

# Elements of Machine Learning and Data Science

Part I: Data Science — Exam Notes (Living Document)

Emir Pisirici

January 29, 2026

Exam likelihood: High (overall Data Science part)

This document is structured to match the lecture topics exactly and is designed for adding **exam-style notes**, **common traps**, and **visual summaries**.

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# 1 Introduction to Data Science

## 1.1 Introduction

## 1.2 Tabular Data

## 1.3 Data Science Process

Exam likelihood: High

Framework questions are easy to grade and strongly test “big picture” understanding.

Examiner favorite (what they love to ask)

Typical asks: **ETL vs ELT**, **CRISP-DM phases**, and mapping a scenario to the correct phase. Also: where data leakage/bias lives (data understanding + evaluation).

### 1.3.1 ETL vs ELT (Definitions + Differences)

Cheat sheet / must-memorize

**ETL:** Extract → Transform → Load (transform before target).

**ELT:** Extract → Load → Transform (transform inside target platform).

**Key contrast:** where transformations happen; governance vs flexibility; raw history availability.

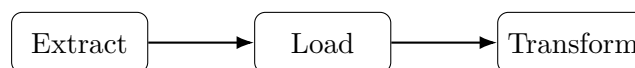
Common pitfall

People confuse “ELT = no cleaning”. Wrong. It means cleaning happens *after loading*, often in warehouse/lakehouse layers (staging → curated).

Visual



**ETL**



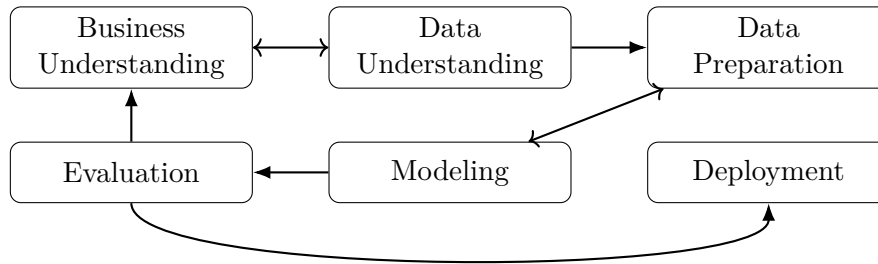
**ELT**

### 1.3.2 CRISP-DM

Cheat sheet / must-memorize

**CRISP-DM:** Business Understanding → Data Understanding → Data Preparation → Modeling → Evaluation → Deployment (iterative loops).

## Visual



### 1.3.3 PDCA

Cheat sheet / must-memorize

**PDCA:** Plan → Do → Check → Act (continuous improvement loop).

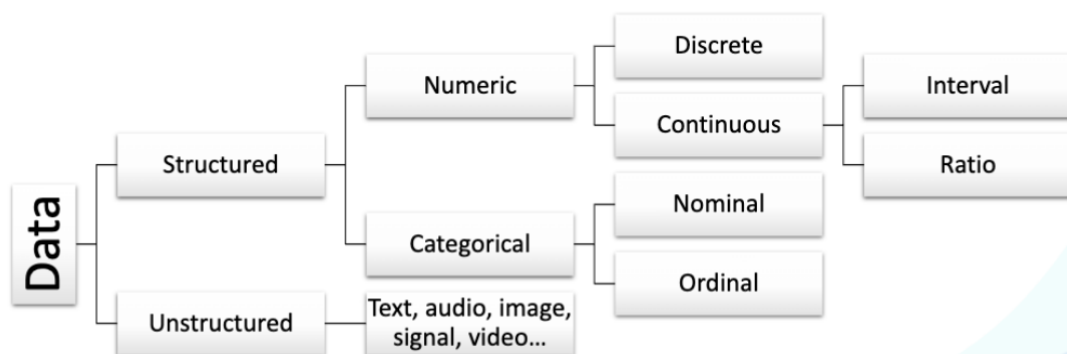
### 1.3.4 DMAIC

Cheat sheet / must-memorize

**DMAIC:** Define → Measure → Analyze → Improve → Control. Often used for process/quality improvement + monitoring and part of the Six Sigma methodology.

