

# Intermediate Python & a Glimpse into AI applications

Class 4

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15<sup>th</sup> January 2024

# Index Class 4

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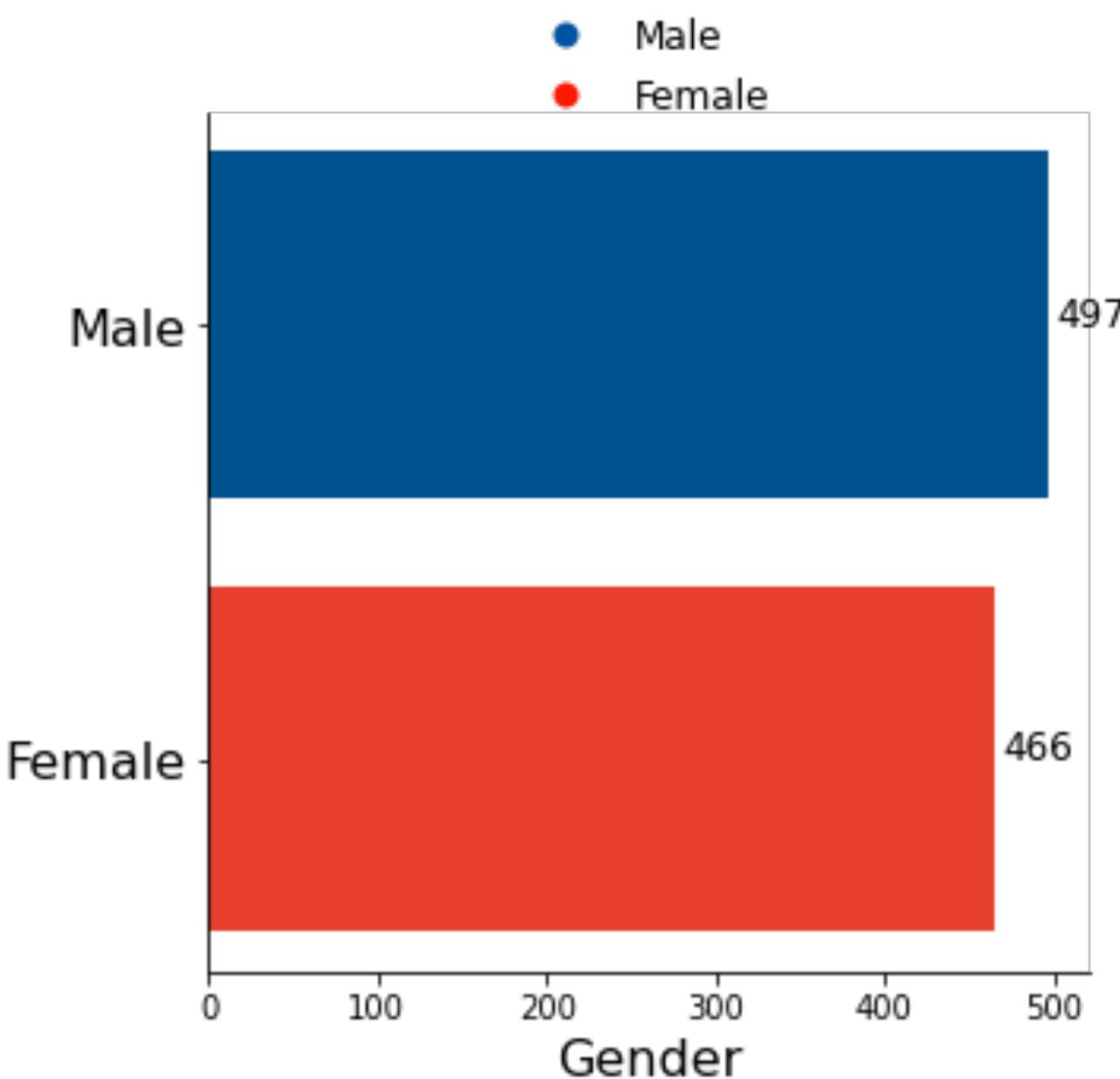
Topic 4: Intro to the World of predictive models

