

Machine Learning and Data Mining

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Acronyms

BI Business Intelligence

CDC Change Data Capture

CRISP-DM Cross Industry Standard Process for Data Mining

DFM Dimensional Fact Model

DM Data Mart

DSS Decision Support System

DWH Data Warehouse

EIS Executive Information System

ERP Enterprise Resource Planning

ETL Extraction, Transformation, Loading

MIS Management Information System

OLAP Online Analytical Processing

OLTP Online Transaction Processing

1 Introduction

1.1 Data

Data Collection of raw values.

Data

Information Organized data (e.g. relationships, context, ...).

Information

Knowledge Understanding information.

Knowledge

1.1.1 Data sources

Transaction Business event that generates or modifies data in an information system (e.g. database).

Transaction

Signal Measure produced by a sensor.

Signal

External subjects

1.1.2 Software

Online Transaction Processing (OLTP) Class of programs to support transaction oriented applications and data storage. Suitable for real-time applications.

Online Transaction Processing

Enterprise Resource Planning (ERP) Integrated system to manage all the processes of a business. Uses a shared database for all applications. Suitable for real-time applications.

Enterprise Resource Planning

1.1.3 Insight

Decision can be classified as:

Structured Established and well understood situations. What is needed is known.

Structured decision

Unstructured Unplanned and unclear situations. What is needed for the decision is unknown.

Unstructured decision

Different levels of insight can be extracted by:

Management Information System (MIS) Standardized reporting system built on existing OLTP. Used for structured decisions.

Management Information System

Decision Support System (DSS) Analytical system to provide support for unstructured decisions.

Decision Support System

Executive Information System (EIS) Formulate high level decisions that impact the organization.

Executive Information System

Online Analytical Processing (OLAP) Grouped analysis of multidimensional data. Involves large amount of data.

Online Analytical Processing

Business Intelligence (BI) Applications, infrastructure, tools and best practices to analyze information. Business Intelligence

Big data Large and/or complex and/or fast changing collection of data that traditional DBMSs are unable to process. Big data

Structured e.g. relational tables.

Unstructured e.g. videos.

Semi-structured e.g. JSON.

Anaylitics Structured decision driven by data. Anaylitics

Data mining Discovery process for unstructured decisions. Data mining

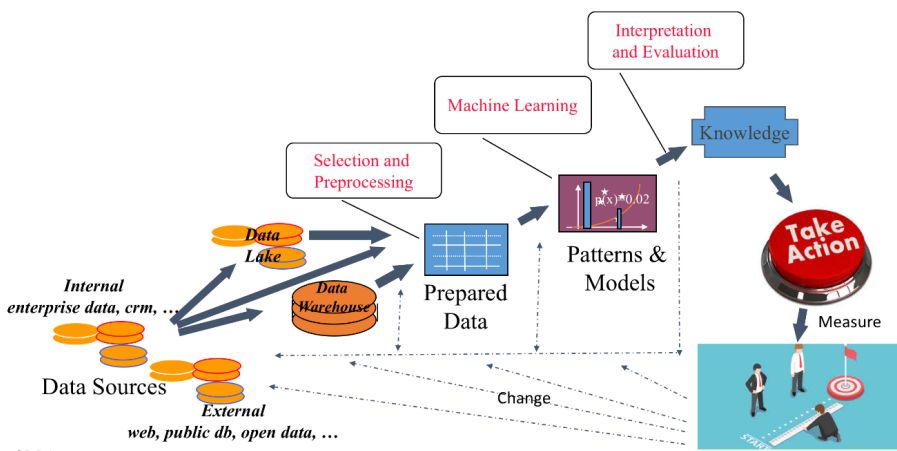


Figure 1.1: Data mining process

Machine learning Learning models and algorithms that allow to extract patterns from data. Machine learning

2 Data warehouse

Business Intelligence Transform raw data into information. Deliver the right information to the right people at the right time through the right channel. Business Intelligence

Data Warehouse (DWH) Optimized repository that stores information for decision making processes. DWHs are a specific type of DSS. Data Warehouse

Features:

- Subject-oriented: focused on enterprise specific concepts.
- Integrates data from different sources and provides an unified view.
- Non-volatile storage with change tracking.

Data Mart (DM) Subset of the primary DWH with information relevant to a specific business area. Data Mart

2.1 Online Analytical Processing (OLAP)

OLAP analyses Able to interactively navigate the information in a data warehouse. Allows to visualize different levels of aggregation. Online Analytical Processing (OLAP)

OLAP session Navigation path created by the operations that a user applied.

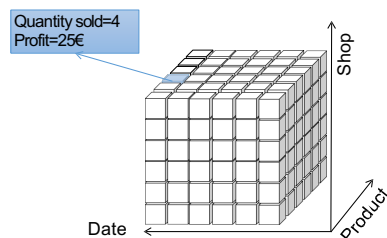
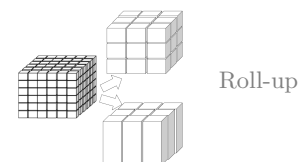


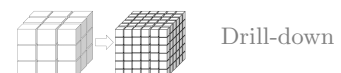
Figure 2.1: OLAP data cube

2.1.1 Operators

Roll-up Increases the level of aggregation (i.e. GROUP BY in SQL). Some details are collapsed together.



Drill-down Reduces the level of aggregation. Some details are reintroduced.



Slide-and-dice

Pivot

Drill-through

Order ID	Order Date	Ship Date	Ship Mode	Customer Name	Segment	City	State	Country
17-1219-128300	12/19/2017	12/20/2017	Same Day	Gunga Industries	Corporate	Mumbai	India	France
18-1214-128297	12/14/2018	12/20/2018	Second Class	Sara Garcia	Corporate	Houston	Texas	France
18-1214-128301	12/14/2018	12/20/2018	Standard Class	Vanessa	Corporate	San Jose	California	Germany
18-1214-128300	12/14/2018	12/20/2018	Standard Class	Vanessa	Corporate	Huyfong	Germany	Germany
18-1214-128302	12/14/2018	12/20/2018	Standard Class	Vanessa	Corporate	Huyfong	Germany	Germany
18-1214-128303	12/14/2018	12/20/2018	Standard Class	Vanessa	Corporate	Waller (Dach)	North Rhine-Westphalia	Germany
18-1214-128302	12/14/2018	12/20/2018	Standard Class	Vanessa	Corporate	Waller (Dach)	North Rhine-Westphalia	Germany
18-1214-128302	12/14/2018	12/20/2018	Standard Class	Vanessa	Corporate	Waller (Dach)	North Rhine-Westphalia	Germany

