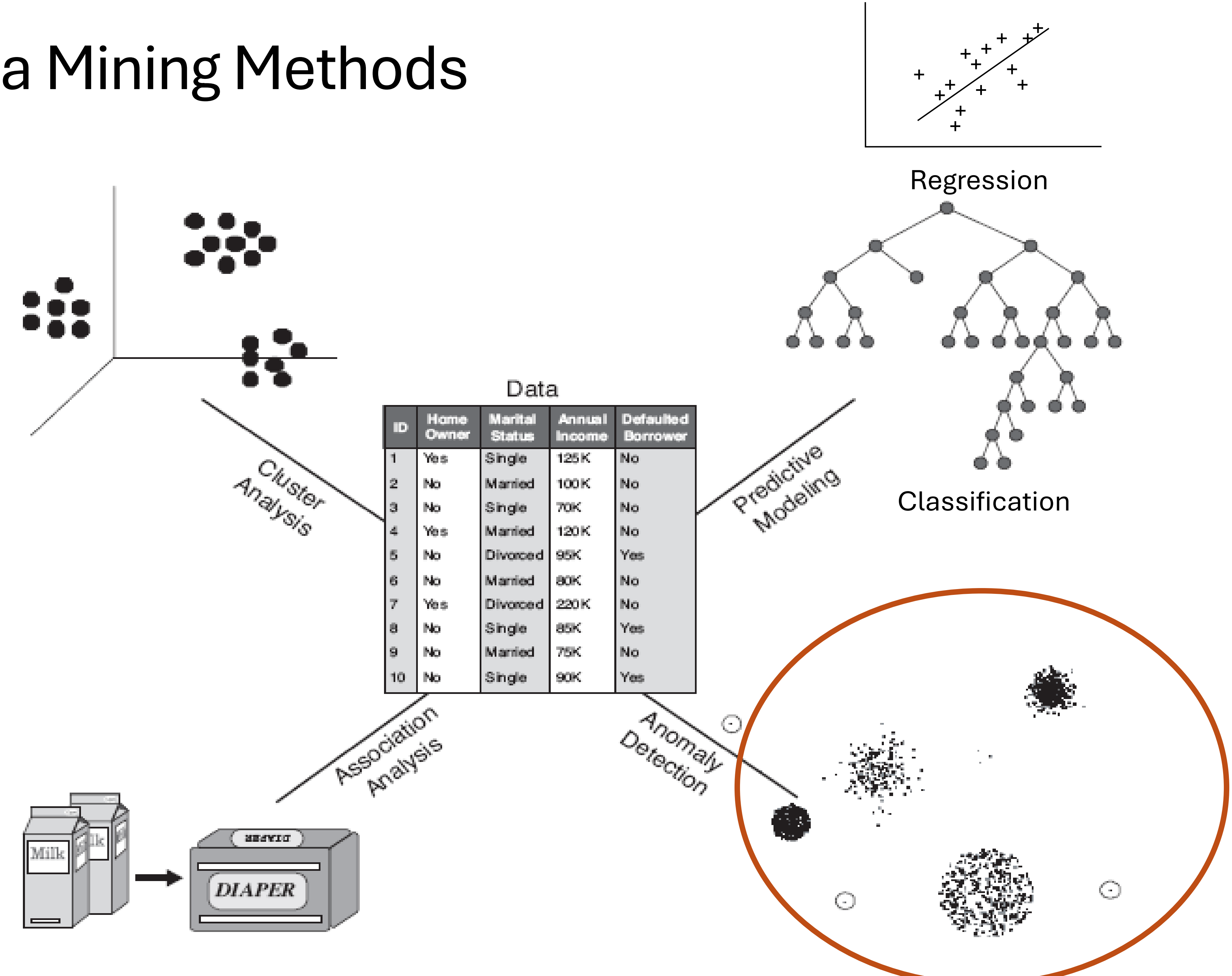

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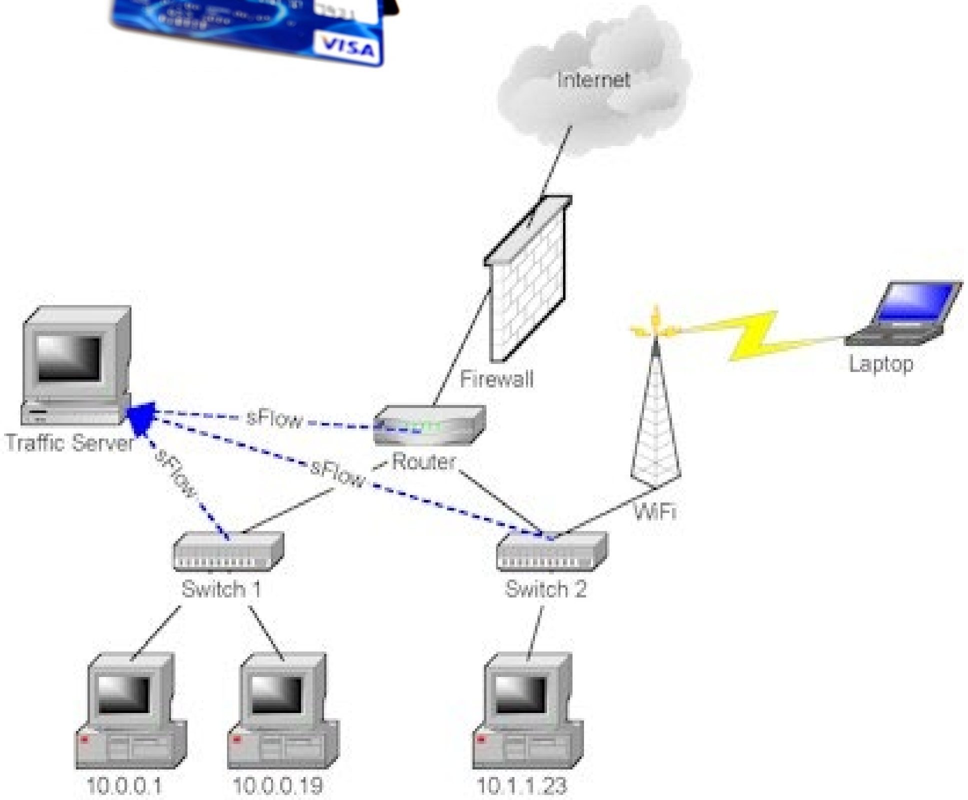
Figure 1.3 Four of the core data mining tasks

Deviation/Anomaly Detection

Concept:
- Probability estimation $P(y\,|X)$

- Detect significant deviations from normal behavior.
- Applications:
  - Credit Card Fraud Detection

  - Network Intrusion Detection



Typical network traffic at University

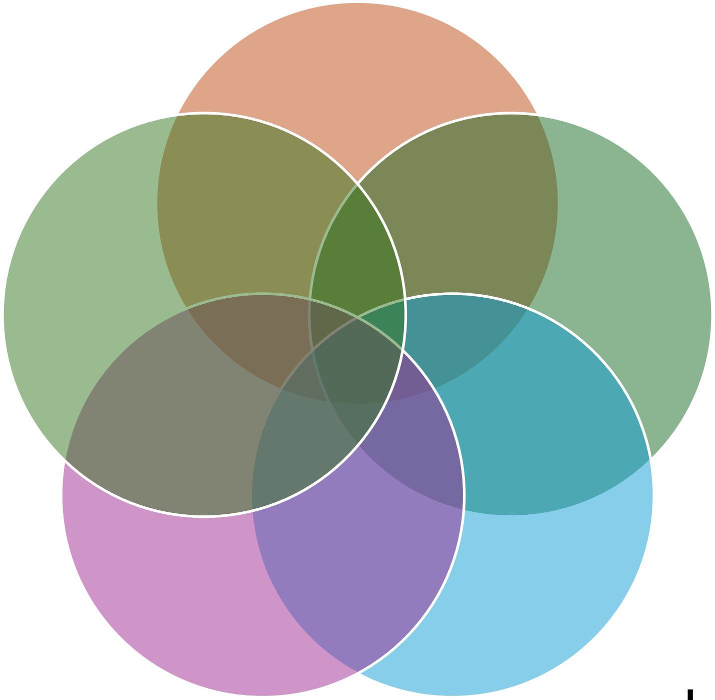
level may reach over 100 million connections per day

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

Scalability



Data ownership and privacy

Dimensionality

Complexity and heterogeneous data

Data quality

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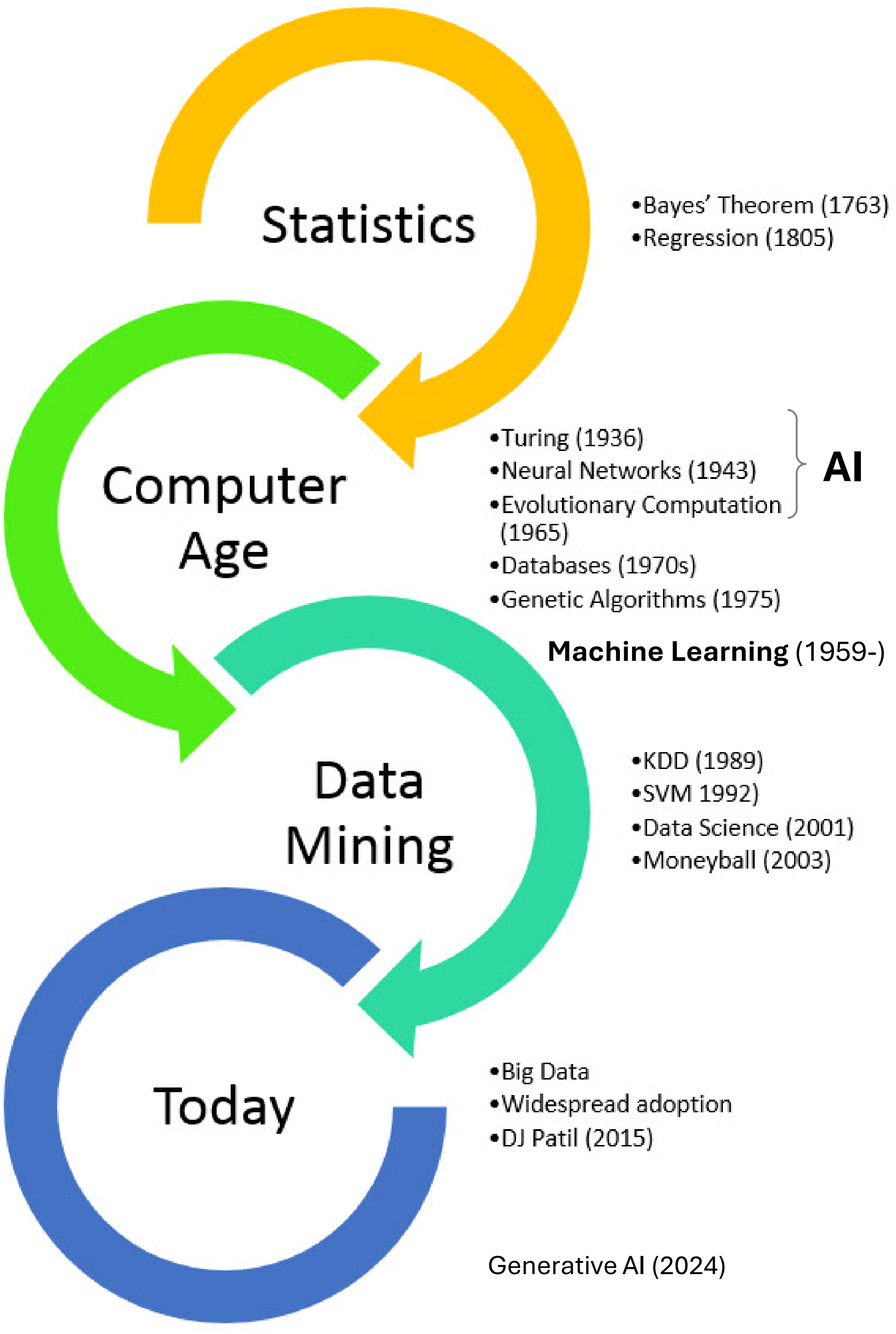
Origins of Data Mining

- Draws ideas from AI, machine learning, pattern recognition, statistics, and database systems.

- There are differences in terms of
  - —used data and
  - —the goals.