Topic 5: Supervised vs. Unsupervised. Regression vs. Classification

Topic 6: Arranging data for models - Data Preparation

# Topic 1: Recap

# Recap: Matplotlib/Seaborn and EDA steps



matplotlib



seaborn

```
#Start Figure
fig, ax = plt.subplots(figsize=(5, 5))

#Body of the figure to build and the data to use
sns.barplot(x=to_plot['gender'], y=to_plot['index'],
             palette=['#08519c', '#f03b20'])

#Change Axes
ax.set_xlabel("Gender", fontsize=16)
ax.set_ylabel("", fontsize=16)
ax.set_yticklabels(['Male', 'Female'], fontsize=16)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

# Add Numbers to plot
for index, row in to_plot.iterrows():
    ax.text(row.gender + 25, index, row.gender,
            color='black', ha="center", fontsize=12)

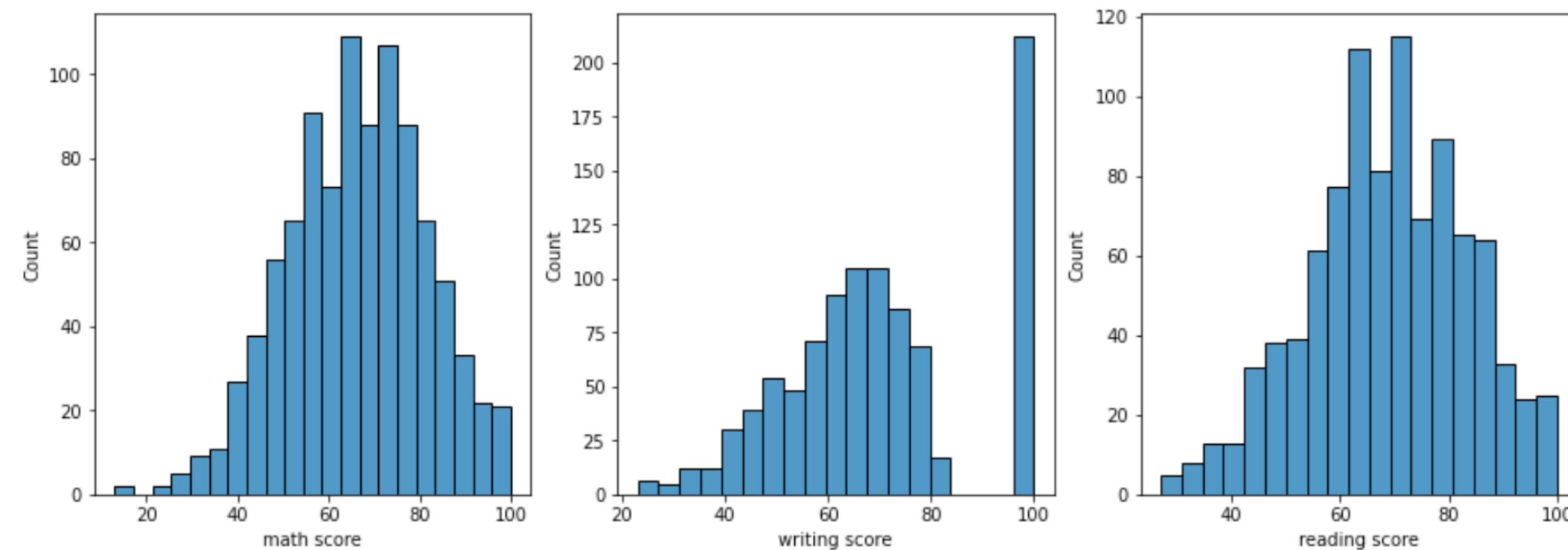
## Add legend
custom_lines = []
for el in [('Male', '#08519c'), ('Female', '#f03b20')]:
    custom_lines.append(
        plt.plot([],[], marker="o", ms=8, ls="", mec='black',
                  mew=0, color=el[1], label=el[0])[0]
    )
ax.legend(
    bbox_to_anchor=(0., 1.05, 1., .102),
    handles=custom_lines, loc='upper center',
    facecolor='white', ncol=1, fontsize=12, frameon=False
)
#Save or show
plt.show()
```

# Recap: EDA & Feature Engineering

---

## EDA

- Is a process where users look at and understand their data with statistical and visualization methods
  - Categorical EDA
  - Numerical EDA



# Topic 2: A bit more of seaborn + Saving outputs

# Exercise

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- Run your code of the second class and save the resulting dataframe after fixing structural errors, imputing missing values etc...
- Load it in the Jupyter notebooks of today and show that it is the cleaned version of it (shape, isna().sum(), df['gender'].value\_counts(), etc...)