Extraction,
Transformation,
Loading (ETL)

Typos

Methods to clean and increase the quality of the data are:

Dictionary-based techniques	Lookup tables to substitute abbreviations, synonyms or typos. Applicable if the domain is known and limited.	Dictionary-based cleaning
Approximate merging	Merging data that do not have a common key.	Approximate merging
Approximate join	Use non-key attributes to join two tables (e.g. using the name and surname instead of a unique identifier).	
Similarity approach	Use similarity functions (e.g. edit distance) to merge multiple instances of the same information (e.g. typo in customer surname).	
Ad-hoc algorithms		Ad-hoc algorithms

2.2.3 Transformation

Data are transformed to respect the format of the data warehouse:

Conversion	Modifications of types and formats (e.g. date format)	Conversion
Enrichment	Creating new information by using existing attributes (e.g. compute profit from receipts and expenses)	Enrichment
Separation and concatenation	Denormalization of the data: introduces redundances (i.e. breaks normal form ¹) to speed up operations.	Separation and concatenation

2.2.4 Loading

Adding data into a data warehouse:

Refresh	The entire DWH is rewritten.	Refresh loading
Update	Only the changes are added to the DWH. Old data are not modified.	Update loading

2.3 Data warehouse architectures

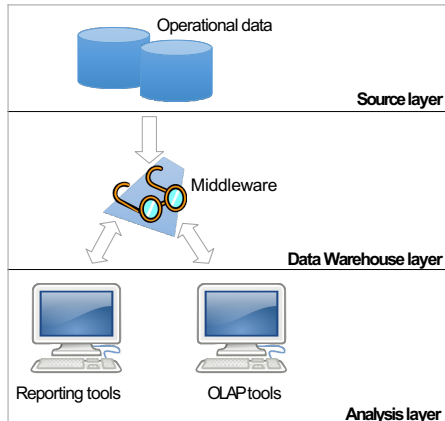
The architecture of a data warehouse should meet the following requirements:

Separation	Separate the analytical and transactional workflows.
Scalability	Hardware and software should be easily upgradable.
Extensibility	Capability to host new applications and technologies without the need to redesign the system.
Security	Access control.
Administrability	Easily manageable.

¹https://en.wikipedia.org/wiki/Database_normalization

2.3.1 Single-layer architecture

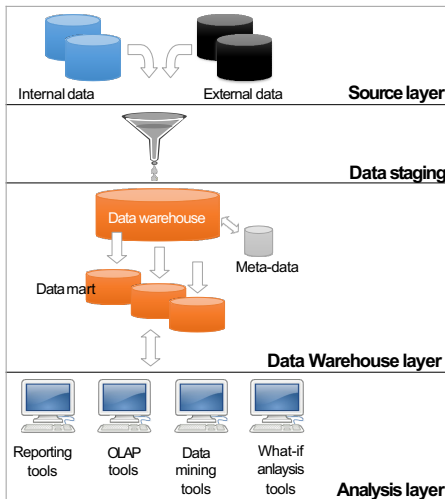
- Minimizes the amount of data stored (i.e. no redundancies).
- The source layer is the only physical layer (i.e. no separation).
- A middleware provides the DWH features.



Single-layer architecture

2.3.2 Two-layer architecture

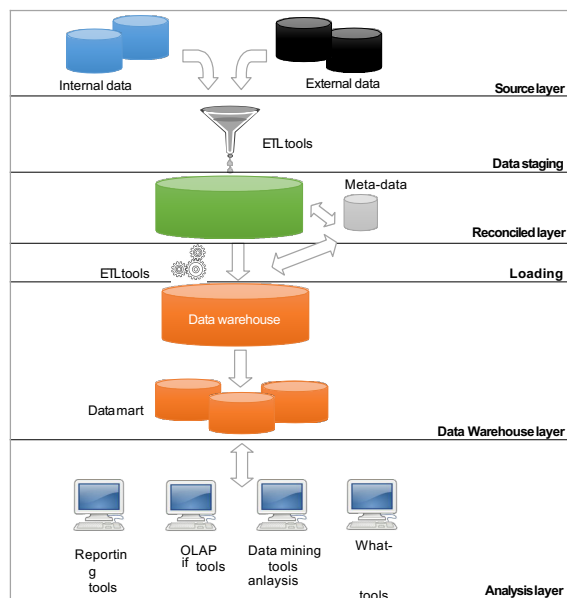
- Source data (source layer) are physically separated from the DWH (data warehouse layer).
- A staging layer applies ETL procedures before populating the DWH.
- The DWH is a centralized repository from which data marts can be created. Metadata repositories store information on sources, staging and data marts schematics.



Two-layer architecture

2.3.3 Three-layer architecture

- A reconciled layer enhances the cleaned data coming from the staging step by adding enterprise-level details (i.e. adds more redundancy before populating the DWH).



Three-layer architecture

2.4 Conceptual modeling

Dimensional Fact Model (DFM) Conceptual model to support the design of data marts.

The main concepts are:

Fact Concept relevant to decision-making processes (e.g. sales).

Measure Numerical property to describe a fact (e.g. profit).

Dimension Property of a fact with a finite domain (e.g. date).

Dimensional attribute Property of a dimension (e.g. month).

Hierarchy A tree where the root is a dimension and nodes are dimensional attributes (e.g. date $\rightarrow$ month).

Primary event Occurrence of a fact. It is described by a tuple with a value for each dimension and each measure.

Secondary event Aggregation of primary events. Measures of primary events are aggregated if they have the same (preselected) dimensional attributes.

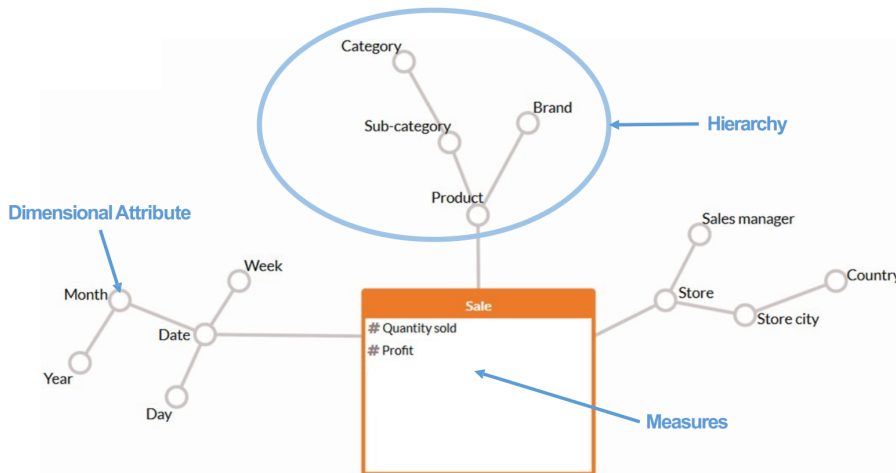


Figure 2.2: Example of DFM

Primary events				
Date	Store	Product	Qty sold	Profit
01/03/15	Central store	Milk	20	60
01/03/15	Central store	Coke	25	50
02/03/15	Central store	Bread	40	70
10/03/15	Central store	Wine	15	150