## 1.4 Data Types

## Visual



## 1.5 Descriptive Statistics

Exam likelihood: High

Frequent: compute variance/STD/covariance/correlation by hand; read a correlation matrix.

Examiner favorite (what they love to ask)

Explain why covariance depends on units, and why correlation is normalized in  $[-1, 1]$ .

Why (motivation): Quantify spread and association between variables.

What (definition): Variance/STD measure spread; covariance/correlation measure linear association.

How (procedure/usage): Compute formulas, then interpret sign/magnitude and check the correlation matrix.

## Cheat sheet / must-memorize

- **Variance (sample):**  $s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$
- **Std dev:**  $s = \sqrt{s^2}$
- **Covariance (sample):**  $\text{cov}(X, Y) = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$
- **Correlation:**  $r = \frac{\text{cov}(X, Y)}{s_X s_Y}$  (unitless,  $-1$  to  $1$ )
- **Correlation matrix:** table of pairwise correlations; symmetric with 1s on the diagonal.

## Common pitfall

Correlation  $\neq$  causation; a strong correlation can be driven by a confounder or Simpson's paradox.

## Visual

1	$r_{12}$	$r_{13}$
$r_{21}$	1	$r_{23}$
$r_{31}$	$r_{32}$	1

Correlation matrix

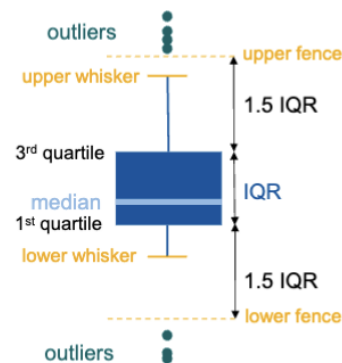
**Key takeaways:** Know formulas + interpretations; correlation matrix is symmetric with 1s on the diagonal.

## 1.6 Basic Visualizations

### Visual

#### Box Plot

- **Median** value (middle), depicted by bar
- **IQR** – Interquartile Range (covers 50% of middle instances), depicted by box
- **Upper fence** – 3<sup>rd</sup> quartile + 1.5 IQR  
**Upper whisker** – maximal value below upper fence
- **Lower fence** – 1<sup>st</sup> quartile - 1.5 IQR  
**Lower whisker** – minimal value above lower fence
- **Outliers** – drawn separately



## 1.7 Feature Transformations

### Exam likelihood: High

Typical: pick the right transform (scale, log, encode) and explain why.

### Examiner favorite (what they love to ask)

Identify data leakage in preprocessing; name the correct order for train/test transformations.

Why (motivation): Turn raw categorical/continuous variables into model-ready features.  
What (definition): Encoding or discretizing features without changing the target meaning.  
How (procedure/usage): Choose encoding by category type; choose binning by distribution.

### Cheat sheet / must-memorize

- **One-hot encoding:** create a 0/1 column per category (nominal).
- **Binary encoding:** represent categories as binary digits (compact one-hot).
- **Ordinal encoding:** map ordered categories to ranks (only if order is real).
- **Binning:** convert continuous to categories.
- **Equal-width binning:** fixed interval sizes across the range.
- **Equal-frequency binning:** same number of samples per bin.

### Common pitfall

Fitting transforms on the full dataset (leakage). Always fit on training data, then apply to validation/test.

**Key takeaways:** Use one-hot for nominal, ordinal for ordered labels, and binning for simplification.

## 1.8 “How to lie with statistics”

## 2 Decision Trees

### 2.1 Introduction to Decision Trees

Exam likelihood: High

Intro questions often ask you to explain how trees split data and what leaves represent.

Examiner favorite (what they love to ask)

Draw a small tree from a toy dataset or explain interpretability vs overfitting.

Why (motivation): Learn a function from labeled training instances to make predictions.

What (definition): A tree partitions the feature space by sequential if-then splits; leaves output a class or value.

How (procedure/usage): Choose splits to improve class purity or reduce prediction error.