# All this process can already give significant value to companies

→ UNNOBA

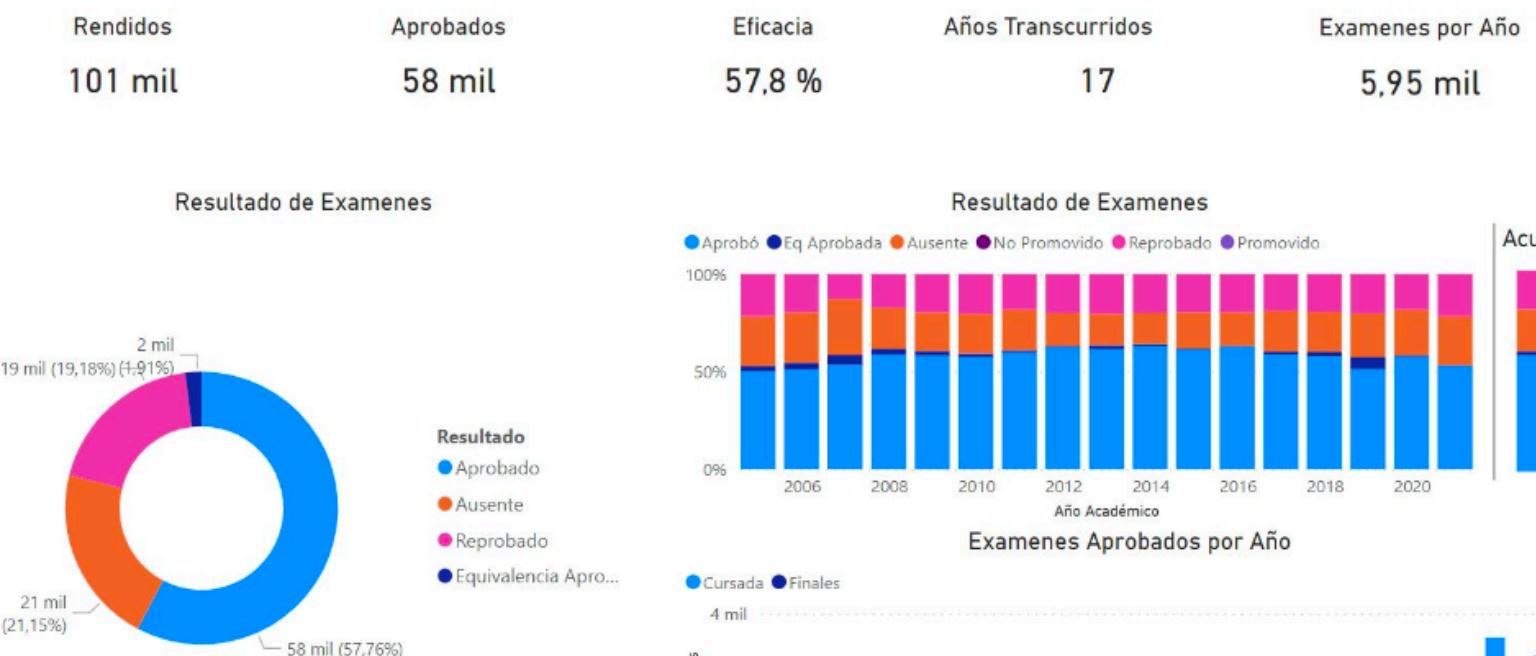
## Overview de Alumnos Activos



→ UNNOBA

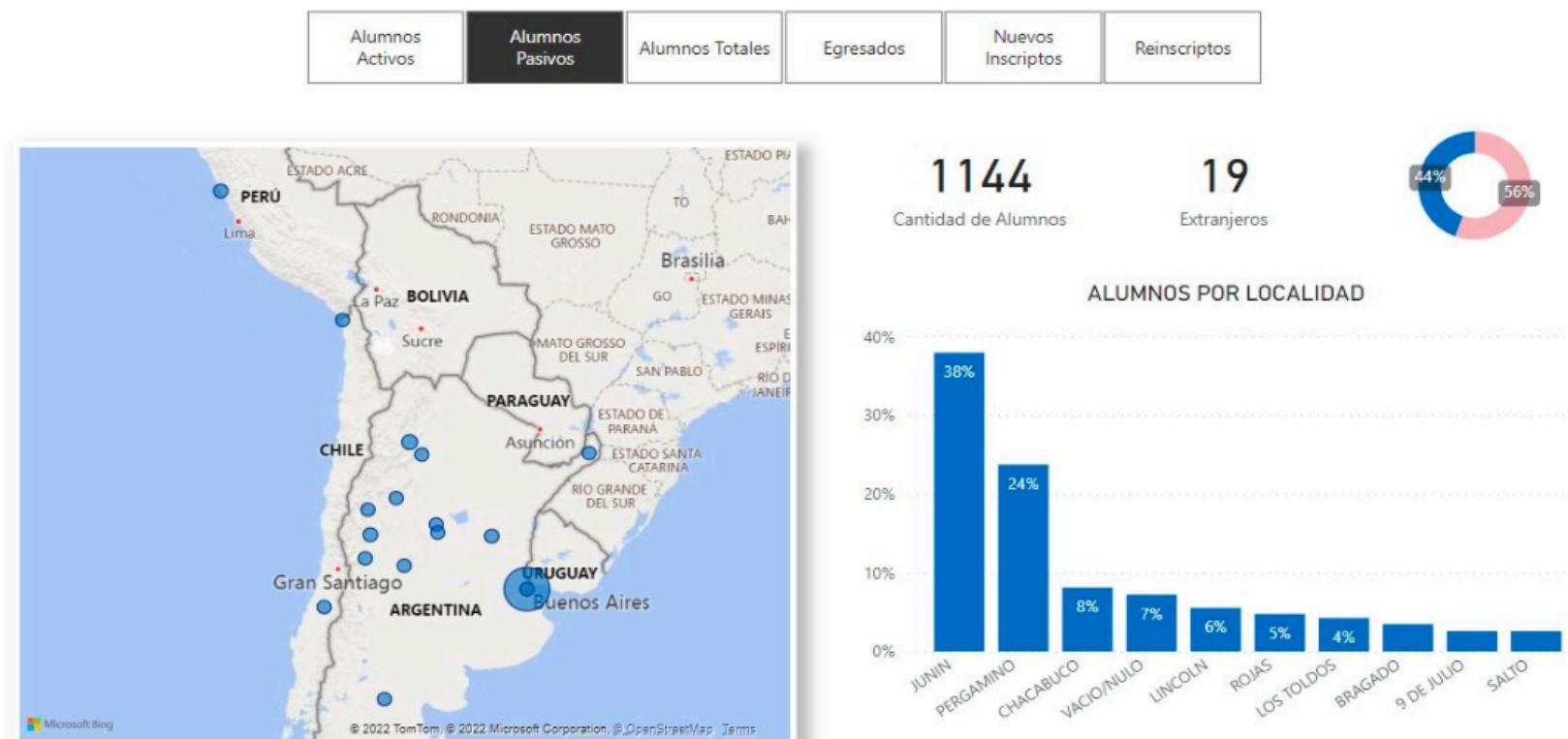
## Ficha de Carrera

VER TABLA DE DATOS