Secondary event				
Month	Store	Category	Qty sold	Profit
March 2015	Central store	Food and Beverages	100	330

SUM SUM

Figure 2.3: Example of primary and secondary events

2.4.1 Aggregation operators

Measures can be classified as:

- Flow measures** Evaluated cumulatively with respect to a time interval (e.g. quantity sold). Flow measures
- Level measures** Evaluated at a particular time (e.g. number of products in inventory). Level measures
- Unit measures** Evaluated at a particular time but expressed in relative terms (e.g. unit price). Unit measures

Aggregation operators can be classified as:

- Distributive** Able to calculate aggregates from partial aggregates (e.g. SUM, MIN, MAX). Distributive operators
- Algebraic** Requires a finite number of support measures to compute the result (e.g. AVG). Algebraic operators
- Holistic** Requires an infinite number of support measures to compute the result (e.g. RANK). Holistic operators
- Additivity** A measure is additive along a dimension if an aggregation operator can be applied. Additive measure

	Temporal hierarchies	Non-temporal hierarchies
Flow measures	SUM, AVG, MIN, MAX	SUM, AVG, MIN, MAX
Level measures	AVG, MIN, MAX	SUM, AVG, MIN, MAX
Unit measures	AVG, MIN, MAX	AVG, MIN, MAX

Table 2.1: Allowed operators for each measure type

2.4.2 Logical design

Defining the data structures (e.g. tables and relationships) according to a conceptual model. There are mainly two strategies:

- Star schema** A fact table that contains all the measures and linked to dimensional tables. Star schema

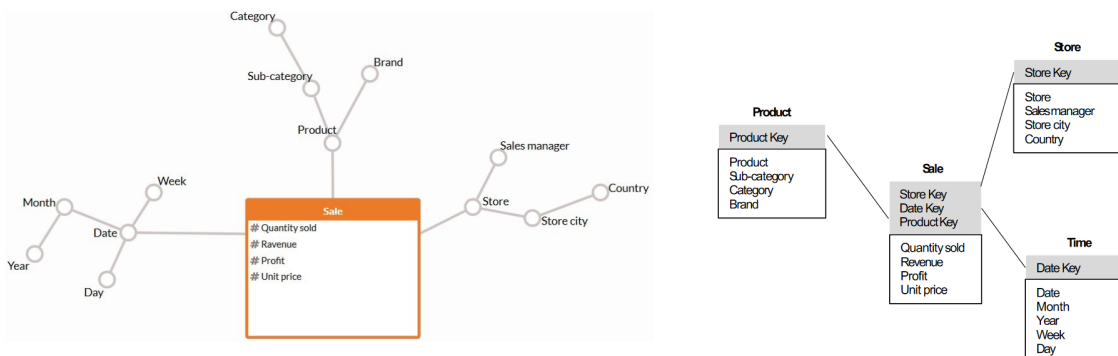


Figure 2.4: Example of star schema

- Snowflake schema** A star schema variant with partially normalized dimension tables. Snowflake schema

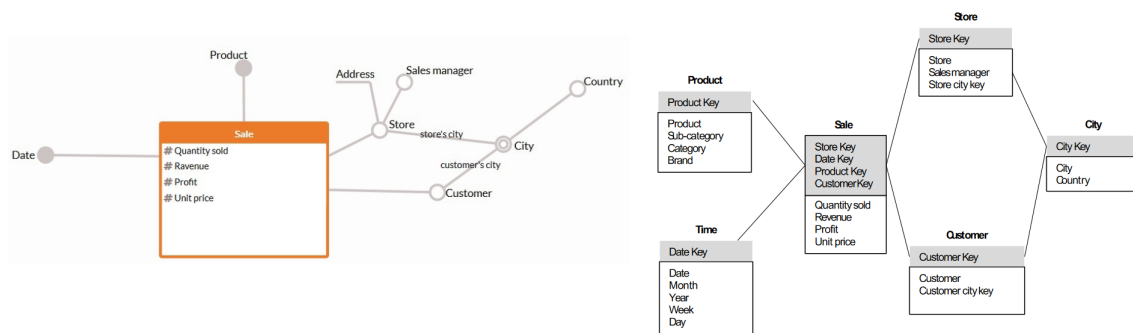


Figure 2.5: Example of snowflake schema

3 Data lake

Dark data Acquired and stored data that are never used for decision-making processes. Dark data

Data lake Repository to store raw (unstructured) data. It has the following features: Data lake

- Does not enforce a schema on write.
- Allows flexible access and applies schemas on read.
- Single source of truth.
- Low cost and scalable.

Storage Stored data can be classified as:

Hot A low volume of highly requested data that require low latency. More expensive HW/SW. Hot storage

Cold A large amount of data that does not have latency requirements. Less expensive. Cold storage

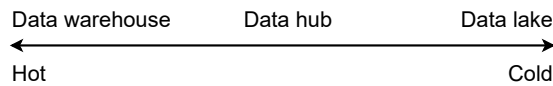


Figure 3.1: Data storage technologies

3.1 Traditional vs insight-driven data systems

	Traditional (data warehouse)	Insight-driven (data lake)
Sources	Structured data	Structured, semi-structured and unstructured data
Storage	Limited ingestion and storage capability	Virtually unlimited ingestion and storage capability
Schema	Schema designed upfront	Schema not fixed
Transformations	ETL upfront	Transformations on query
Analytics	SQL, BI tools, full-text search	Traditional methods, self-service BI, big data, machine learning, ...
Price	High storage cost	Low storage cost
Performance	Fast queries	Scalability/speed/cost tradeoffs
Quality	High data quality	Depends on the use case

3.2 Data architecture evolution

Traditional data warehouse (i.e. in-house data warehouse)

- Structured data with predefined schemas.
- High setup and maintenance cost. Not scalable.

Traditional data warehouse

- Relational high-quality data.
- Slow data ingestion.

Modern cloud data warehouse

Modern cloud data warehouse

- Structured and semi-structured data.
- Low setup and maintenance cost. Scalable and easier disaster recovery.
- Relational high-quality data and mixed data.
- Fast data ingestion if supported.