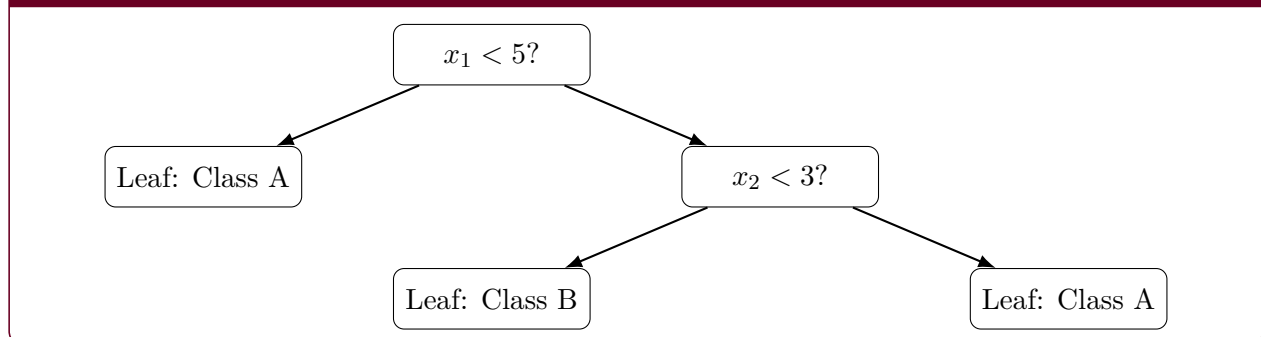
Cheat sheet / must-memorize

- **Goal:** learn a function  $f(X)$  from labeled data to predict labels/values.
- **Tree structure:** root node, internal (non-leaf) nodes, leaf nodes.
- **Split rule:** one feature + threshold; paths are if-then rules.
- **Leaf meaning:** prediction (class/value) for that region of the space.

Common pitfall

Overly deep trees memorize training data; control with max depth, min samples, or pruning.

Visual



**Key takeaways:** Trees learn  $f$  from labeled data using splits; nodes/leaf roles are core.

### 2.2 Entropy and Information Gain

Exam likelihood: Very High

Almost guaranteed: compute entropy and information gain for candidate splits.

Examiner favorite (what they love to ask)

Given a small labeled dataset, compare splits and pick the one with highest information gain.

Why (motivation): Choose splits that make child nodes as pure as possible.

What (definition): Entropy measures impurity; information gain is impurity reduction.

How (procedure/usage): Compute parent entropy, child entropies, then  $IG = \text{parent} - \text{weighted children}$ .

## Cheat sheet / must-memorize

- **Entropy:**  $H(S) = -\sum_c p_c \log_2 p_c$  (define  $0 \log 0 = 0$ ).
- **Weighted child entropy:**  $\sum_k \frac{|S_k|}{|S|} H(S_k)$ .
- **Information gain:**  $IG(S, \text{split}) = H(S) - \sum_k \frac{|S_k|}{|S|} H(S_k)$ .
- **Goal:** choose split with highest IG (most impurity reduction).

## Common pitfall

Forgetting to weight child entropies by subset size; using raw entropy sums gives wrong IG.

## Visual

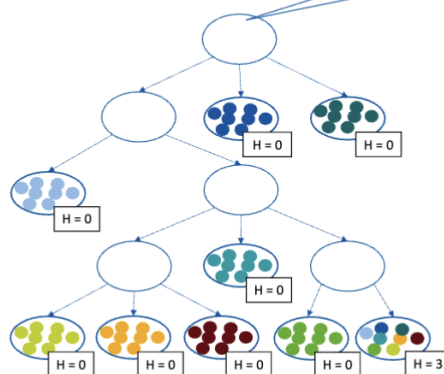
### Entropy - Formula

$$H(t) = -\sum_{k=1}^K (P(t=k) \cdot \log_2(P(t=k)))$$



$$H(\text{color}) = -\left(\frac{7}{14} \cdot \log_2\left(\frac{7}{14}\right) + \frac{3}{14} \cdot \log_2\left(\frac{3}{14}\right) + \frac{4}{14} \cdot \log_2\left(\frac{4}{14}\right)\right) \approx 1.49$$