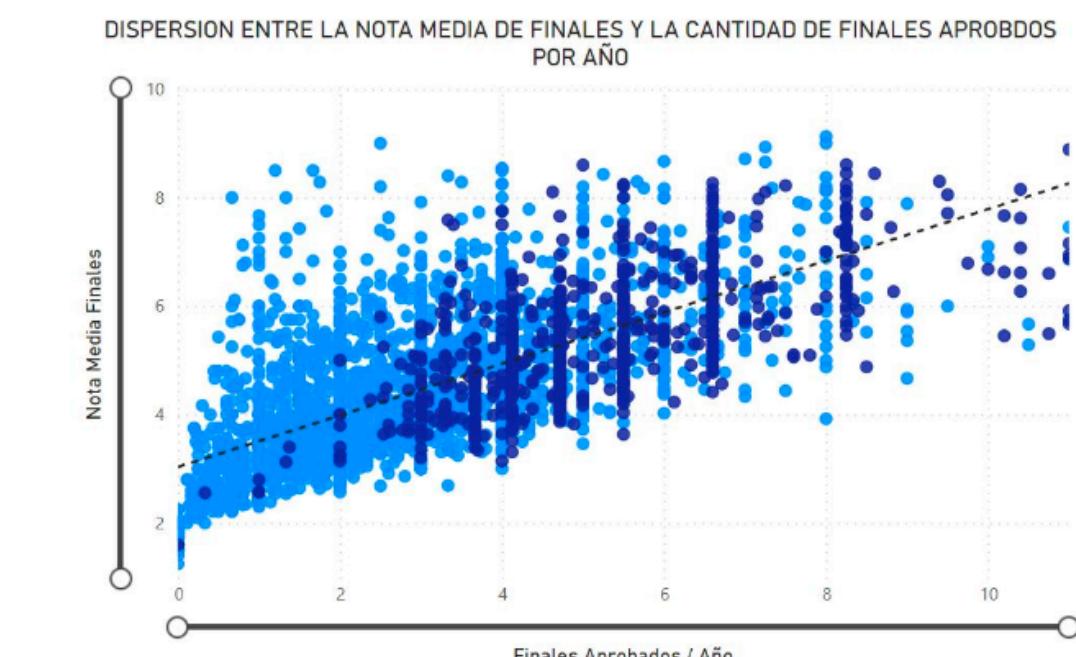
→ UNNOBA

## Procedencia de Alumnos Pasivos



→ UNNOBA

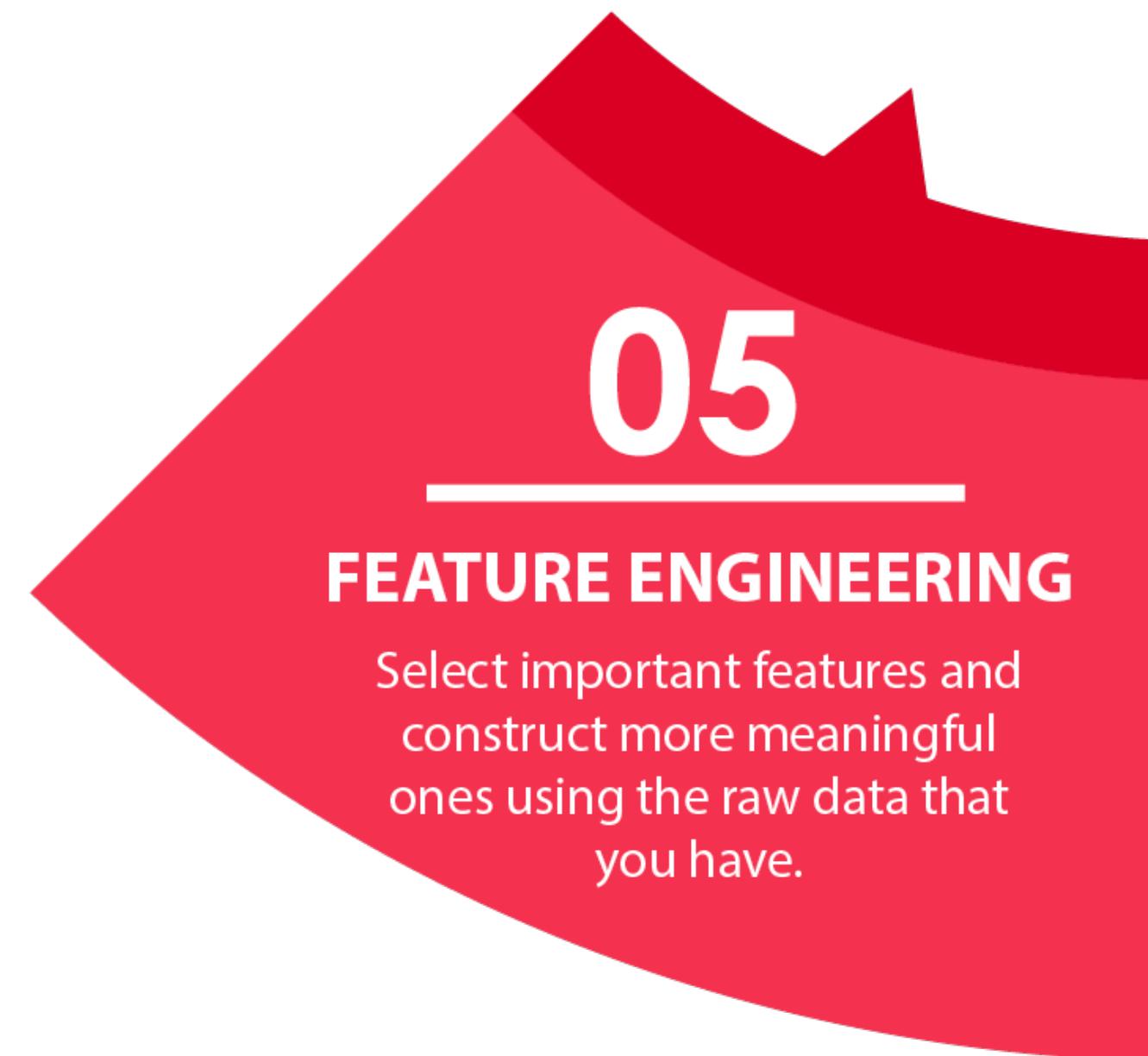
## Rendimiento de Alumnos



# Topic 3: Feature Engineering

# Feature engineering

---



- Is the process of using domain knowledge to extract features (characteristics, properties, attributes) from raw data
- Examples of current projects:
  - Chatbot: #TimesAsking4help, #Words
  - Universities: #PassedSubjects, GradeMean