On-premise big data (i.e. in-house data lake)

On-premise big data

- Any type of data with schemas on read.
- High setup and maintenance cost.
- Fast data ingestion.

Cloud data lake

Cloud data lake

- Any type of data with schemas on read.
- Low setup and maintenance cost. Scalable and easier disaster recovery.
- Fast data ingestion.

3.3 Components

3.3.1 Data ingestion

Data ingestion

Workload migration Inserting all the data from an existing source.

Incremental ingestion Inserting changes since the last ingestion.

Streaming ingestion Continuously inserting data.

Change Data Capture (CDC) Mechanism to detect changes and insert the new data into the data lake (possibly in real-time).

Change Data Capture (CDC)

3.3.2 Storage

Raw Immutable data useful for disaster recovery.

Raw storage

Optimized Optimized raw data for faster query.

Optimized storage

Analytics Ready to use data.

Analytics storage

Columnar storage

- Homogenous data are stores contiguously.
- Speeds up methods that process entire columns (i.e. all the values of a feature).
- Insertion becomes slower.

Data catalog Methods to add descriptive metadata to a data lake. This is useful to prevent an unorganized data lake (data swamp).

3.3.3 Processing and analytics

Processing and analytics

Interactive analytics Interactive queries to large volumes of data. The results are stored back in the data lake.

Big data analytics Data aggregations and transformations.

Real-time analytics Streaming analysis.

3.4 Architectures

3.4.1 Lambda lake

Lambda lake

Batch layer Receives and stores the data. Prepares the batch views for the serving layer.

Serving layer Indexes batch views for faster queries.

Speed layer Receives the data and prepares real-time views. The views are also stored in the serving layer.

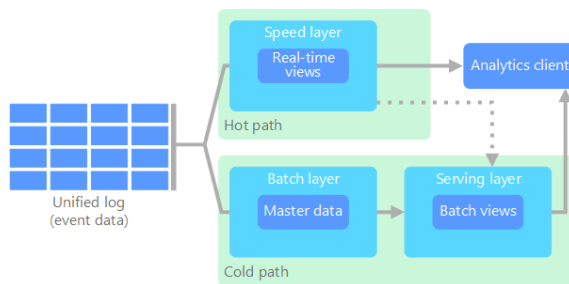


Figure 3.2: Lambda lake architecture

3.4.2 Kappa lake

The data are stored in a long-term store. Computations only happen in the speed layer (avoids lambda lake redundancy between batch layer and speed layer).

Kappa lake

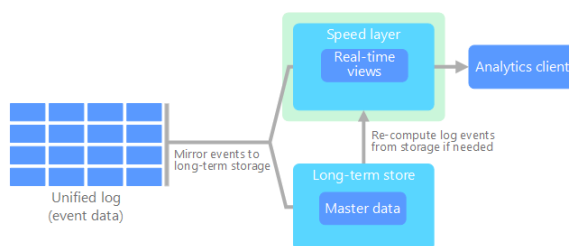


Figure 3.3: Kappa lake architecture

3.4.3 Delta lake

Framework that adds features on top of an existing data lake.

Delta lake

- ACID transactions
- Scalable metadata handling
- Data versioning
- Unified batch and streaming
- Schema enforcement

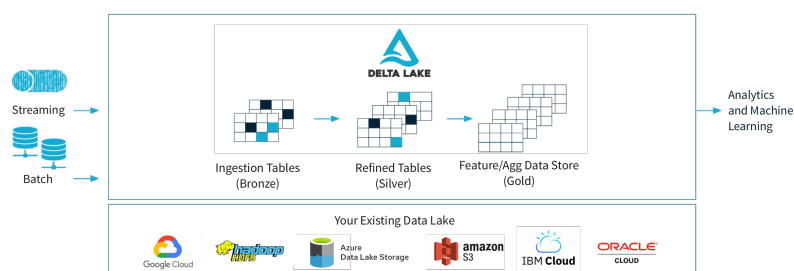


Figure 3.4: Delta lake architecture

3.5 Metadata

Metadata are used to organize a data lake. Useful metadata are:

Metadata

Source Origin of the data.

Schema Structure of the data.

Format File format or encoding.

Quality metrics (e.g. percentage of missing values).

Lifecycle Retention policies and archiving rules.

Ownership

Lineage History of applied transformations or dependencies.

Access control

Classification Sensitivity level of the data.

Usage information Record of who accessed the data and how it is used.

4 CRISP-DM

Cross Industry Standard Process for Data Mining Standardized process for data mining. CRISP-DM

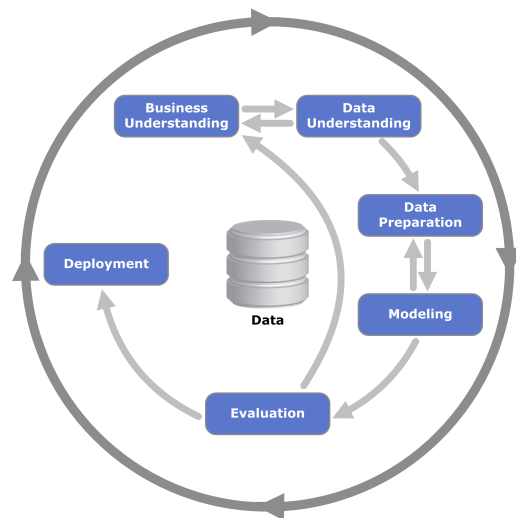


Figure 4.1: CRISP-DM workflow

4.1 Business understanding

- Determine the objective and the success criteria.
- Feasibility study.
- Produce a plan.

Business understanding

4.2 Data understanding

- Determine the available (raw) data.
- Determine the cost of the data.
- Collect, describe, explore and verify data.

Data understanding

4.3 Data preparation

- Data cleaning.
- Data transformations.

Data preparation

4.4 Modelling

- Select modelling technique.
- Build/train the model.

Modelling

4.5 Evaluation

- Evaluate results.
- Review process.

Evaluation

4.6 Deployment

- Plan deployment.
- Plan monitoring and maintenance.
- Final report and review.

Deployment

5 Machine learning

Machine learning Application of methods and algorithms to extract patterns from data. Machine learning

5.1 Tasks

Classification Estimation of a finite number of classes.

Regression Estimation of a numeric value.

Similarity matching Identify similar individuals.

Clustering Grouping individuals based on their similarities.

Co-occurrence grouping Identify associations between entities based on the transactions in which they appear together.

Profiling Behavior description.

Link analysis Analysis of connections (e.g. in a graph).

Data reduction Reduce the dimensionality of data with minimal information loss.