Statistics

- •Bayes' Theorem (1763)
- •Regression (1805)

Computer Age

- •Turing (1936)
- •Neural Networks (1943)
- •Evolutionary Computation (1965)
- •Databases (1970s)
- •Genetic Algorithms (1975)

AI

Machine Learning (1959-)

Data Mining

- •KDD (1989)
- •SVM 1992)
- •Data Science (2001)
- •Moneyball (2003)

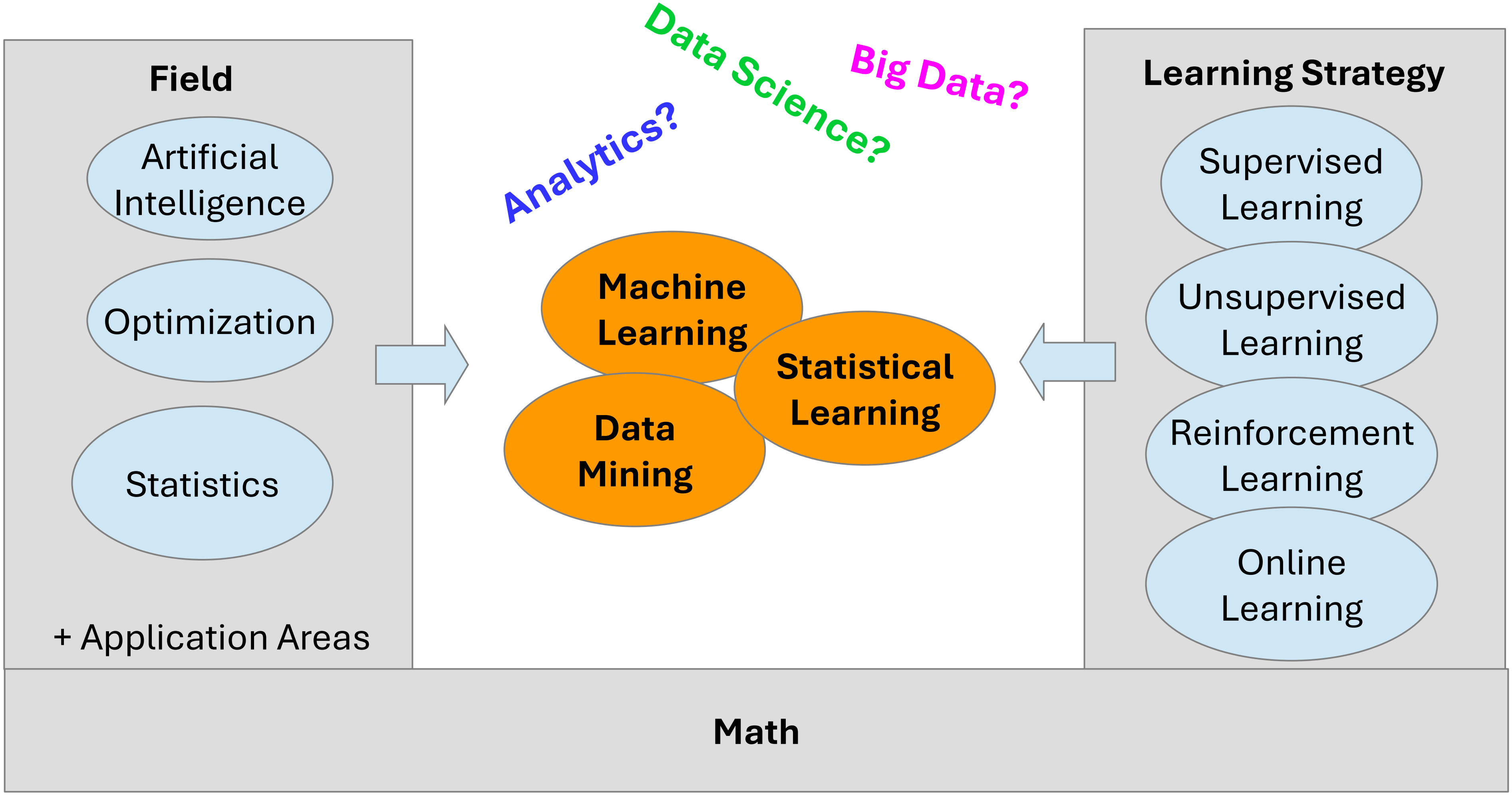
Today

- •Big Data
- •Widespread adoption
- •DJ Patil (2015)

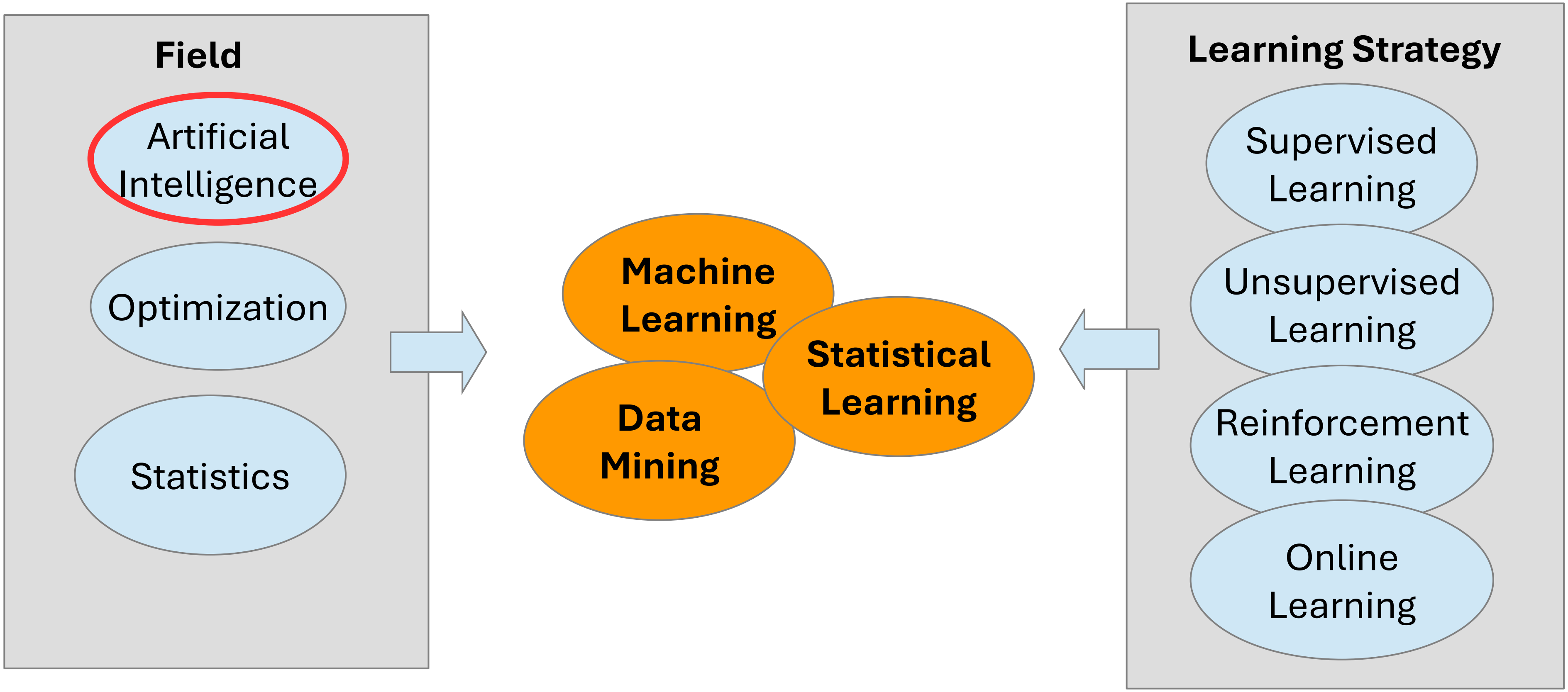
Generative AI (2024)

https://rayli.net/blog/data/history-of-data-mining/

Relationship to other Fields

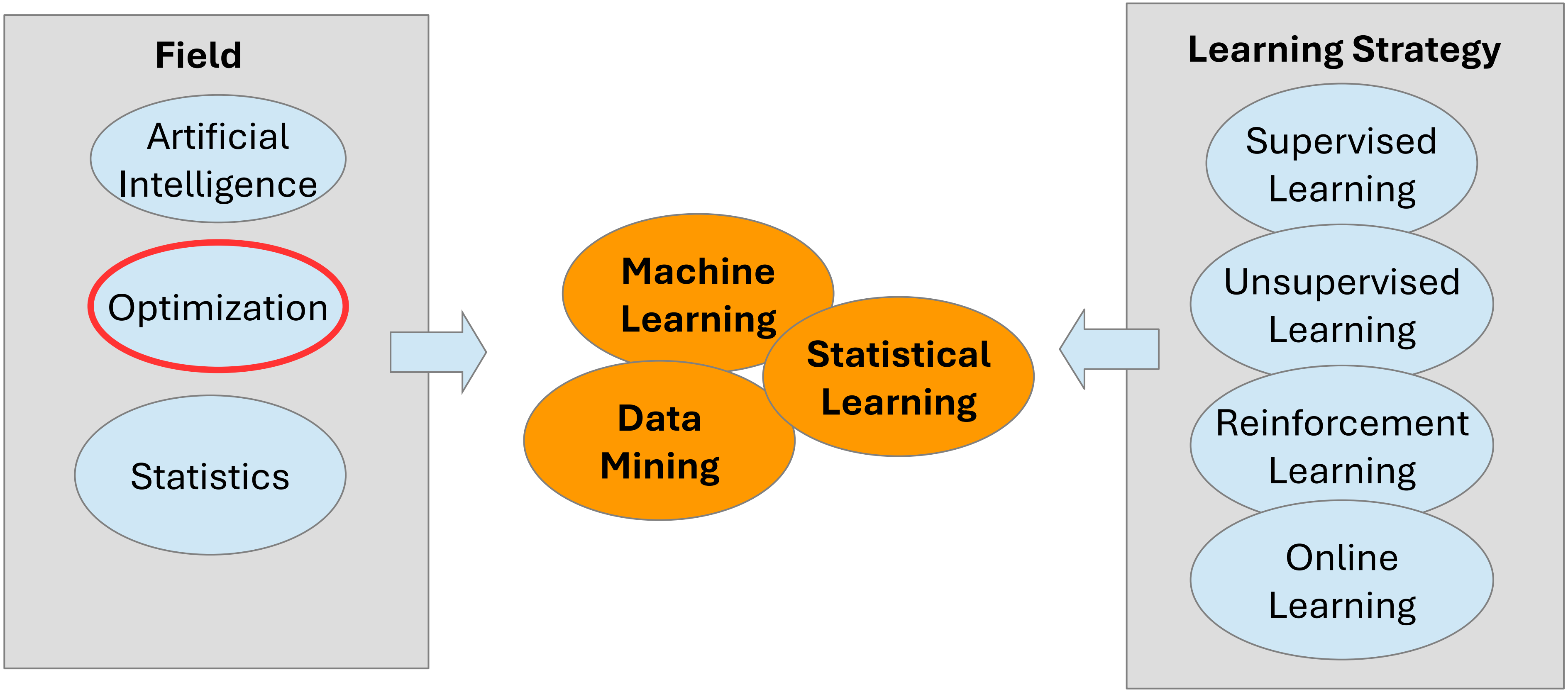


Relationship to other Fields



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.

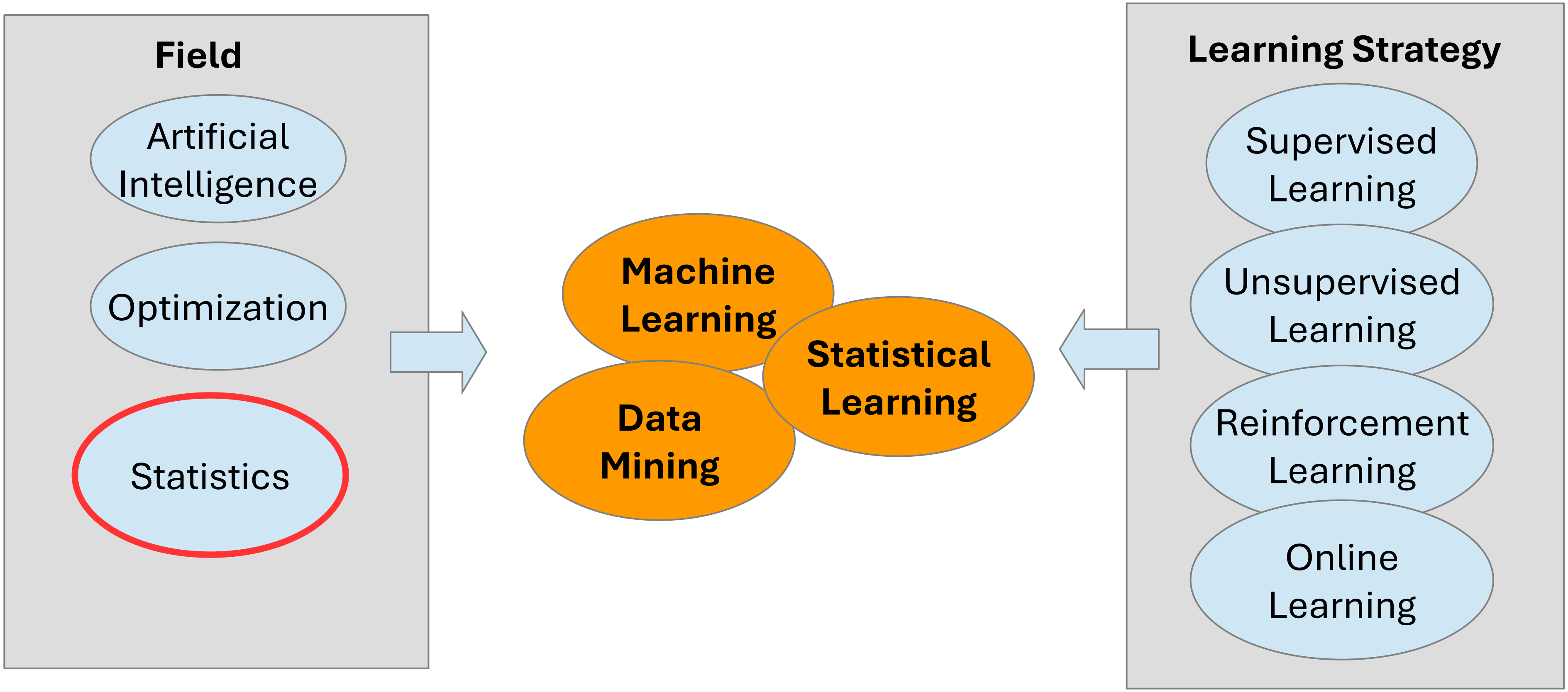
Relationship to other Fields



Optimization: Selection of a best alternative from some set of available alternatives using an objective criterion.