### Overall Entropy



Even distribution of 8 colors over 72 balls:

$$H_W(\text{color}) = \frac{72}{72} \cdot \left(-\sum_{k=1}^8 \left(\frac{9}{72} \cdot \log_2\left(\frac{9}{72}\right)\right)\right) = \log_2(8) = 3$$

Overall entropy  $H_W$  is the weighted average of the individual entropies:

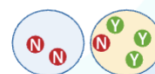
$$H_W(t) = \sum_{\text{node} \in \text{nodes}} \left(\frac{|\text{node}|}{N} \cdot H^{\text{node}}(t)\right)$$

Example:  $N = 72, K = 8$

$$\begin{aligned} H_W(\text{color}) &= \frac{8}{72} \cdot 0 + \frac{8}{72} \cdot 0 + \frac{8}{72} \cdot 0 + \frac{8}{72} \cdot 0 \\ &+ \frac{8}{72} \cdot 0 + \frac{8}{72} \cdot 0 + \frac{8}{72} \cdot 0 + \frac{8}{72} \cdot 0 \\ &+ \frac{8}{72} \cdot 3 = \frac{24}{72} \approx 0.33 \end{aligned}$$

### Information Gain – Another Flight Example

$H(\text{delayed}) = 1$				$H^{\text{cloudy}}(\text{delayed}) = 0$		$H^{\text{traffic, yes}}(\text{delayed}) = 0.92$		$H^{\text{night, yes}}(\text{delayed}) = 0$	
				$H^{\text{clear}}(\text{delayed}) = 0$		$H^{\text{traffic, no}}(\text{delayed}) = 0.92$		$H^{\text{night, no}}(\text{delayed}) \approx 0.81$	
				$H_W^{\text{weather}}(\text{delayed}) = 0$		$H_W^{\text{traffic}}(\text{delayed}) = 0.92$		$H_W^{\text{night, flight}}(\text{delayed}) \approx 0.54$	
Weather	Traffic	Night flight	Flight delayed	Weather	Flight delayed	Traffic	Flight delayed	Night flight	Flight delayed
Cloudy	No	No	Yes	Cloudy	Yes	No	Yes	No	Yes
Cloudy	Yes	No	Yes	Cloudy	Yes	Yes	Yes	No	Yes
Cloudy	Yes	No	Yes	Cloudy	Yes	Yes	Yes	No	Yes
Clear	Yes	Yes	No	Clear	No	Yes	No	Yes	No
Clear	No	Yes	No	Clear	No	No	No	Yes	No
Clear	No	No	No	Clear	No	No	No	No	No



**Key takeaways:** Compute entropy, weight children, pick split with highest IG.



Exam likelihood: Very High

Almost guaranteed: compute entropy / information gain on a small dataset.

## 2.3 ID3 Algorithm

Exam likelihood: Very High

Common: list the ID3 steps or run one iteration to choose the best split.

Examiner favorite (what they love to ask)

Explain stopping conditions and why ID3 prefers high information gain.

Why (motivation): Build a decision tree that best separates labeled data.

What (definition): ID3 is a greedy, top-down tree induction algorithm using information gain.

How (procedure/usage): Compute IG for each attribute, split on the best, and recurse.

Cheat sheet / must-memorize

- **Input:** labeled dataset  $S$  with categorical attributes (ID3 original).
- **Step 1:** if all labels same  $\rightarrow$  make a leaf.
- **Step 2:** if no attributes left  $\rightarrow$  leaf with majority class.
- **Step 3:** choose attribute with highest IG.
- **Step 4:** split  $S$  by attribute values and recurse.
- **Output:** a decision tree; leaves store class label.

Common pitfall

ID3 favors attributes with many values; without corrections (e.g., gain ratio) it can overfit.