Casual modeling Understand the connections between events and actions.

5.2 Categories

Supervised learning Problem where the target(s) is defined. Supervised learning

Unsupervised learning Problem where no specific target is known. Unsupervised learning

Reinforcement learning Learn a policy to generate a sequence of actions. Reinforcement learning

5.3 Data

Dataset Set of N individuals, each described by D features. Dataset

5.3.1 Data types

Categorical Values with a discrete domain.

Nominal The values are a set of non-ordered labels.

Operators. $=$, $\neq$

Example. Name, surname, zip code.

Ordinal The values are a set of totally ordered labels.

Operators. $=$, $\neq$, $<$, $>$, $\leq$, $\geq$

Example. Non-numerical quality evaluations (excellent, good, fair, poor, bad).

Categorical nominal data

Categorical ordinal data

Numerical Values with a continuous domain.

Interval Numerical values without an univocal definition of 0 (i.e. 0 is not used as reference). It is not reasonable to compare the magnitude of this type of data.

Numerical interval data

Operators. =, $\neq$, <, >, $\leq$, $\geq$, +, -

Example. Celsius and Fahrenheit temperature scales, CGPA, time.

For instance, there is a 6.25% increase from 16°C to 17°C, but converted in Fahrenheit, the increase is of 2.96% (from 60.8°F to 62.6°F).

Ratio Values with an absolute 0 point.

Numerical ratio data

Operators. =, $\neq$, <, >, $\leq$, $\geq$, +, -

Example. Kelvin temperature scale, age, income, length.

For instance, there is a 10% increase from 100\$ to 110\$. Converted in euro (1€= 1.06\$), the increase is still of 10% (from 94.34€ to 103.77€).

5.3.2 Transformations

Data type		Transformation
Categorical	Nominal	One-to-one transformations
	Ordinal	Order preserving transformations (i.e. monotonic functions)
Numerical	Interval	Linear transformations
	Ratio	Any mathematical function, standardization, variation in percentage

5.3.3 Dataset format

Relational table The attributes of each record are the same.

Relational table

Data matrix Matrix with N rows (entries) and D columns (attributes).

Data matrix

Sparse matrix Data matrix with lots of zeros.

Sparse matrix

Example (Bag-of-words). Each row represents a document, each column represents a term. The i, j -th cell contains the frequency of the j -th term in the i -th document.

Transactional data Each record contains a set of objects (not necessarily a relational table).

Transactional data

Graph data Set of nodes and edges.

Graph data

Ordered data e.g. temporal data.

Ordered data

5.3.4 Data quality

Noise Alteration of the original values.

Noise

Outliers Data that considerably differ from the majority of the dataset. May be caused by noise or rare events.

Outliers

Box plots can be used to visually detect outliers.

Missing values Data that have not been collected. Sometimes they are not easily recognizable (e.g. when special values are used, instead of `null`, to mark missing data).

Missing values

Can be handled in different ways:

- Ignore the records with missing values.
- Estimate or default missing values.
- Ignore the fact that some values are missing (not always applicable).
- Insert all the possible values and weight them by their probability.

Duplicated data Data that may be merged.

Duplicated data

6 Classification

(Supervised) classification Given a finite set of classes C and a dataset $\mathbf{X}$ of N individuals, each associated to a class $y(\mathbf{x}) \in C$, we want to learn a model $\mathcal{M}$ able to guess the value of $y(\bar{\mathbf{x}})$ for unseen individuals.

Classification

Classification can be:

Crisp Each individual has one and only one label.

Crisp classification

Probabilistic Each individual is assigned to a label with a certain probability.

Probabilistic classification

Classification model A classification model (classifier) makes a prediction by taking as input a data element $\mathbf{x}$ and a decision function y_θ parametrized on θ :

Classification model

$$\mathcal{M}(\mathbf{x}, \theta) = y_\theta(\mathbf{x})$$

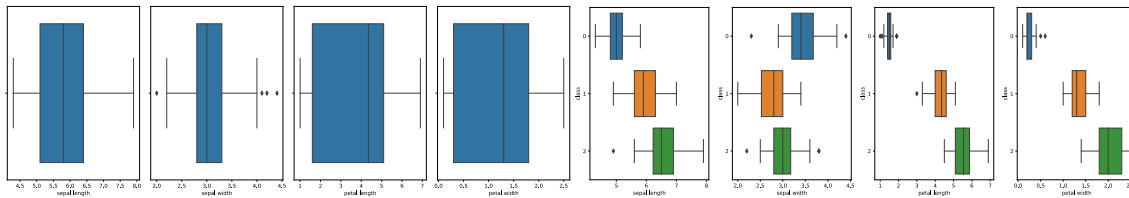
Vapnik-Chervonenkis dimension A dataset with N elements defines 2^N learning problems. A model $\mathcal{M}$ has Vapnik-Chervonenkis (VC) dimension N if it is able to solve all the possible learning problems with N elements.

Vapnik-Chervonenkis dimension

Example. A straight line has VC dimension 3.

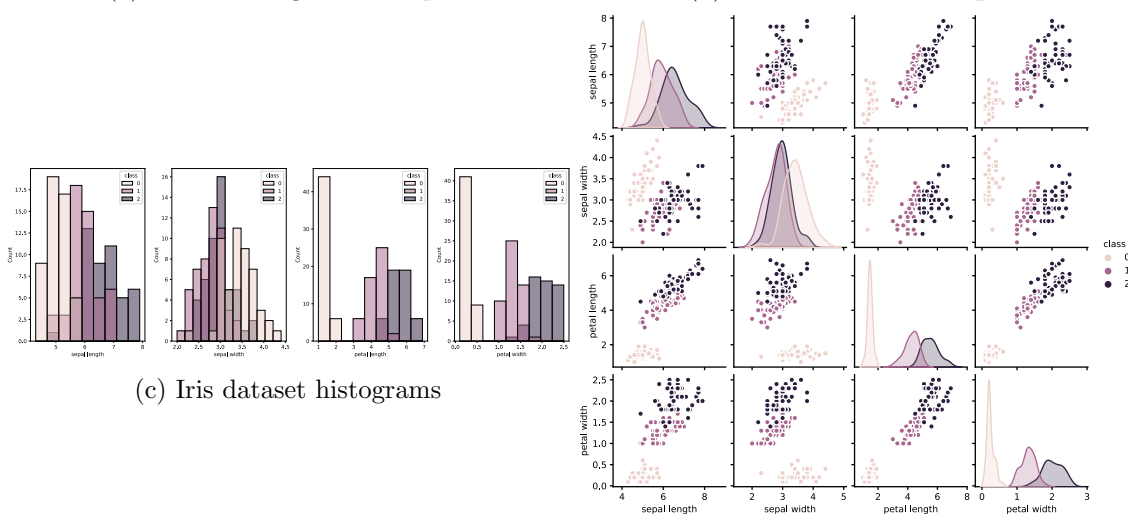
Data exploration

Data exploration



(a) Iris dataset general boxplot

(b) Iris dataset class boxplot



(c) Iris dataset histograms

(d) Iris dataset pairplots

Hyperparameters Parameters of the model that have to be manually chosen.