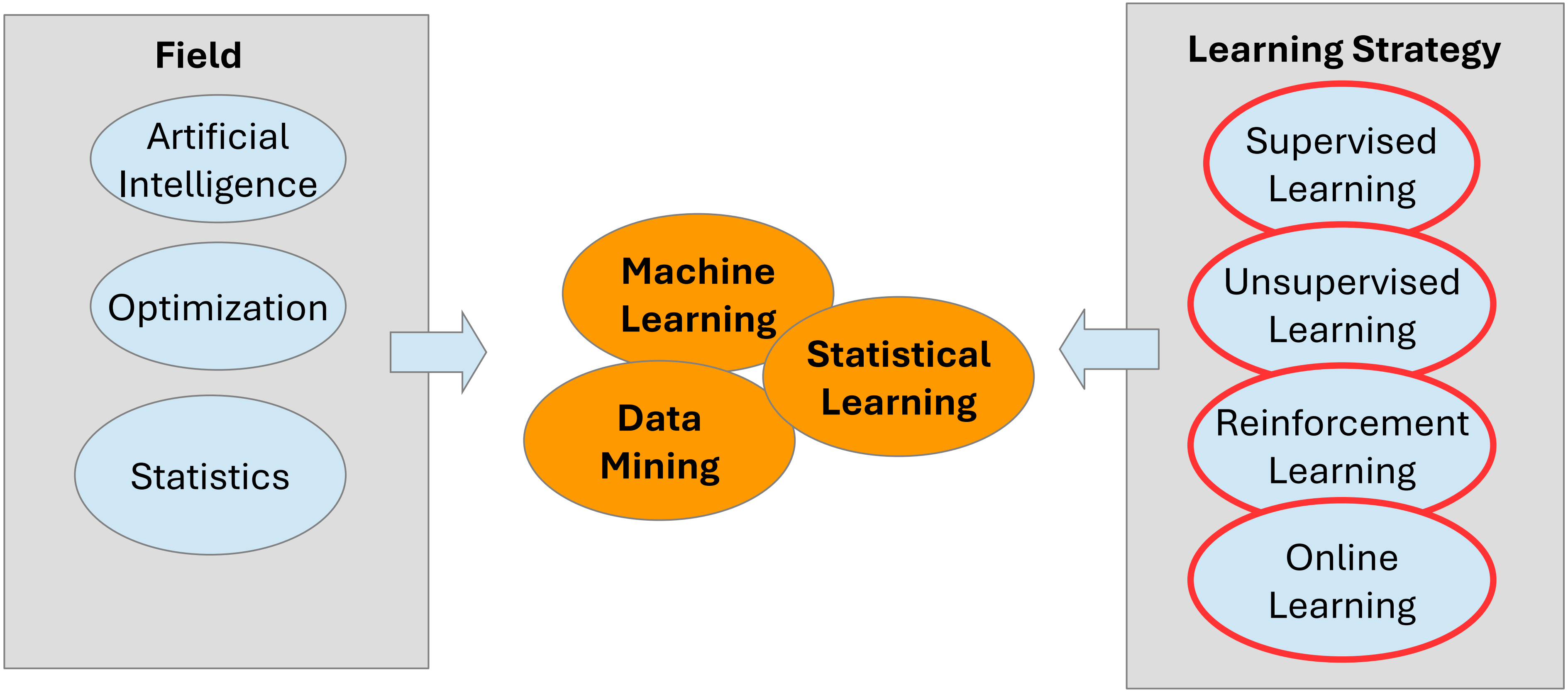
Techniques: Linear programming, integer programming, nonlinear programming, stochastic and robust optimization, heuristics, etc.

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.

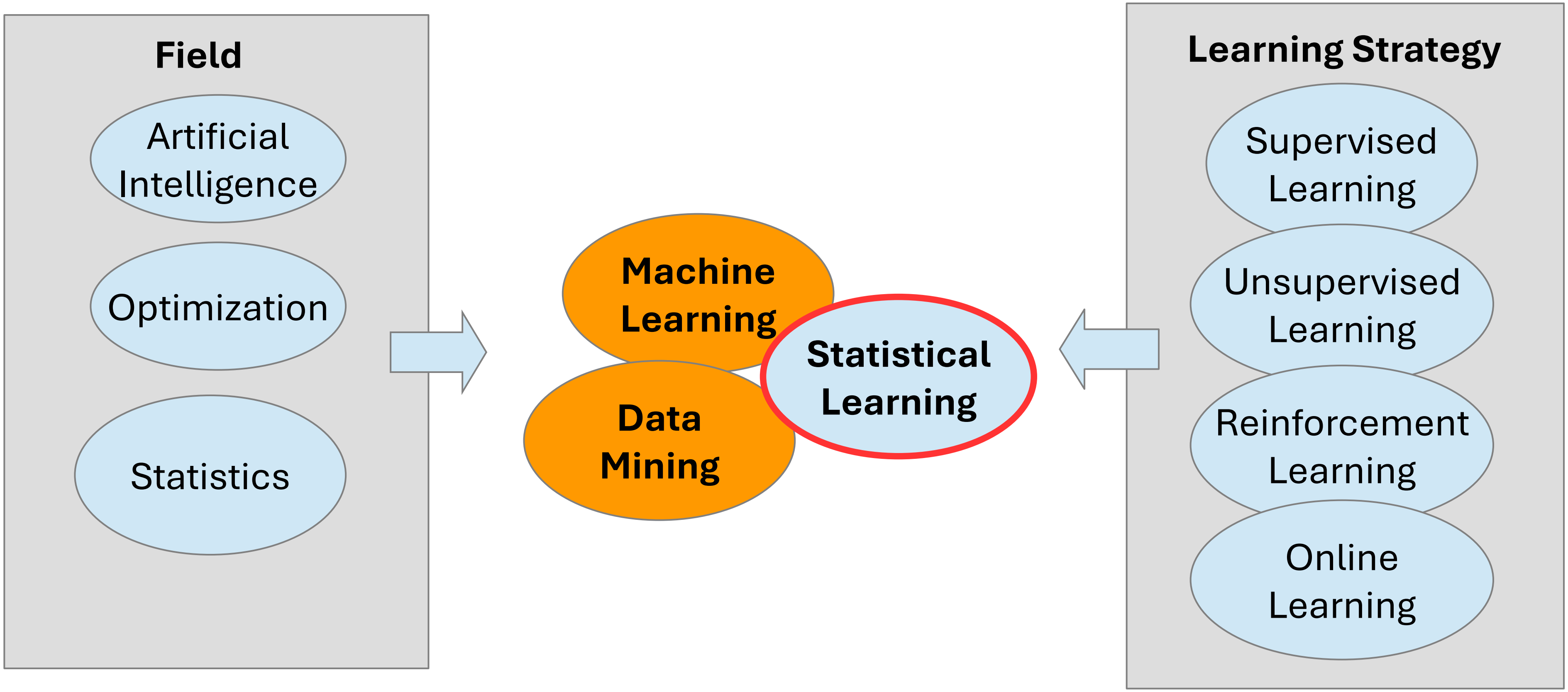
Relationship to other Fields



Learning Strategy: From what data do we learn?

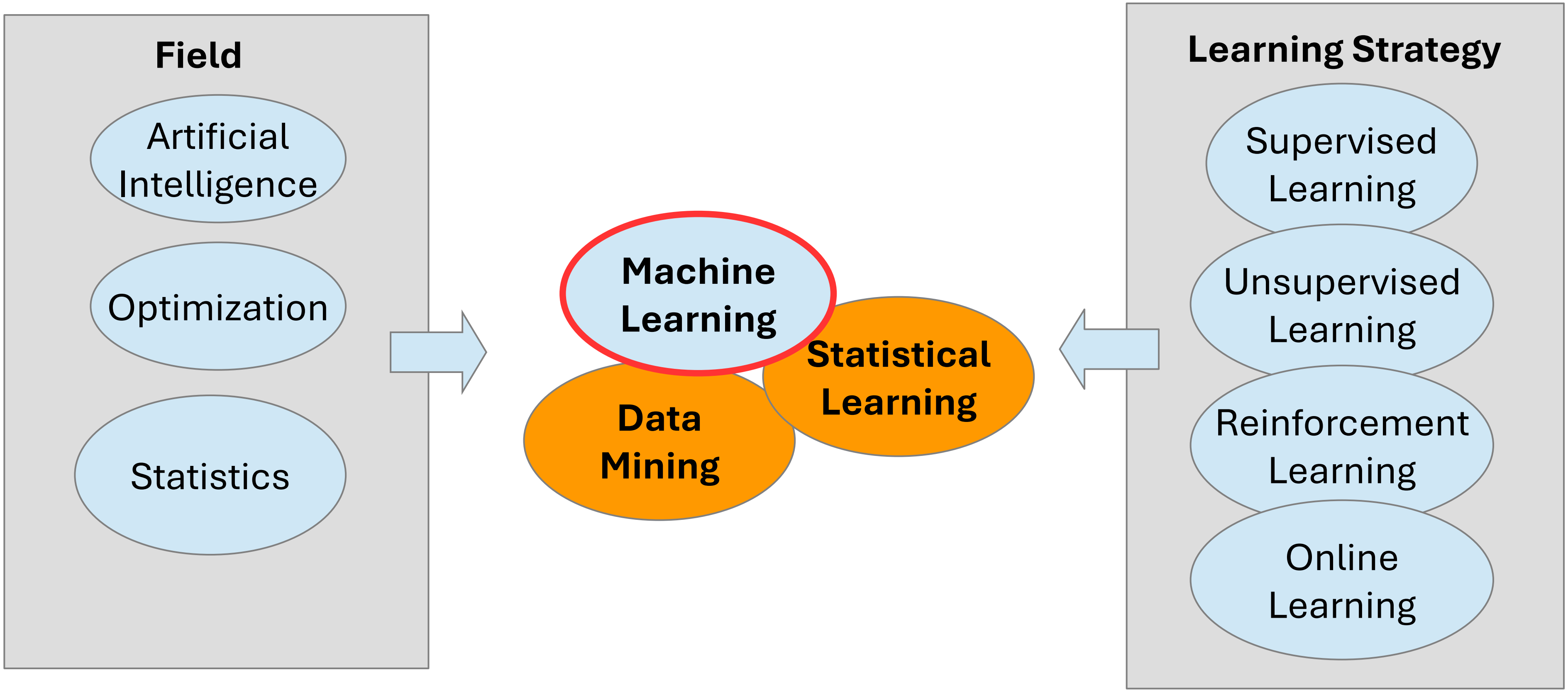
- Is a training set with correct answers available? → Supervised learning
- Long-term structure of rewards? → Reinforcement learning
- No answer and no reward structure available? → Unsupervised learning
- Do we have to update the model regularly? → Online learning

Relationship to other Fields



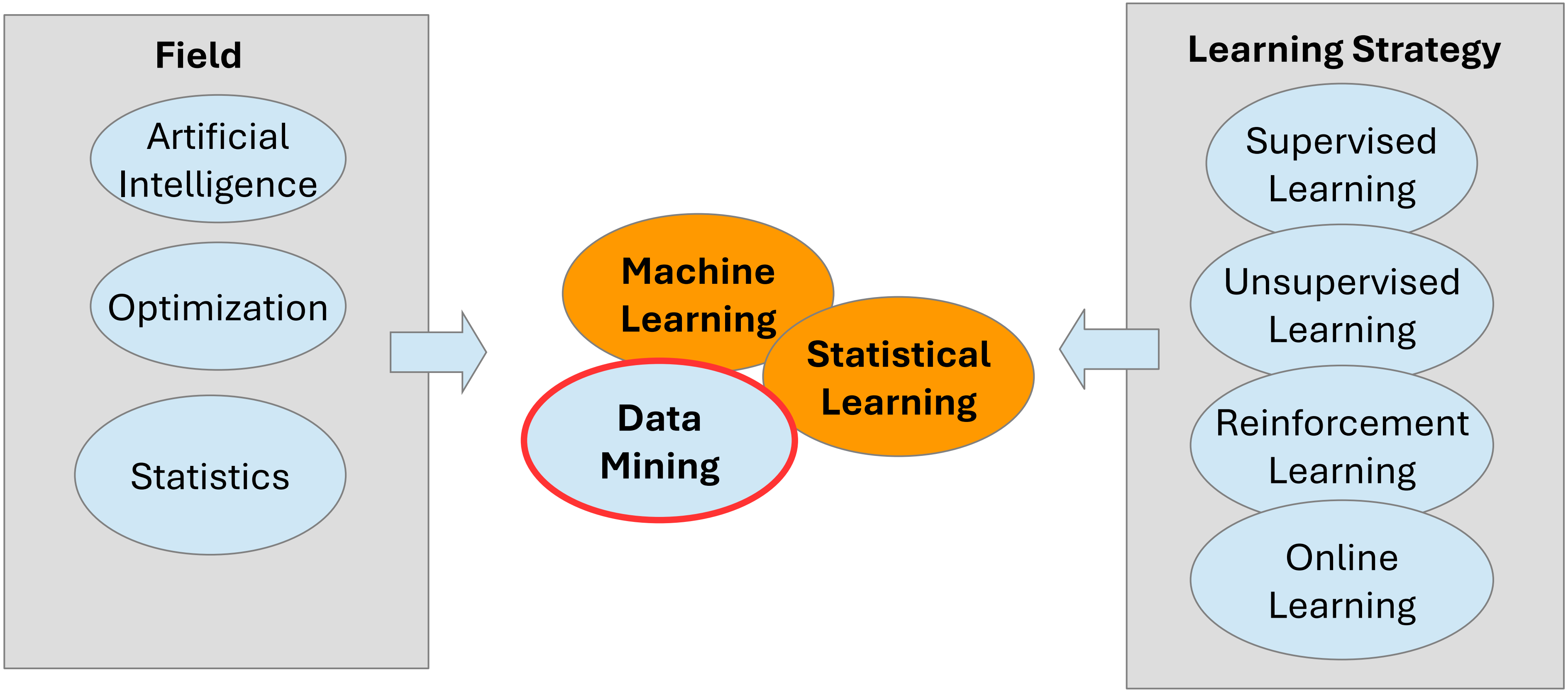
Statistical learning: deals with the problem of finding a **predictive function** based on data.
Techniques: (Linear) classifiers, regression and regularization.