# Feature engineering

---

Transform the parental level of education

```
df['parental level of education'].value_counts()
```

```
some college      219
associate's degree 196
high school       194
some high school  180
bachelor's degree 107
master's degree    67
Name: parental level of education, dtype: int64
```

```
new_col = []
for el in df['parental level of education'].tolist():
    if el in ["master's degree", "bachelor's degree", "some college"]:
        new_col.append('went to college')
    else:
        new_col.append('no college')
df['Education'] = new_col
```

# Feature engineering

---

## Transform the parental level of education

```
df['parental level of education'].value_counts()

some college      219
associate's degree 196
high school       194
some high school   180
bachelor's degree    107
master's degree      67
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for el in df['parental level of education'].tolist():
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        new_col.append('went to college')
    else:
        new_col.append('no college')
df['Education'] = new_col
```

## BMI Calculation

```
df['height'] = 1.70
df['weight'] = 70

df['BMI'] = round(df['weight'] / (df['height'] * df['height']), 2)

df.drop(['height', 'weight'], axis=1, inplace=True)
```

# Exercise

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- Add a new feature (column) to the dataset named *scores mean* that represents the mean of all three grades (math, writing and reading)

# Exercise

---

- Add a new feature (column) to the dataset named *scores mean* that represents the mean of all three grades (math, writing and reading)

```
df['scores mean'] = df[['math score', 'writing score', 'reading score']].mean(axis=1)

df = df.assign(mean = round((df['writing score'] + df['math score'] + df['reading score'])/3, 2))

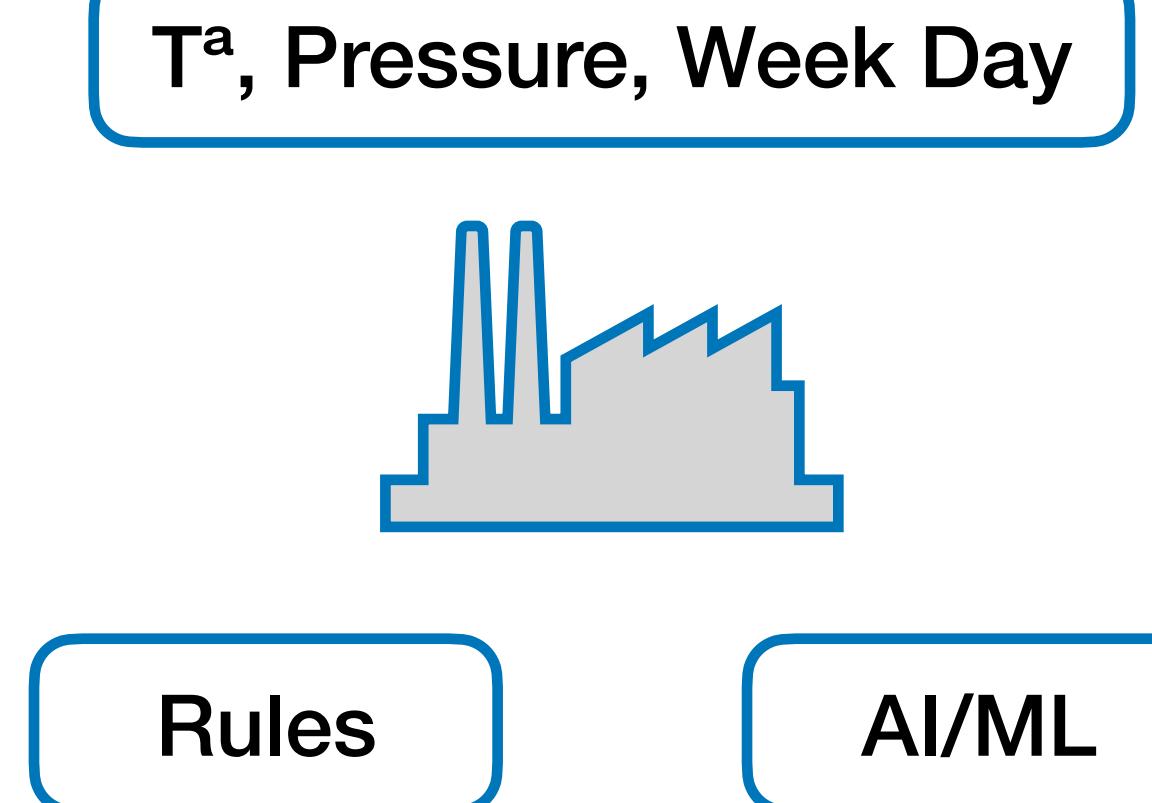
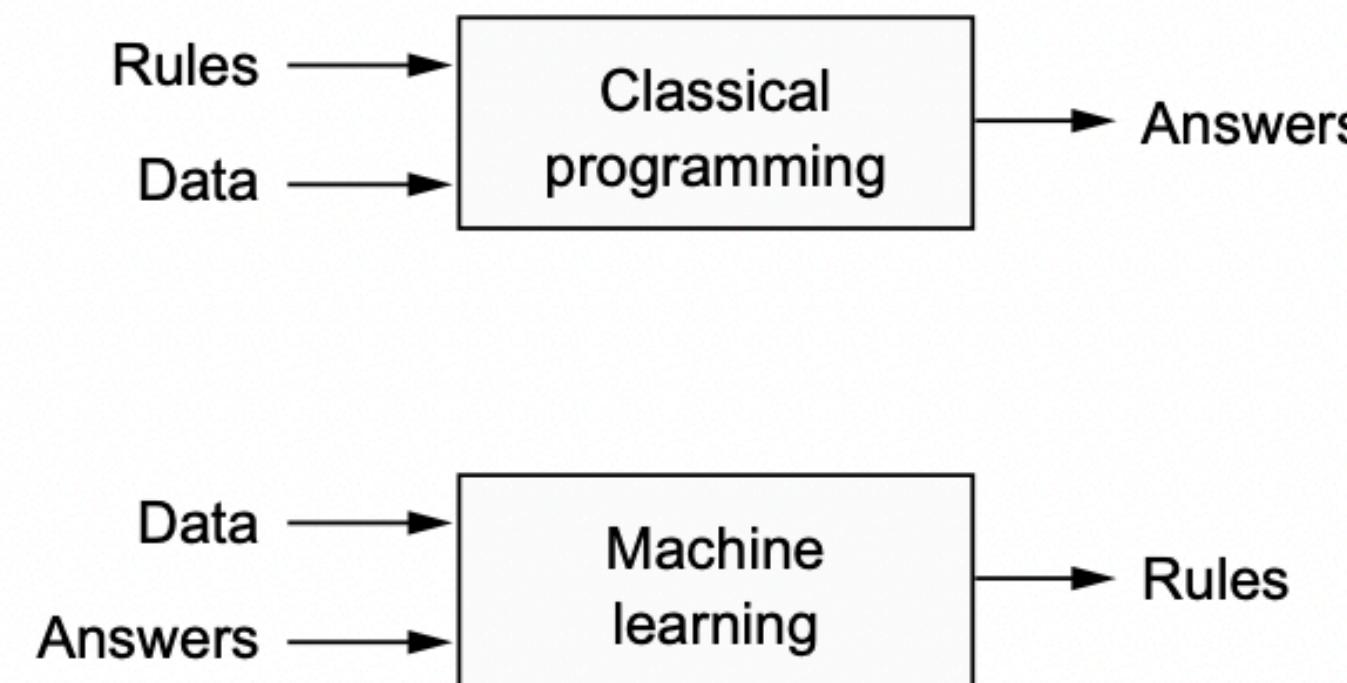
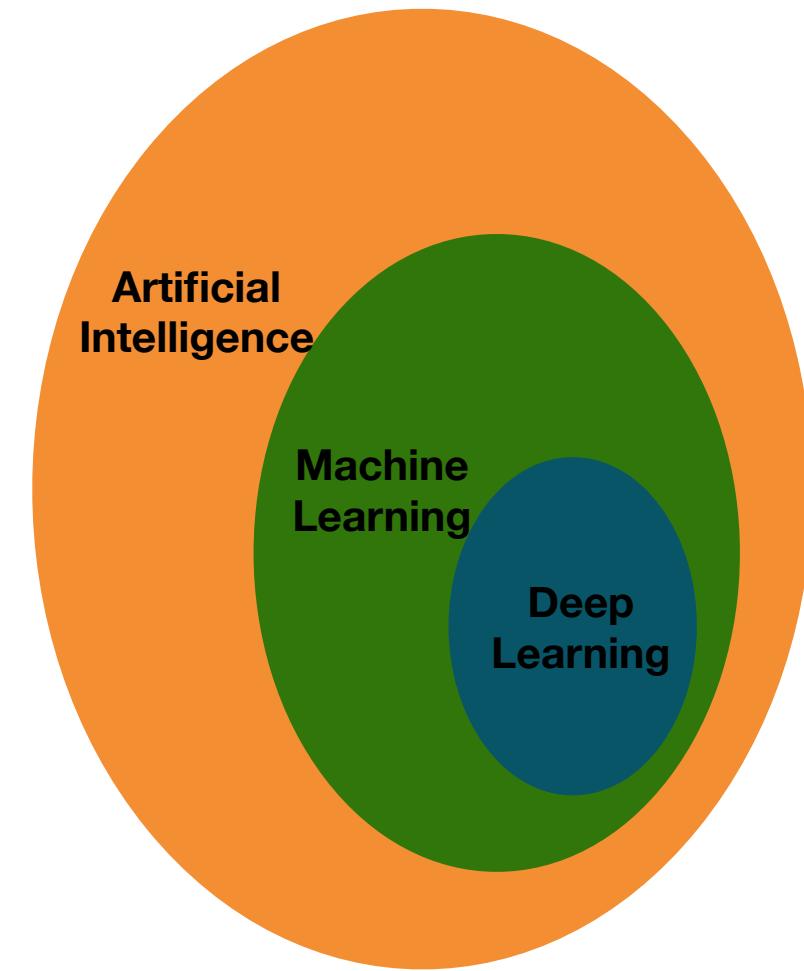
df = df.assign(Scores_Mean = lambda x: (x['math score']+x['writing score']+x['reading score'])/3)

df['scores_mean'] = round((df['writing score'] + df['math score'] + df['reading score'])/3, 2)
```