## ID3 Algorithm

### ID3 algorithm:

1. **if** all the instances in  $X$  have the same classification
  - (a) **return** a decision tree with one leaf node with consensus value as a label
2. **else if** there are no features left
  - (a) **return** a decision tree with one leaf node with majority value as a label
3. **else if** the dataset is empty
  - (a) **return** a decision tree with one leaf node with majority parent value as a label
4. **else**
  - (a) pick a feature that maximizes information gain
  - (b) once a feature is picked along a path from the root, it cannot be used again
  - (c) create subproblems based on the selected feature

three  
stopping  
criteria

recursively  
constructing  
the tree

### ID3 Algorithm

#### Example

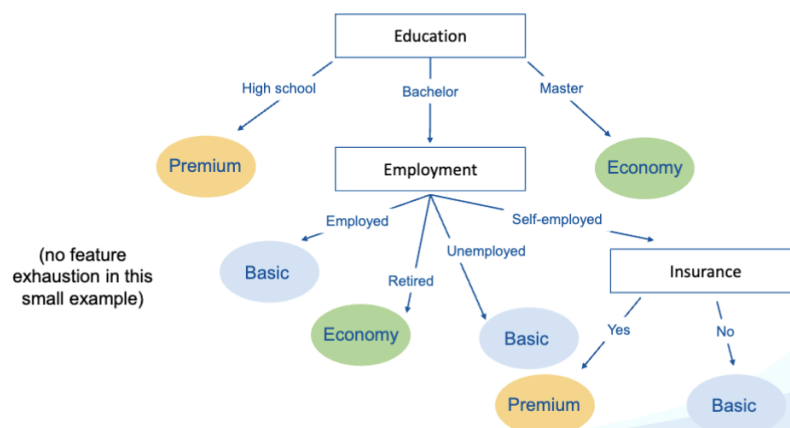
$$H(\text{Customer}) = 1.5567$$

ID	Insurance	Education	Employment	Customer
1	Yes	Bachelor	Employed	Basic
2	Yes	High school	Unemployed	Premium
3	Yes	Bachelor	Self-employed	Premium
4	No	Bachelor	Self-employed	Basic
5	No	Master	Employed	Economy
6	Yes	Bachelor	Retired	Economy
7	Yes	High school	Employed	Premium

Split by feature	Possible Values	Instances	Entropy	Overall Entropy	Information Gain
Insurance	No	4, 5	1	1.265	$1.5567 - 1.265 = 0.2917$
	Yes	1, 2, 3, 6, 7	1.3710		
Education	High school	2, 7	0	0.8571	$1.5567 - 0.8571 = 0.6996$
	Master	5	0		
	Bachelor	1, 3, 4, 6	1.5		
Employment	Employed	1, 5, 7	1.5850	0.9650	$1.5567 - 0.9650 = 0.5917$
	Unemployed	2	0		
	Self-employed	3, 4	1		
	Retired	6	0		

### ID3 Algorithm

#### Example



**Key takeaways:** ID3 is greedy; compute IG, split, recurse, stop with pure/majority leaves.

## 2.4 Pruning

## 2.5 Continuous Data (Threshold splits)

## 2.6 Ensembles (Bagging/Random Forest/Boosting)

## **3 Clustering**

### **3.1 Introduction to Unsupervised Learning**

### **3.2 Introduction to Clustering**

### **3.3 Similarity and Dissimilarity**

### **3.4 K-means and K-medoids**

### **3.5 Agglomerative Clustering**

### **3.6 DBSCAN**

### **3.7 Closing**

## 4 Frequent Itemsets

### 4.1 Introduction

### 4.2 Properties of Frequent Itemsets

### 4.3 Apriori Algorithm

### 4.4 FP-Growth Algorithm

## 5 Association Rules

### 5.1 Introduction

### 5.2 Generating Association Rules

### 5.3 Evaluation (support, confidence, lift, conviction)

### 5.4 Applications

### 5.5 Simpson's Paradox

## **6 Time Series**

### **6.1 Temporal Data**

### **6.2 Introduction to Time Series**

### **6.3 Analysis**

### **6.4 Forecasting**