Relationship to other Fields



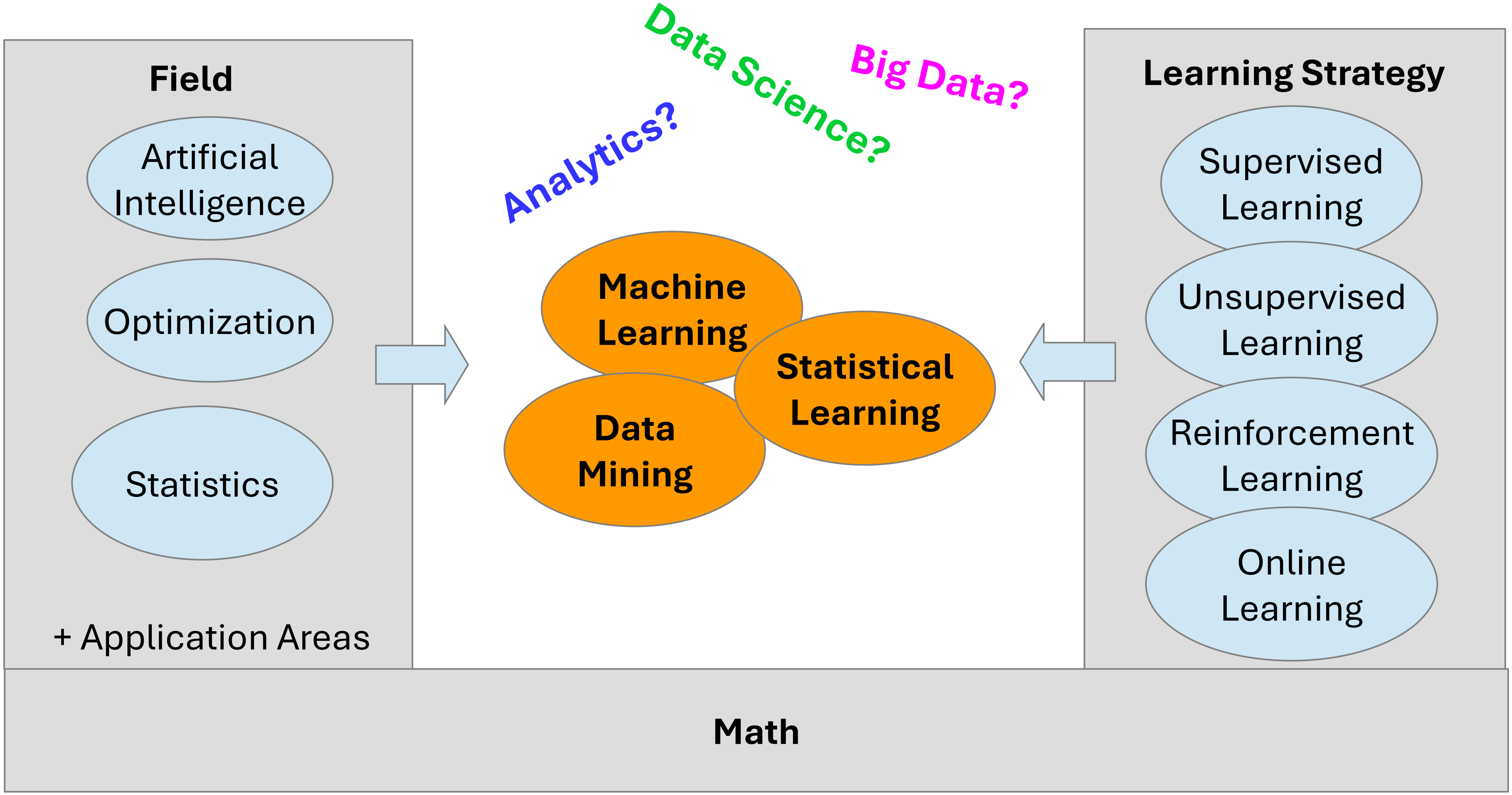
Machine Learning create algorithms that can learn from data and generalize to unseen data to perform a task without explicit instructions.
Techniques: Focus on supervised learning (e.g., classification).

Relationship to other Fields

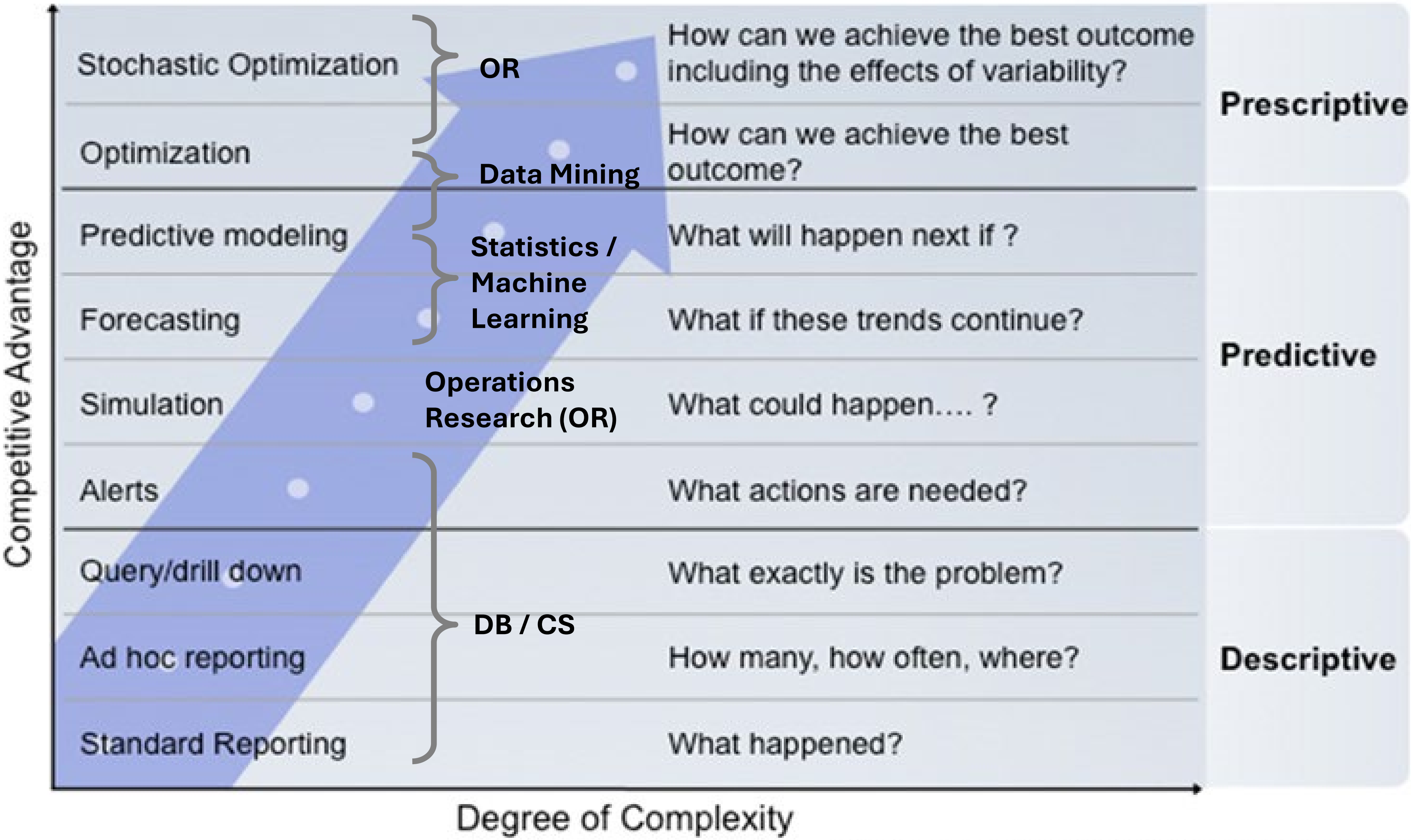


Data Mining: Analyze a given dataset to gain insights (knowledge) that can be used to improve outcomes.
Techniques: Any applicable technique from databases, statistics, machine/statistical learning. New methods were developed by the data mining community.

Analytics, Data Science and Big Data



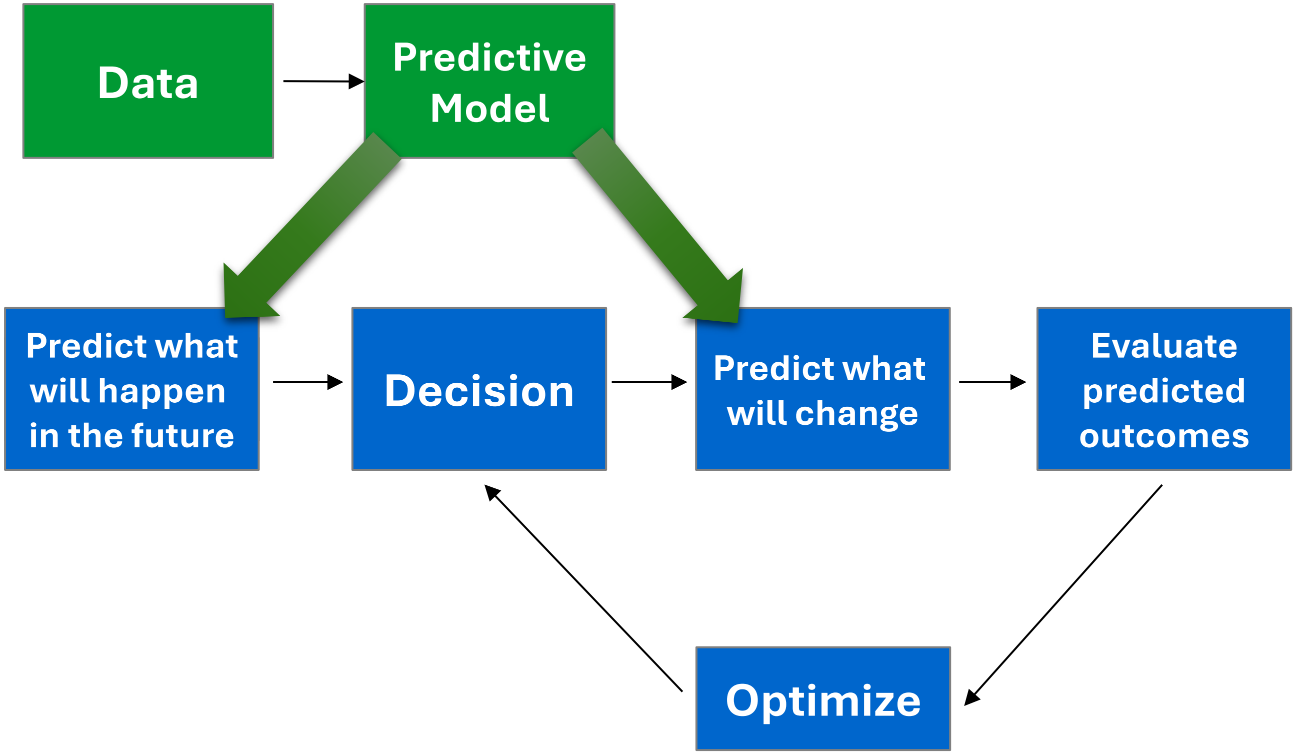
Analytics covers Data Mining



Based on: Competing on Analytics, Davenport and Harris, 2007

The Prescriptive Analytics Approach

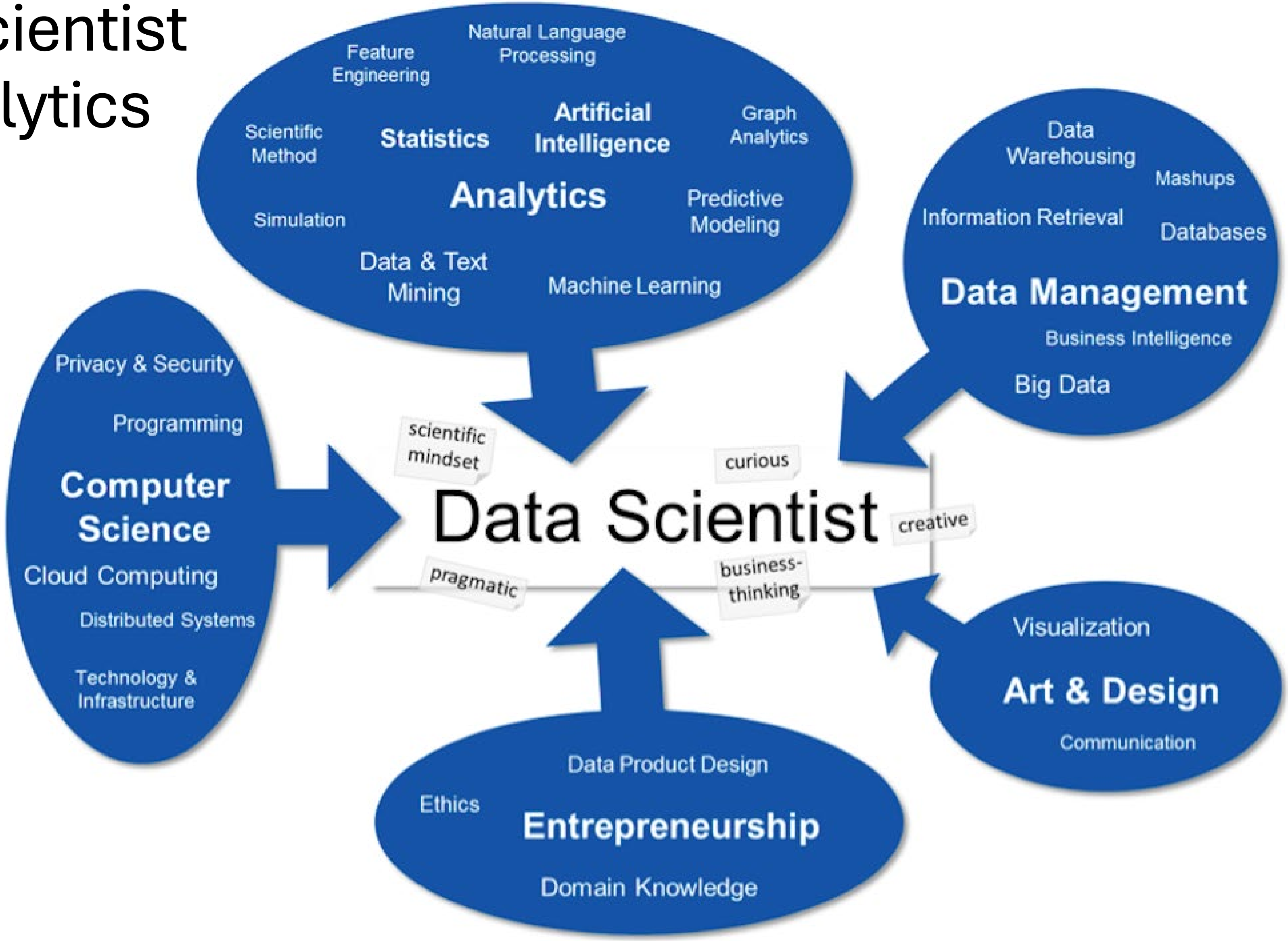
What decisions should we make now to achieve the best future outcome? This is also the objective of Data Mining.