6.1 Evaluation

Dataset split A supervised dataset can be randomly split into:

Train set Used to learn the model. Usually the largest split. Can be seen as an upper-bound of the model performance.	Train set
Test set Used to evaluate the trained model. Can be seen as a lower-bound of the model performance.	Test set
Validation set Used to evaluate the model during training and/or for tuning parameters.	Validation set

It is assumed that the splits have similar characteristics.

Overfitting Given a dataset $\mathbf{X}$, a model $\mathcal{M}$ is overfitting if there exists another model $\mathcal{M}'$ such that:

$$\begin{aligned}\text{error}_{\text{train}}(\mathcal{M}) &< \text{error}_{\text{train}}(\mathcal{M}') \\ \text{error}_{\mathbf{X}}(\mathcal{M}) &> \text{error}_{\mathbf{X}}(\mathcal{M}')\end{aligned}$$

Possible causes of overfitting are:

- Noisy data.
- Lack of representative instances.

6.1.1 Test set error

Disclaimer: I'm very unsure about this part

The error on the test set can be seen as a lower-bound error of the model. If the test set error ratio is x , we can expect an error of $(x \pm \text{confidence interval})$.

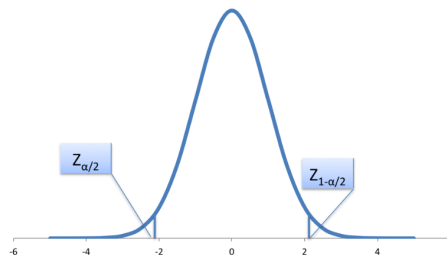
Predicting the elements of the test set can be seen as a binomial process (i.e. a series of N Bernoulli processes). We can therefore compute the empirical frequency of success as $f = (\text{correct predictions}/N)$. We want to estimate the probability of success p .

We assume that the deviation between the empirical frequency and the true frequency is due to a normal noise around the true probability (i.e. the true probability p is the mean).

Fixed a confidence level α (i.e. the probability of a wrong estimate), we want that:

$$\mathcal{P} \left(z_{\frac{\alpha}{2}} \leq \frac{f - p}{\sqrt{\frac{1}{N}p(1-p)}} \leq z_{(1-\frac{\alpha}{2})} \right) = 1 - \alpha$$

In other words, we want the middle term to have a high probability to be between the $\frac{\alpha}{2}$ and $(1 - \frac{\alpha}{2})$ quantiles of the gaussian.

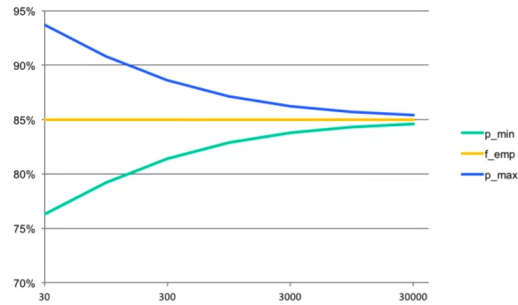


We can estimate p using the Wilson score interval¹:

$$p = \frac{1}{1 + \frac{1}{N}z^2} \left(f + \frac{1}{2N}z^2 \pm z\sqrt{\frac{1}{N}f(1-f) + \frac{z^2}{4N^2}} \right)$$

where z depends on the value of α . For a pessimistic estimate, $\pm$ becomes a $+$. Vice versa, for an optimistic estimate, $\pm$ becomes a $-$.

As N is at the denominator, this means that for large values of N , the uncertainty becomes smaller.



6.1.2 Dataset splits

Holdout The dataset is split into train, test and, if needed, validation.

Holdout

Cross validation The training data is partitioned into k chunks. For k iterations, one of the chunks is used to test and the others to train a new model. The overall error is obtained as the average of the errors of the k iterations.

Cross validation

At the end, the final model is still trained on the entire training data, while cross validation results are used as an evaluation and comparison metric. Note that cross validation is done on the training set, so a final test set can still be used to evaluate the final model.

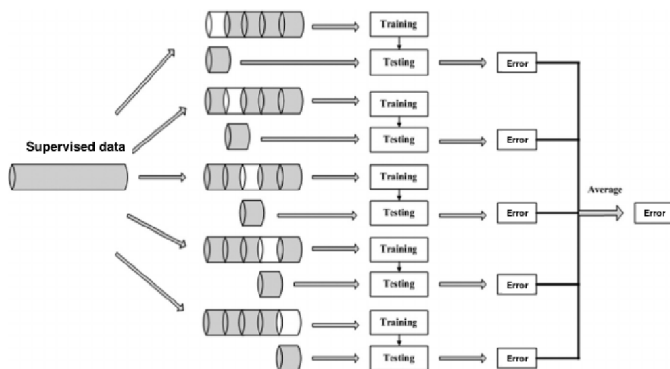


Figure 6.2: Cross validation example

Leave-one-out Extreme case of cross validation with $k = N$, the size of the training set. In this case the whole dataset but one element is used for training and the remaining entry for testing.

Leave-one-out

Bootstrap Statistical sampling of the dataset with replacement (i.e. an entry can be selected multiple times). The selected entries form the training set while the elements that have never been selected are used for testing.

Bootstrap

¹https://en.wikipedia.org/wiki/Binomial_proportion_confidence_interval

6.1.3 Binary classification performance measures

In binary classification, the two classes can be distinguished as the positive and negative labels. The prediction of a classifier can be a:

True positive (TP) · False positive (FP) · True negative (TN) · False negative (FN)

		Predicted	
		Pos	Neg
True	Pos	TP	FN
	Neg	FP	TN

Given a test set of N element, possible metrics are:

Accuracy Number of correct predictions.

Accuracy

$$\text{accuracy} = \frac{TP + TN}{N}$$

Error rate Number of incorrect predictions.

Error rate

$$\text{error rate} = 1 - \text{accuracy}$$

Precision Number of true positives among what the model classified as positive (i.e. how many samples the model classified as positive are real positives).