Data
Predictive Model
Predict what will happen in the future
Decision
Predict what will change
Evaluate predicted outcomes
Optimize

Issues:

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

A Data Scientist does Analytics



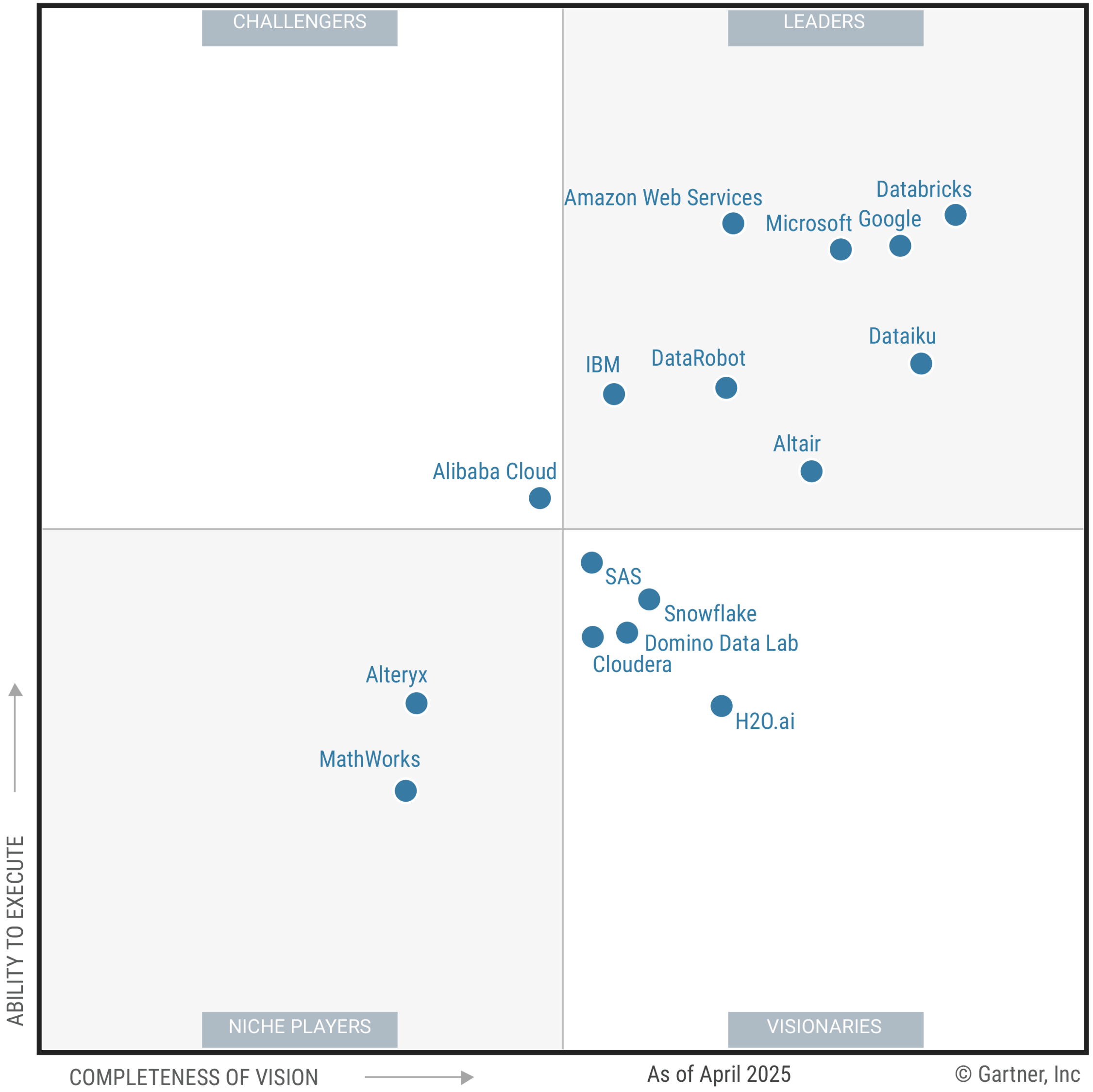
Source: T. Stadelmann, et al., Applied Data Science in Europe

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

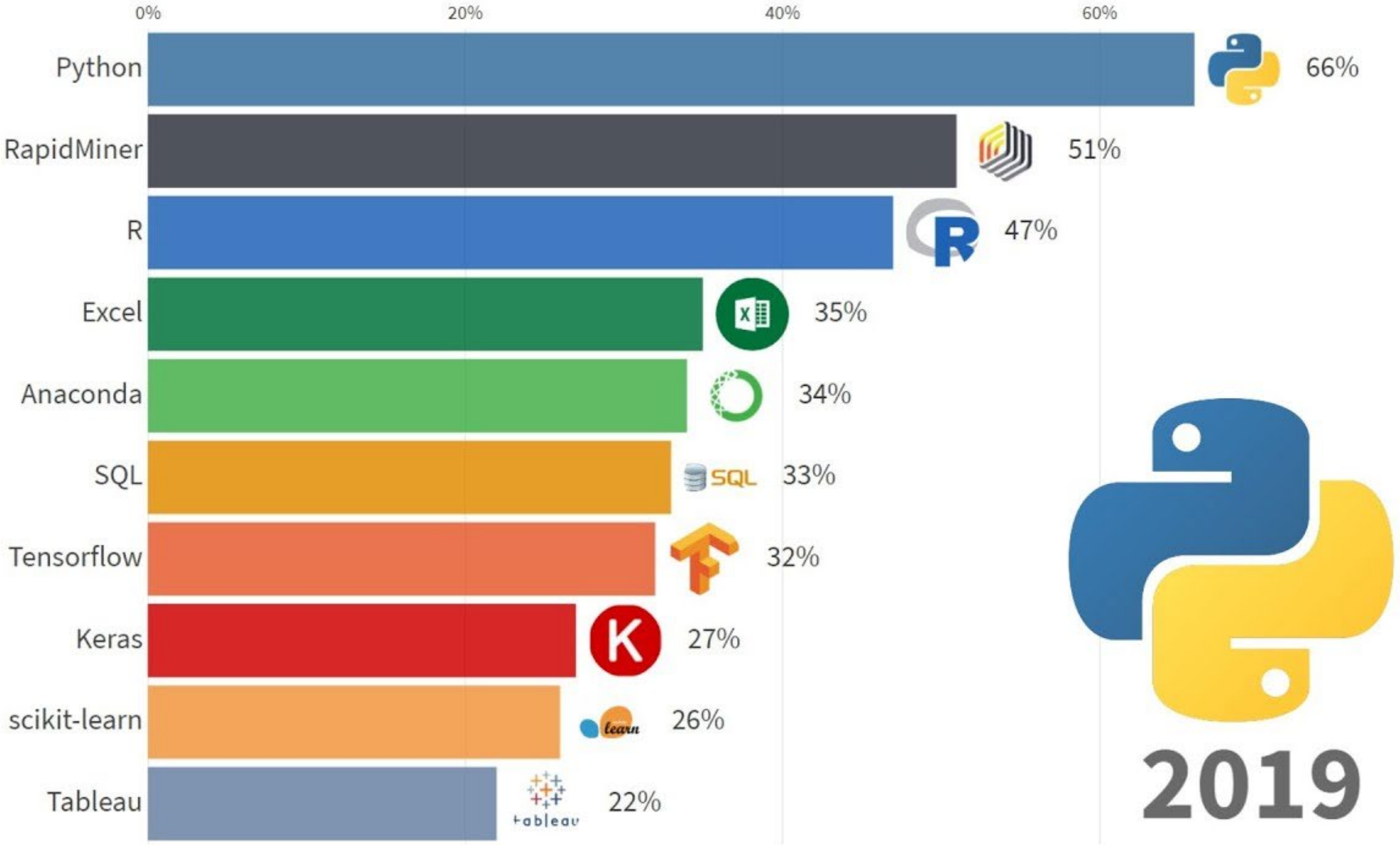


Gartner®

2025 Gartner MQ Data Science and Machine Learning.

Only covers companies, not open-source tools like Python and R.

Tools: Popularity – Data Science Tools Popularity Poll



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

Question: What tools do you use? (multiple answers possible) N = 1800

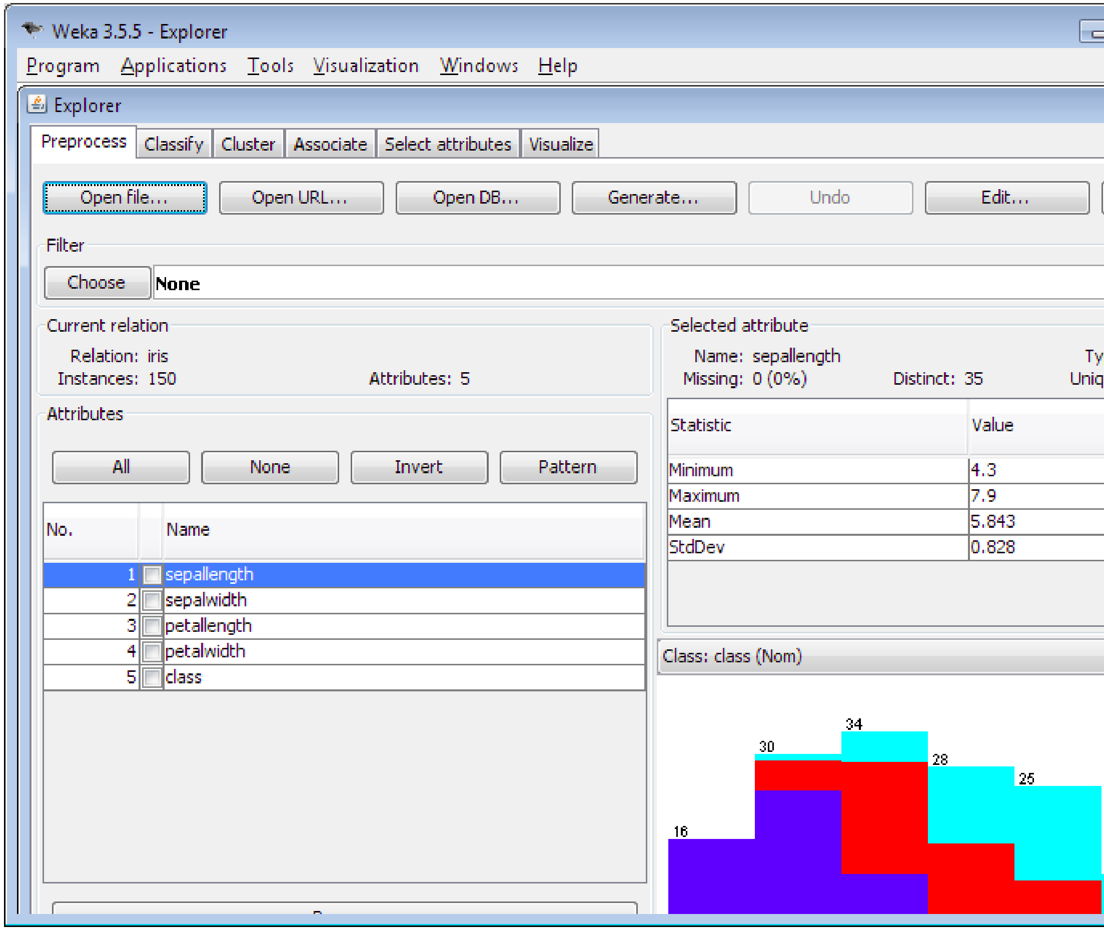
Tools: Types

- Simple graphical user interface
- Process oriented
- Programming oriented

Tools: Simple GUI

- Weka: Waikato Environment for Knowledge Analysis (also has a Java API)

- Rattle: GUI for Data Mining using R


Weka 3.5.5 - Explorer
Program Applications Tools Visualization Windows Help
Explorer
Preprocess Classify Cluster Associate Select attributes Visualize
Open file... Open URL... Open DB... Generate... Undo Edit...
Choose
All None Invert Pattern
34
30
28
25
16

Filter

None

Current relation

Relation: iris

Instances: 150 Attributes: 5

Selected attribute

Name: sepallength Ty

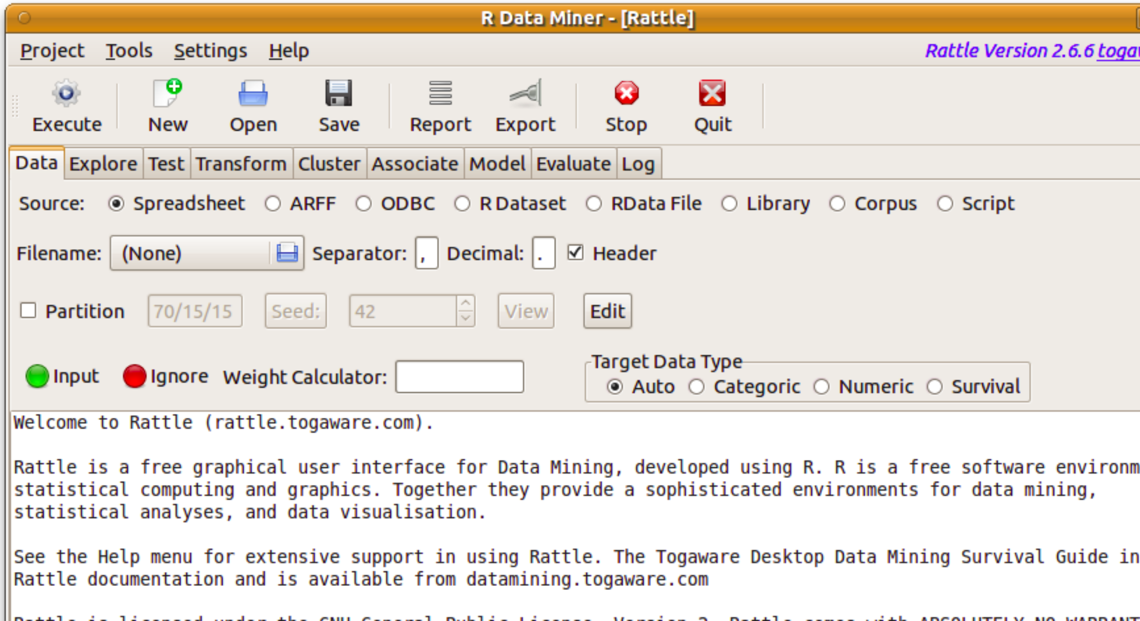
Missing: 0 (0%) Distinct: 35 Uniq

Statistic	Value
Minimum	4.3
Maximum	7.9
Mean	5.843
StdDev	0.828

Attributes

No.		Name
1	□	sepallength
2	□	sepalwidth
3	□	petallength
4	□	petalwidth
5	□	class

Class: class (Nom)


R Data Miner - [Rattle]
Project Tools Settings Help
Rattle Version 2.6.6 togaw
Execute New Open Save Report Export Stop Quit
Data Explore Test Transform Cluster Associate Model Evaluate Log
View Edit

Source: ● Spreadsheet ○ ARFF ○ ODBC ○ R Dataset ○ RData File ○ Library ○ Corpus ○ Script

Filename: (None) Separator: , Decimal: . ☑ Header

□ Partition 70/15/15 Seed: 42

Input Ignore Weight Calculator:

Target Data Type ● Auto ○ Categoric ○ Numeric ○ Survival

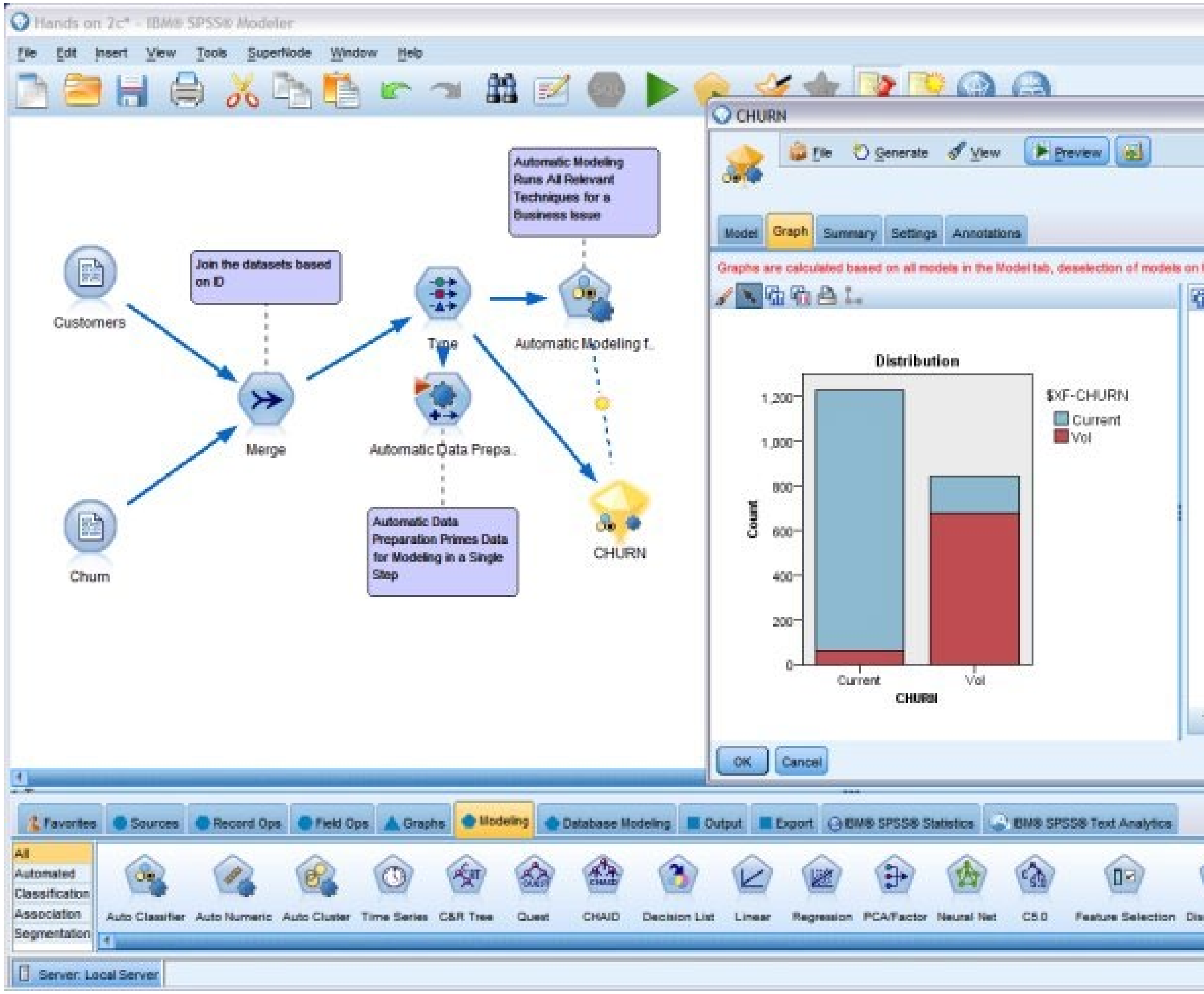
```
Welcome to Rattle (rattle.togaware.com).

Rattle is a free graphical user interface for Data Mining, developed using R. R is a free software environm
statistical computing and graphics. Together they provide a sophisticated environments for data mining,
statistical analyses, and data visualisation.

See the Help menu for extensive support in using Rattle. The Togaware Desktop Data Mining Survival Guide in
Rattle documentation and is available from datamining.togaware.com
```

Tools: Process oriented

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



Join the datasets based on ID

Automatic Modeling Runs All Relevant Techniques for a Business Issue

Automatic Data Preparation Primes Data for Modeling in a Single Step

Graphs are calculated based on all models in the Model tab, deselection of models on t

Tools: Programming oriented

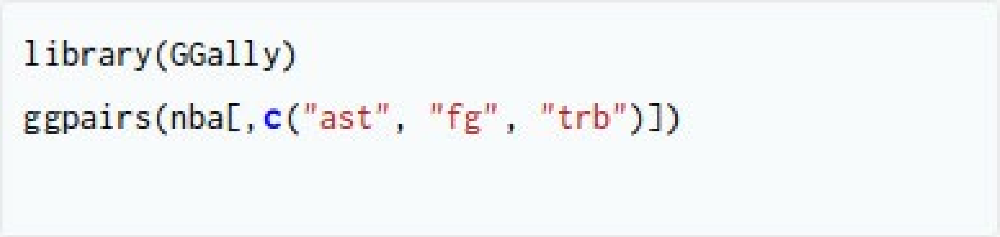
- R
  - Rattle for beginners
  - RStudio IDE, R markdown, shiny

- Python
  - Numpy, scikit-learn, pandas
  - Jupyter notebook

→ Both have similar capabilities but slightly different focus:

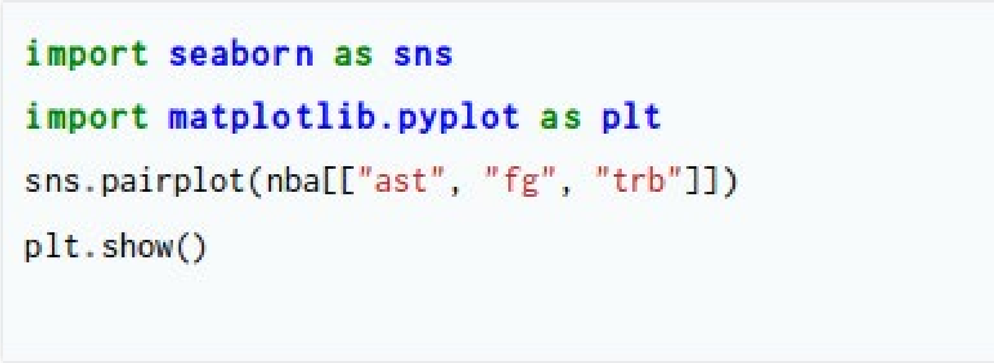
- R: statistical computing and visualization, data mining
- Python: Scripting, big data, deep learning, ML
- Interoperability via rpy2 and reticulate

R

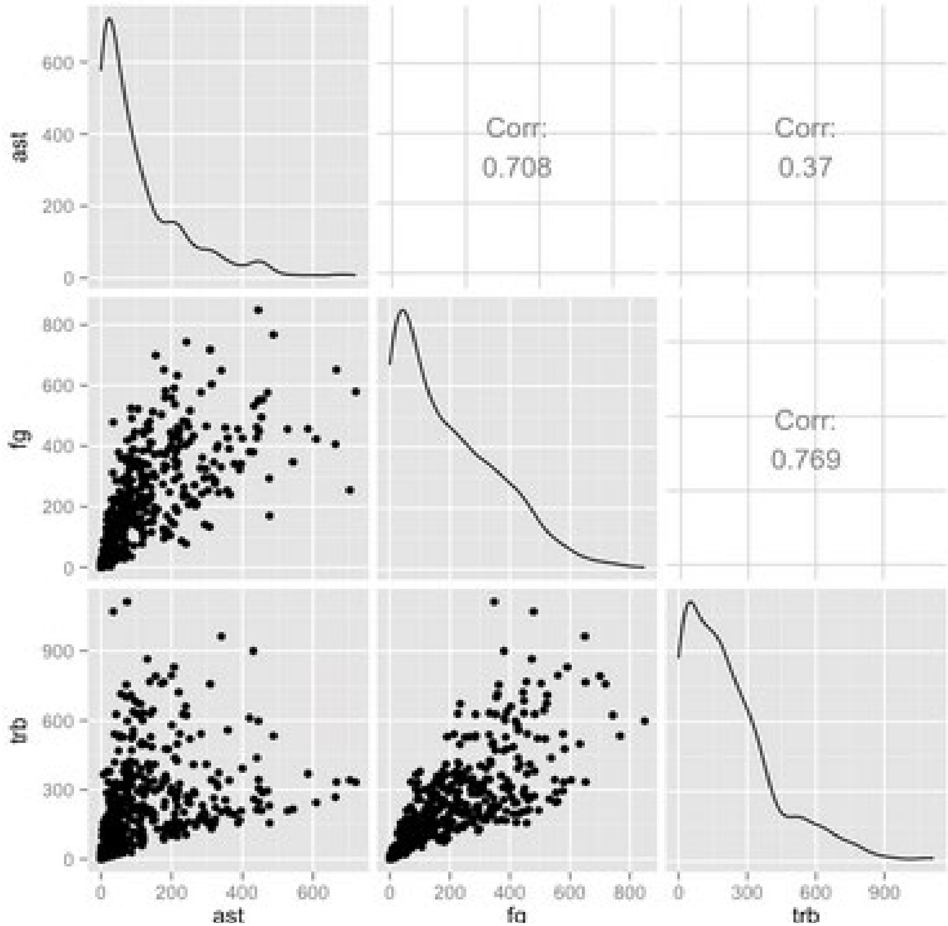


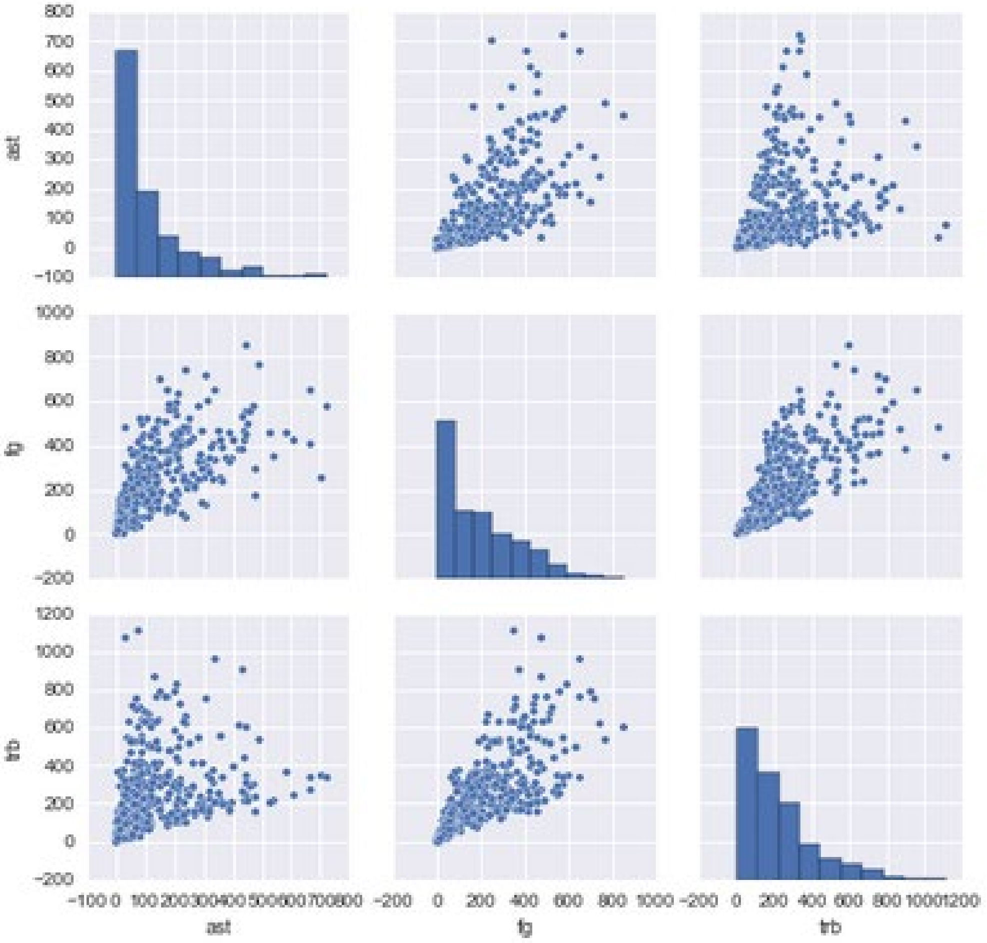
```
library(GGally)
ggpairs(nba[,c("ast", "fg", "trb")])
```