Precision

$$\text{precision} = \frac{TP}{TP + FP}$$

Recall/Sensitivity Number of true positives among the real positives (i.e. how many real positive the model predicted).

Recall

$$\text{recall} = \frac{TP}{TP + FN}$$

Specificity Number of true negatives among the real negatives (i.e. recall for negative labels).

Specificity

$$\text{specificity} = \frac{TN}{TN + FP}$$

F1 score Harmonic mean of precision and recall (i.e. measure of balance between precision and recall).

F1 score

$$F1 = 2 \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

6.1.4 Multi-class classification performance measures

Confusion matrix Matrix to correlate the predictions of n classes:

Confusion matrix

		Predicted			
		a	b	c	Total
True	a	TP_a	FP_{a-b}	FP_{a-c}	T_a
	b	FP_{b-a}	TP_b	FP_{b-c}	T_b
	c	FP_{c-a}	FP_{c-b}	TP_c	T_c
	Total	P_a	P_b	P_c	N

where:

- a , b and c are the classes.
- T_x is the true number of labels of class x in the dataset.
- P_x is the predicted number of labels of class x in the dataset.
- TP_x is the number of times a class x was correctly predicted (true predictions).
- FP_{i-j} is the number of times a class i was predicted as j (false predictions).

Accuracy Accuracy is extended from the binary case as:

Accuracy

$$\text{accuracy} = \frac{\sum_i TP_i}{N}$$

Precision Precision is defined w.r.t. a single class:

Precision

$$\text{precision}_i = \frac{TP_i}{P_i}$$

Recall Recall is defined w.r.t. a single class:

Recall

$$\text{recall}_i = \frac{TP_i}{T_i}$$

If a single value of precision or recall is needed, the mean can be used by computing a macro (unweighted) average or a class-weighted average.

κ -statistic Evaluates the concordance between two classifiers (in our case, the predictor and the ground truth). It is based on two probabilities:

κ -statistic

Probability of concordance $\mathcal{P}(c) = \frac{\sum_i^{\text{classes}} TP_i}{N}$

Probability of random concordance $\mathcal{P}(r) = \frac{\sum_i^{\text{classes}} T_i P_i}{N^2}$

κ -statistic is given by:

$$\kappa = \frac{\mathcal{P}(c) - \mathcal{P}(r)}{1 - \mathcal{P}(r)} \in [-1, 1]$$

When $\kappa = 1$, there is perfect agreement ($\sum_i^{\text{classes}} TP_i = 1$), when $\kappa = -1$, there is total disagreement ($\sum_i^{\text{classes}} TP_i = 0$) and when $\kappa = 0$, there is random agreement.

Cost sensitive learning Assign a cost to the errors. This can be done by:

Cost sensitive learning

- Altering the proportions of the dataset by duplicating samples to reduce its misclassification.
- Weighting the classes (possible in some algorithms).

6.1.5 Probabilistic classifier performance measures

Lift chart Used in binary classification. Given the resulting probabilities of the positive class of a classifier, sort them in decreasing order and plot a 2d-chart with increasing sample size on the x-axis and the number of positive samples on the y-axis.

Lift chart

Then, plot a straight line to represent a baseline classifier that makes random choices. As the probabilities are sorted in decreasing order, it is expected a high concentration of positive labels on the right side. When the area between the two curves is large and the curve is above the random classifier, the model can be considered a good classifier.

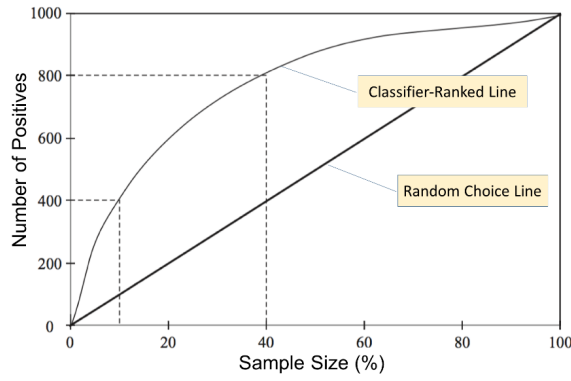


Figure 6.3: Example of lift chart

ROC curve The ROC curve can be seen as a way to represent multiple confusion matrices of a classifier that uses different thresholds. The x-axis of a ROC curve represent the false positive rate while the y-axis represent the true positive rate.

ROC curve

A straight line is used to represent a random classifier. A threshold can be considered good if it is high on the y-axis and low on the x-axis.

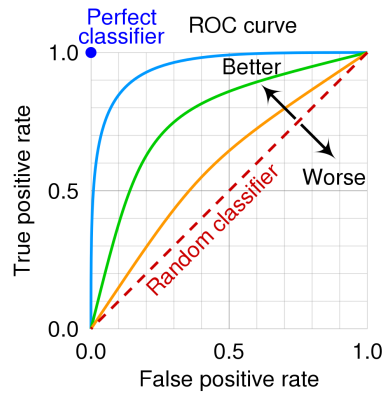


Figure 6.4: Example of ROC curves

6.2 Decision trees

6.2.1 Information theory

Shannon theorem Let $\mathbf{X} = \{\mathbf{v}_1, \dots, \mathbf{v}_V\}$ be a data source where each of the possible value has probability $p_i = \mathcal{P}(\mathbf{v}_i)$. The best encoding allows to transmit $\mathbf{X}$ with an average number of bits given by the **entropy** of $\mathbf{X}$:

Shannon theorem

Entropy

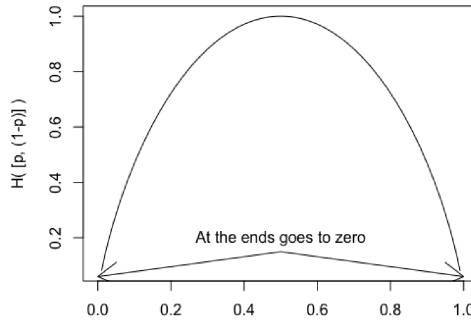
$$H(\mathbf{X}) = - \sum_j p_j \log_2(p_j)$$

$H(\mathbf{X})$ can be seen as a weighted sum of the surprise factor $-\log_2(p_j)$. If $p_j \sim 1$, then the surprise of observing $\mathbf{v}_j$ is low, vice versa, if $p_j \sim 0$, the surprise of observing $\mathbf{v}_j$ is high.

Therefore, when $H(\mathbf{X})$ is high, $\mathbf{X}$ is close to an uniform distribution. When $H(\mathbf{X})$ is low, $\mathbf{X}$ is close to a constant.

Example (Binary source).

The two values of a binary source $\mathbf{X}$ have respectively probability p and $(1 - p)$.
 When $p \sim 0$ or $p \sim 1$, $H(\mathbf{X}) \sim 0$.
 When $p \sim 0.5$, $H(\mathbf{X}) \sim \log_2(2) = 1$



Entropy threshold split Given a dataset $\mathbf{D}$, a real-valued attribute $d \in \mathbf{D}$, a threshold t in the domain of d and the class attribute c of $\mathbf{D}$. The entropy of the class c of the dataset $\mathbf{D}$ split with threshold t on d is a weighted sum:

Entropy threshold split

$$H(c|d : t) = \mathcal{P}(d < t)H(c|d < t) + \mathcal{P}(d \geq t)H(c|d \geq t)$$

Information gain Information gain measures the reduction in entropy after applying a split. It is computed as:

Information gain

$$IG(c|d : t) = H(c) - H(c|d : t)$$

When $H(c|d : t)$ is low, $IG(c|d : t)$ is high as splitting with threshold t result in purer groups. Vice versa, when $H(c|d : t)$ is high, $IG(c|d : t)$ is low as splitting with threshold t is not very useful.

The information gain of a class c split on a feature d is given by:

$$IG(c|d) = \max_t IG(c|d : t)$$

6.2.2 Tree construction

Decision tree (C4.5) Tree-shaped classifier where leaves are class predictions and inner nodes represent conditions that guide to a leaf. This type of classifier is non-linear (i.e. does not represent a linear separation).

Decision tree

Each node of the tree contains:

- The applied splitting criteria (i.e. feature and threshold). Leaves do not have this value.
- The purity (e.g. entropy) of the current split.
- Dataset coverage of the current split.
- Classes distribution.

Note: the weighted sum of the entropies of the children is always smaller than the entropy of the parent.

Possible stopping conditions are:

- When most of the leaves are pure (i.e. nothing useful to split).
- When some leaves are impure but none of the possible splits have positive IG . Impure leaves are labeled with the majority class.

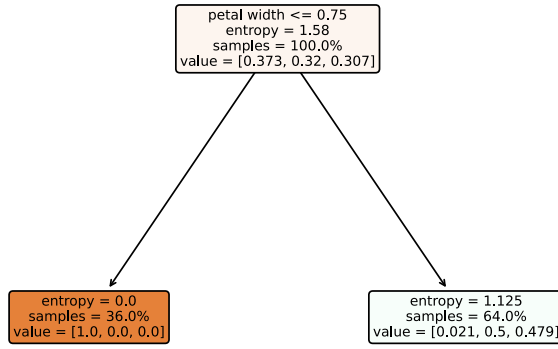


Figure 6.5: Example of decision tree

Purity Value to maximize when splitting a node of a decision tree.

Purity

Nodes with uniformly distributed classes have a low purity. Nodes with a single class have the highest purity.

Possible impurity measures are:

Entropy/Information gain See Section 6.2.1.

Gini index Let $\mathbf{X}$ be a dataset with classes C . The Gini index measures how often an element of $\mathbf{X}$ would be misclassified if the labels were randomly assigned based on the frequencies of the classes in $\mathbf{X}$.

Gini index

Given a class $i \in C$, p_i is the probability (i.e. frequency) of classifying an element with i and $(1 - p_i)$ is the probability of classifying it with a different label. The Gini index is given by:

$$\begin{aligned} GINI(\mathbf{X}) &= \sum_i^C p_i(1 - p_i) = \sum_i^C p_i - \sum_i^C p_i^2 \\ &= 1 - \sum_i^C p_i^2 \end{aligned}$$

When $\mathbf{X}$ is uniformly distributed, $GINI(\mathbf{X}) \sim (1 - \frac{1}{|C|})$. When $\mathbf{X}$ is constant, $GINI(\mathbf{X}) \sim 0$.

Given a node x split in n children $x_1, \dots, x_n$, the Gini gain of the split is given by:

$$GINI_{\text{gain}} = GINI(x) - \sum_{i=1}^n \frac{|x_i|}{|x|} GINI(x_i)$$

Misclassification error Skipped.

Misclassification error

Compared to Gini index, entropy is more robust to noise.

Misclassification error has a bias toward the major class.

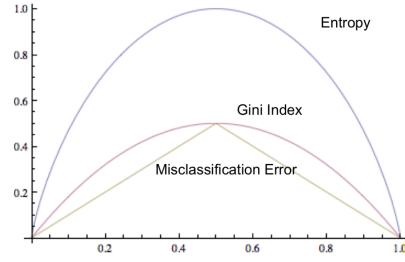


Figure 6.6: Comparison of impurity measures

Algorithm 1 Decision tree construction using information gain as impurity measure

```
def buildTree(split):
    node = Node()
    if len(split.classes) == 1: # Pure split
        node.label = split.classes[0]
        node.isLeaf = True
    else:
        ig, attribute, threshold = getMaxInformationGain(split)
        if ig < 0:
            node.label = split.majorityClass()
            node.isLeaf = True
        else:
            node.left = buildTree(split[attribute < threshold])
            node.right = buildTree(split[attribute >= threshold])
    return node
```

Pruning Remove branches to reduce overfitting. Different pruning techniques can be employed: Pruning

Maximum depth Maximum depth allowed for the tree.

Minimum samples for split Minimum number of samples a node is required to have to apply a split.

Minimum samples for a leaf Minimum number of samples a node is required to have to become a leaf.

Minimum impurity decrease Minimum decrease in impurity for a split to be made.

Statistical pruning Prune the children of a node if the weighted sum of the maximum errors of the children is greater than the maximum error of the node if it was a leaf.

6.2.3 Complexity

Given a dataset $\mathbf{X}$ of N instances and D attributes, each level of the tree requires to evaluate all the dataset and each node requires to process all the attributes. Assuming an average height of $O(\log N)$, the overall complexity for induction (parameters search) is $O(DN \log N)$.

Moreover, The other operations of a binary tree have complexity:

- Threshold search and binary split: $O(N \log N)$ (scan the dataset for the threshold).
- Pruning: $O(N \log N)$ (requires to scan the dataset).

For inference, to classify a new instance it is sufficient to traverse the tree from the root to a leaf. This has complexity $O(h)$, with h the height of the tree.

6.2.4 Characteristics

- Decision trees are non-parametric in the sense that they do not require any assumption on the distribution of the data.
- Finding the best tree is an NP-complete problem.
- Decision trees are robust to noise if appropriate overfitting methods are applied.
- Decision trees are robust to redundant attributes (correlated attributes are very unlikely to be chosen for multiple splits).
- In practice, the impurity measure has a low impact on the final result, while the pruning strategy is more relevant.