Python



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





https://www.dataquest.io/blog/python-vs-r/

Agenda

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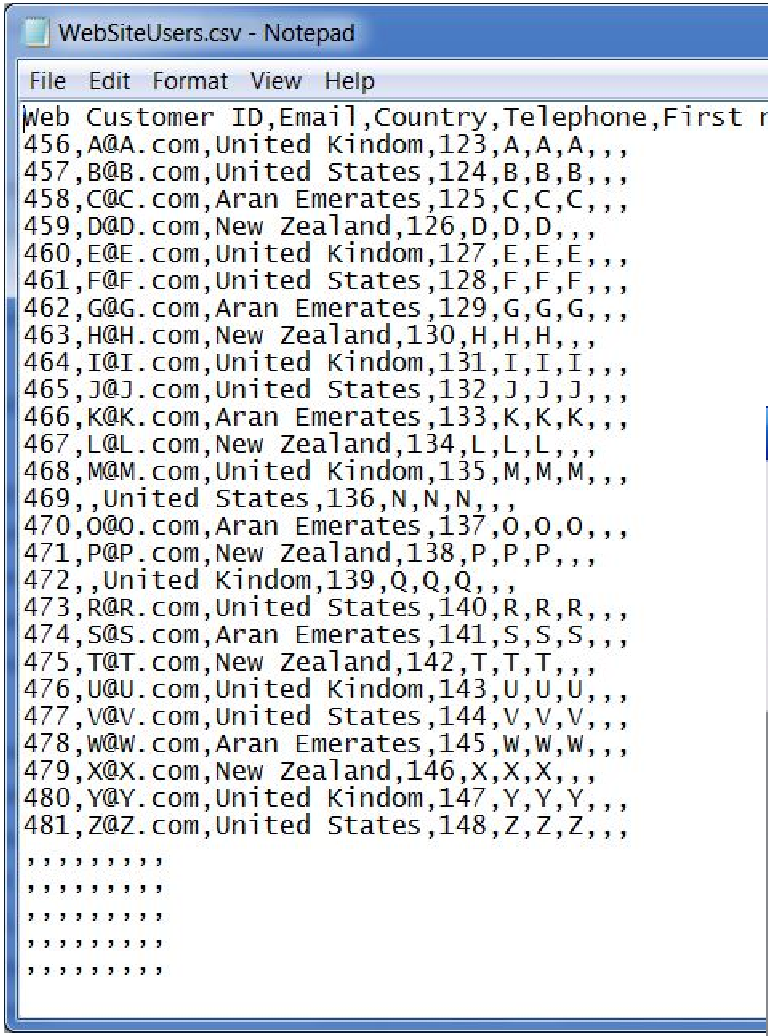
- Tools
- **Data**
- Legal, Privacy and Security Issues

Data



```
Web Customer ID,Email,Country,Telephone,First name,Surname,Company,,,
456,A@A.com,United Kindom,123,A,A,A,,,
457,B@B.com,United States,124,B,B,B,,,
458,C@C.com,Aran Emerates,125,C,C,C,,,
459,D@D.com,New Zealand,126,D,D,D,,,
460,E@E.com,United Kindom,127,E,E,E,,,
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```

Comma Separated Values format

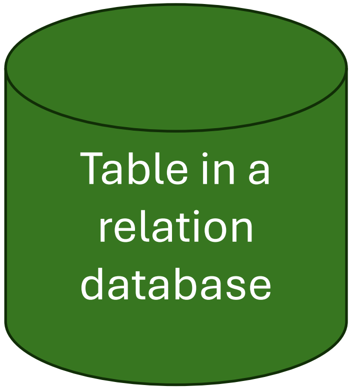
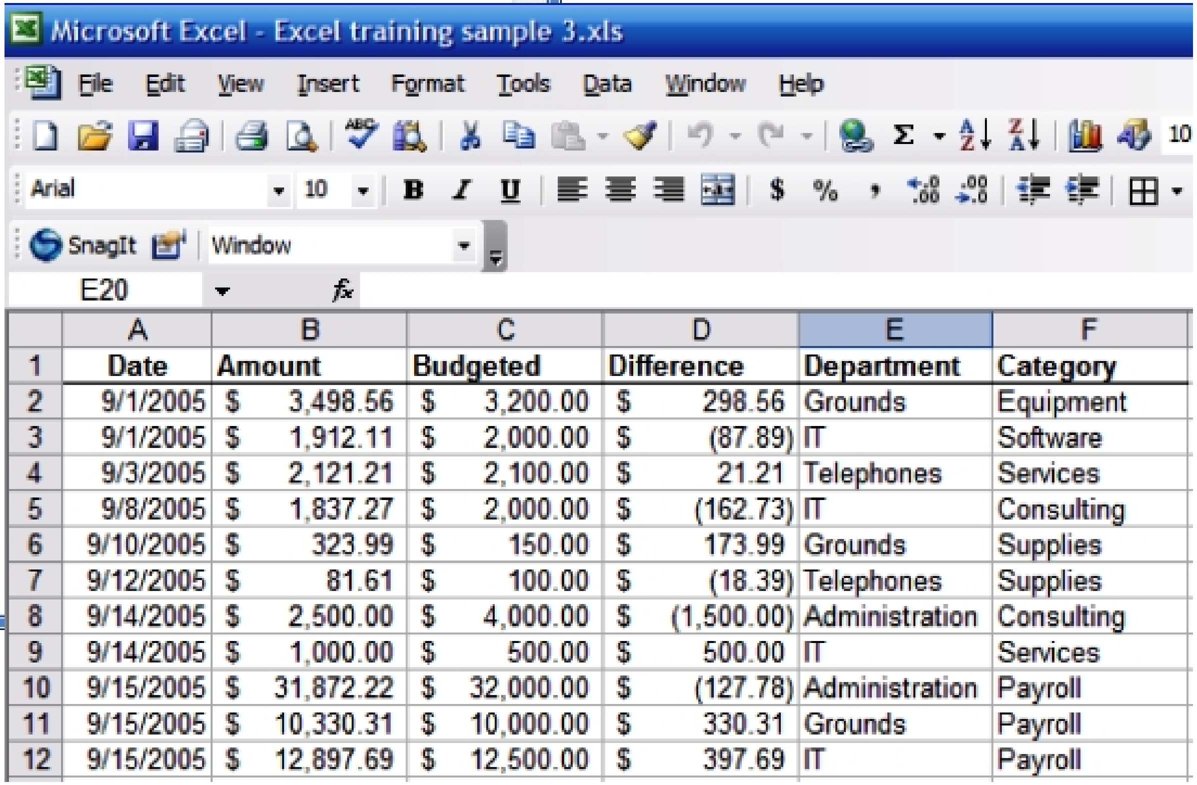
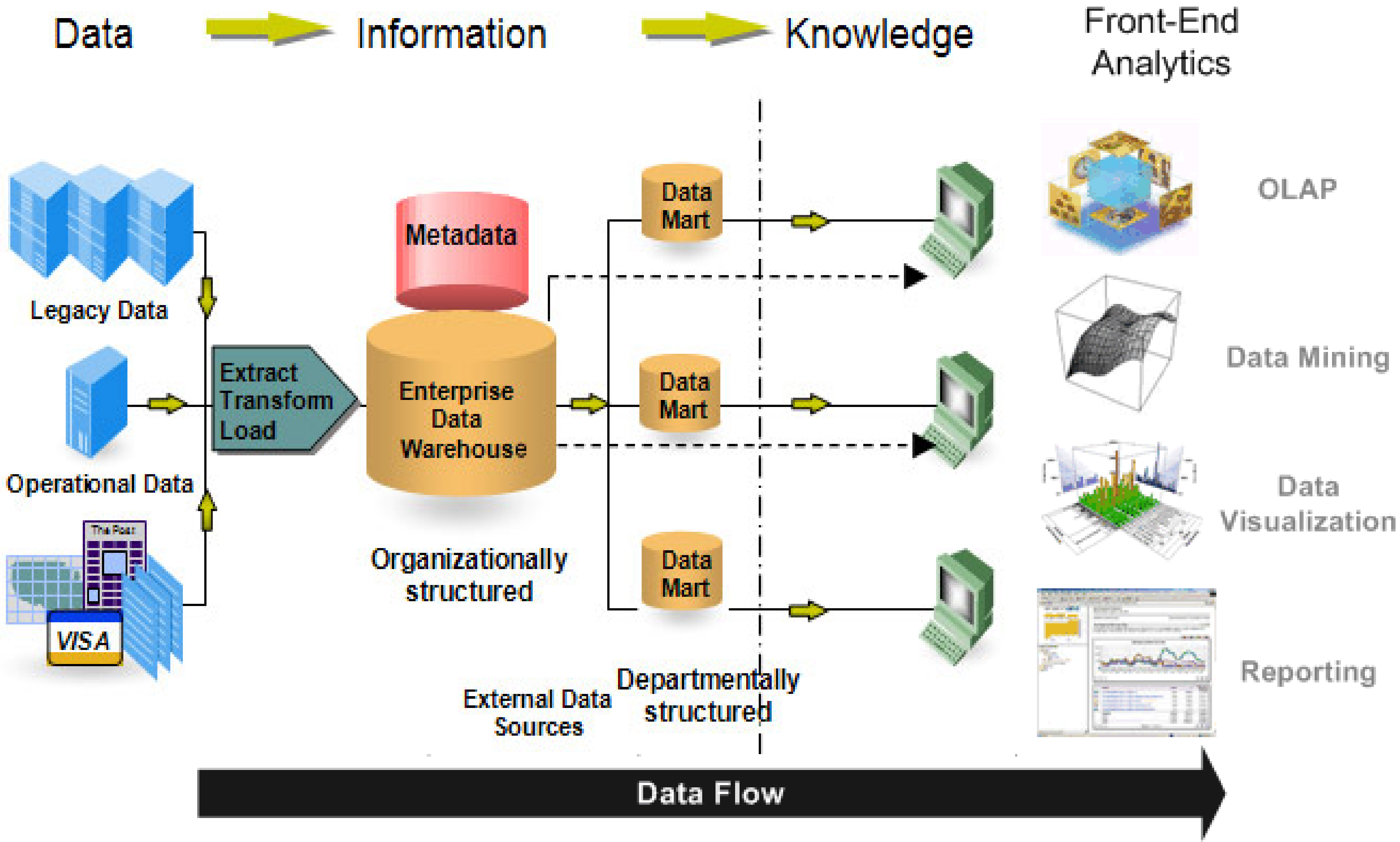


Table in a relation database


Microsoft Excel - Excel training sample 3.xls
File Edit View Insert Format Tools Data Window Help
Arial
10
SnagIt
Window
E20
fx

	A	B	C	D	E	F
1	Date	Amount	Budgeted	Difference	Department	Category
2	9/1/2005	$ 3,498.56	$ 3,200.00	$ 298.56	Grounds	Equipment
3	9/1/2005	$ 1,912.11	$ 2,000.00	$ (87.89)	IT	Software
4	9/3/2005	$ 2,121.21	$ 2,100.00	$ 21.21	Telephones	Services
5	9/8/2005	$ 1,837.27	$ 2,000.00	$ (162.73)	IT	Consulting
6	9/10/2005	$ 323.99	$ 150.00	$ 173.99	Grounds	Supplies
7	9/12/2005	$ 81.61	$ 100.00	$ (18.39)	Telephones	Supplies
8	9/14/2005	$ 2,500.00	$ 4,000.00	$ (1,500.00)	Administration	Consulting
9	9/14/2005	$ 1,000.00	$ 500.00	$ 500.00	IT	Services
10	9/15/2005	$ 31,872.22	$ 32,000.00	$ (127.78)	Administration	Payroll
11	9/15/2005	$ 10,330.31	$ 10,000.00	$ 330.31	Grounds	Payroll
12	9/15/2005	$ 12,897.69	$ 12,500.00	$ 397.69	IT	Payroll

Data Warehouse

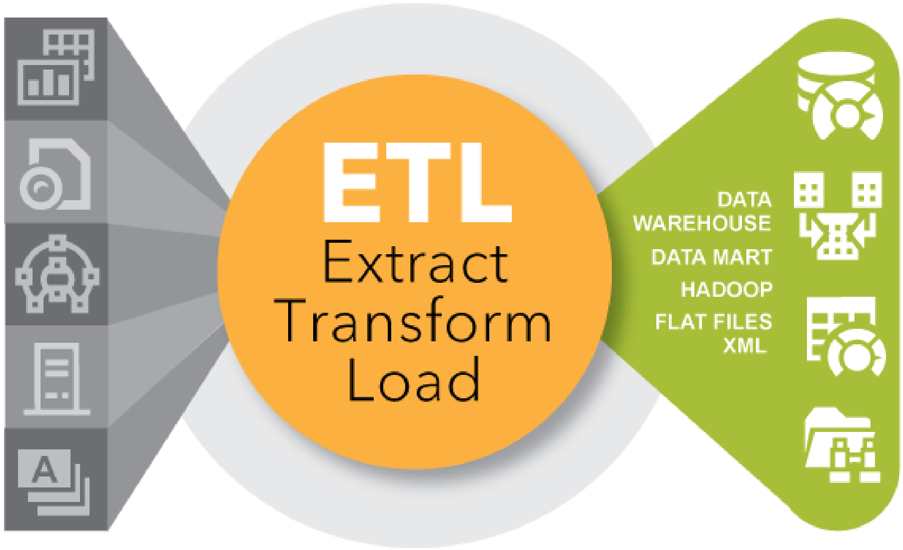


http://www.fulcrumlogic.com/data_warehousing.shtml

Data Warehouse

- Subject Oriented: Data warehouses are designed to help you analyze data (e.g., sales data is organized by product and customer).
- Integrated: Integrates data from disparate sources into a consistent format.
- Nonvolatile: Data in the data warehouse are never overwritten or deleted.
- Time Variant: maintains both historical and (nearly) current data.

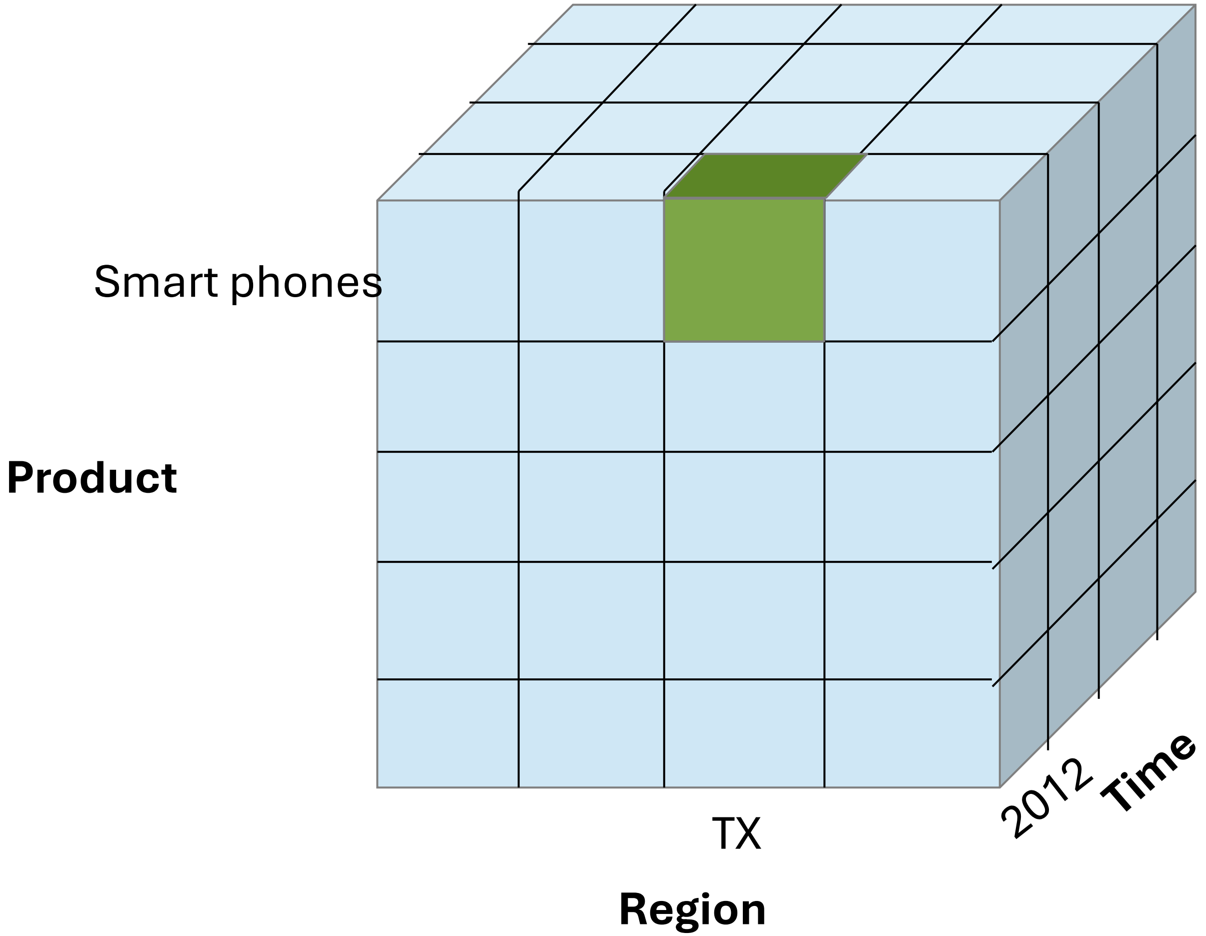
ETL: Extract, Transform and Load



Source: SAS, ETL: What it is and why it matters

- Extracting data from outside sources
- Transforming data to fit analytical needs. E.g.,
  - —Clean missing data, wrong data, etc.
  - —Normalize and translate (e.g., 1 → "female")
  - —Join from several sources
  - —Calculate and aggregate data
- Loading data into the data warehouse

OnLine Analytical Processing (OLAP)



Operations:

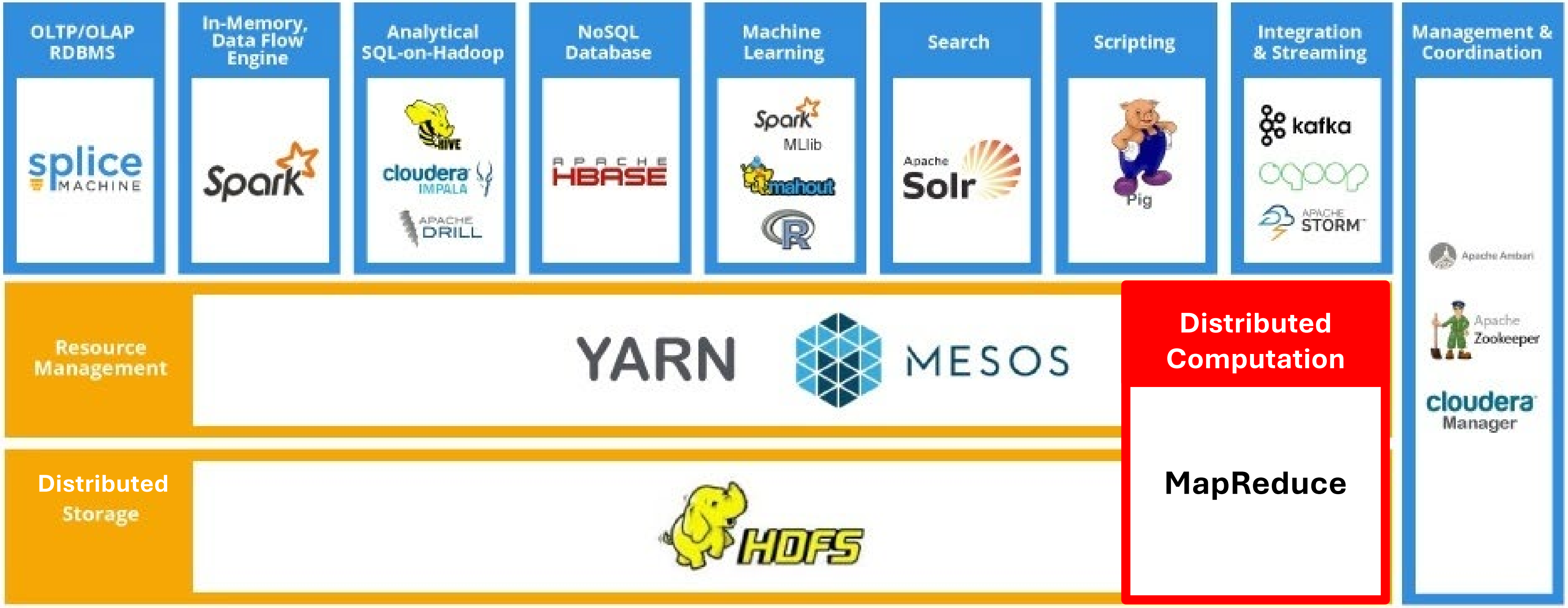
- Slice
- Dice
- Drill-down
- Roll-up
- Pivot

Store data in "data cubes" for fast OLAP operations.
Requires a special database structure (Snow-flake scheme).

Big Data

- "Big data is a term for data sets that are so large or complex that traditional data processing applications are inadequate to deal with them." Wikipedia
- 3 V's: Volume, velocity, variety, (veracity) Gartner

THE APACHE SOFTWARE FOUNDATION


OLTP/OLAP RDBMS

In-Memory, Data Flow Engine

Analytical SQL-on-Hadoop

NoSQL Database

Machine Learning

Search

Scripting

Integration & Streaming

Management & Coordination

Resource Management

Distributed Storage

Distributed Computation

MapReduce

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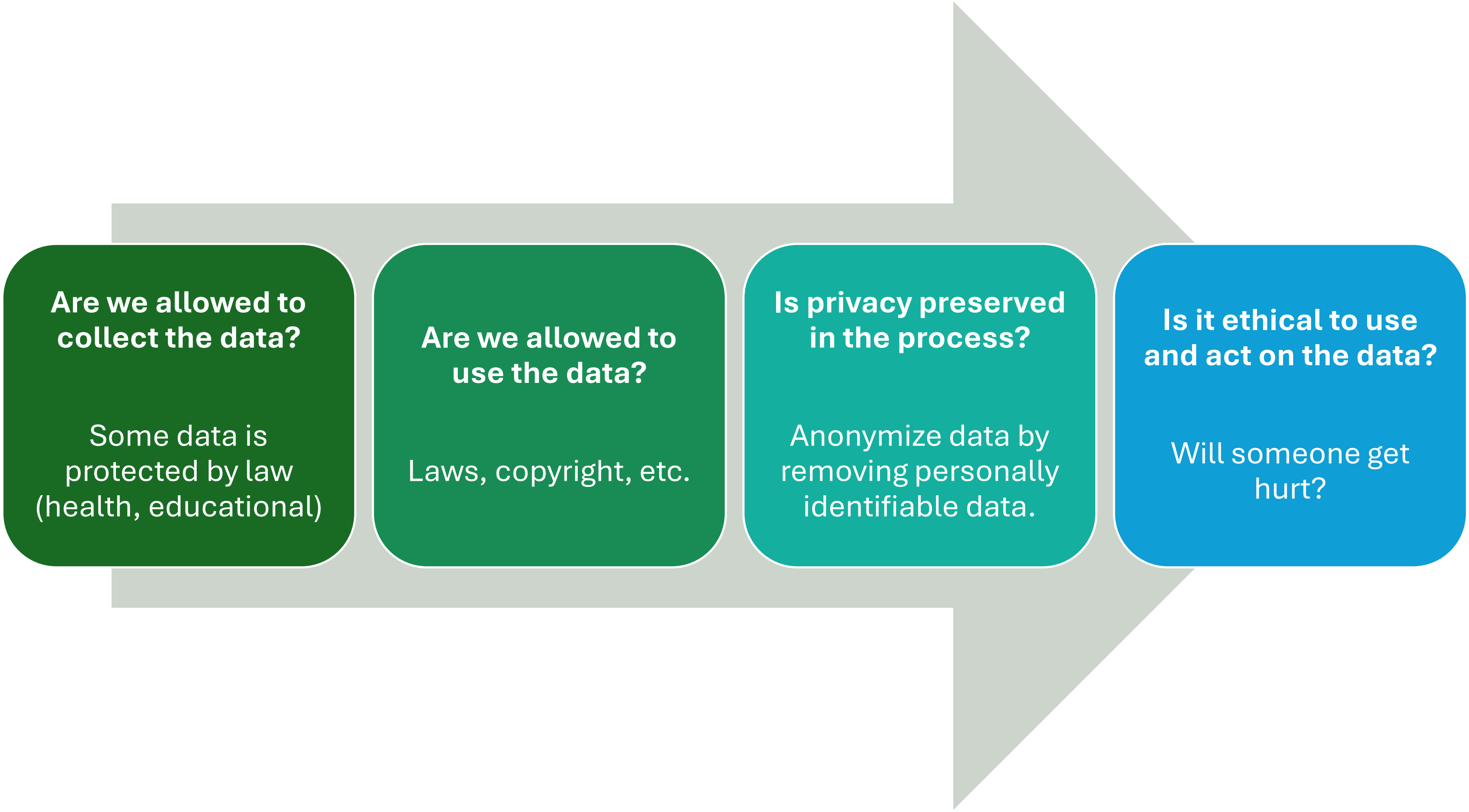
- **Ethics, Privacy and Security Issues**

Legal, Privacy and Security Issues

DID YOU EVER THINK ABOUT SELLING OUR CONFIDENTIAL DATABASE OF CUSTOMER INFORMATION?
IT WOULD BE MASSIVELY PROFITABLE WHILE VIRTUALLY UNDETECTABLE.
BUT HIGHLY UNETHICAL.
I DON'T KNOW YOU ANYMORE.
I'M YANKING YOUR CHAIN. WHEN DO WE START?
scottadams@aol.com
www.dilbert.com
© 2004 Scott Adams, Inc./Dist. by UFS, Inc.

?

Legal, Privacy and Security Issues



Are we allowed to collect the data?

Some data is protected by law (health, educational)

Are we allowed to use the data?

Laws, copyright, etc.

Is privacy preserved in the process?

Anonymize data by removing personally identifiable data.

Is it ethical to use and act on the data?

Will someone get hurt?

Problem: Internet is global, but legislation is local!

Ethics, Privacy and Security Issues

The New York Times

Data-Gathering via Apps
Presents a Gray Legal Area
By KEVIN J. O’BRIEN
Published: October 28, 2012

BERLIN — Angry Birds, the top-selling paid mobile app for the iPhone in the United States and Europe, has been downloaded more than a billion times by devoted game players around the world, who often spend hours slinging squawking fowl at groups of egg-stealing pigs.

When Jason Hong, an associate professor at the Human-Computer Interaction Institute at Carnegie Mellon University, surveyed 40 users, all but two were **unaware that the game was storing their locations so that they could later be the targets of ads**….

POKÉMON
GO

Here is what the small print says…

USA Today Network Josh Hafner, 2:38 p.m. EDT July 13, 2016

USA TODAY

Pokémon Go’s constant location tracking and camera access required for gameplay, paired with its skyrocketing popularity, could provide data like no app before it.

“Their privacy policy is vague,” Hong said. “I’d say deliberately vague, because of the lack of clarity on the business model.”

…

The agreement says **Pokémon Go collects data about its users as a “business asset.”** This includes data used to personally identify players such as email addresses and other information pulled from Google and Facebook accounts players use to sign up for the game.

If Niantic is ever sold, the agreement states, all that data can go to another company.

Conclusion

Data Mining is interdisciplinary and overlaps significantly with many fields

- Statistics
- CS (machine learning, AI, data bases)
- Optimization (Operations Research)
- (Business) Analytics
- Data Science

Data Mining requires a team effort with members who have expertise in several areas

- Data management
- Statistics
- Programming
- Communication
- + Application domain