# Topic 4: Intro to the world of predictive models

# A shift of paradigm

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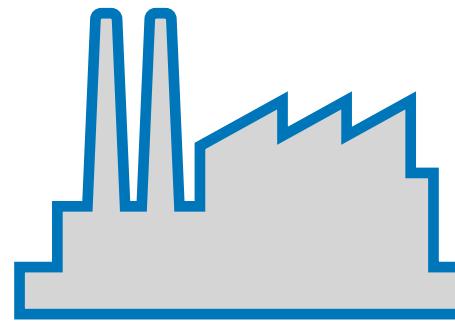


- AI: Effort to automate intellectual tasks normally performed by humans
- ~ 1950-1980 Symbolic AI. Rules + Data → Answers
- ML: Data + Answers → Rules

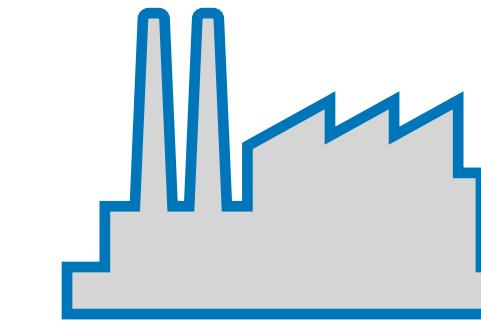
# Learning from the past to predict the future

---

Rules



AI/ML



Collect data throughout time

```
if  $T^a > 50^\circ$ :  
    return "We are in danger!"  
elif  $T^a < 10^\circ$ :  
    return "The tank is too cold!"  
else:  
    return "Everything is fine!"
```

Identifier	Features			Label
ID	$T^a$	Pressure	Week Day	Fault
1	35	10	1	No
2	68	25	2	Yes
3	42	10	1	No
4	15	12	6	No

# Learning from the past to predict the future

---

Identifier	Features			Label
ID	T <sup>a</sup>	Pressure	Week Day	Fault
1	35	10	1	No
2	68	25	2	Yes
3	42	10	1	No
4	15	12	6	No

**Predict Failure**

# Learning from the past to predict the future

---

Identifier	Features			Label
ID	T <sup>a</sup>	Pressure	Week Day	Fault
1	35	10	1	No
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3	42	10	1	No
4	15	12	6	No

Predict Failure

ID	#Bedrooms	#bathrooms	M2	Price(Euro)
1	3	2	120	190.000
2	3	3	150	250.000
3	1	1	60	100.000
4	2	2	80	140.000

Predict House Prices

# Learning from the past to predict the future

---

Identifier

Features

Label

ID	T <sup>a</sup>	Pressure	Week Day	Fault
1	35	10	1	No
2	68	25	2	Yes
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4	15	12	6	No

Predict Failure

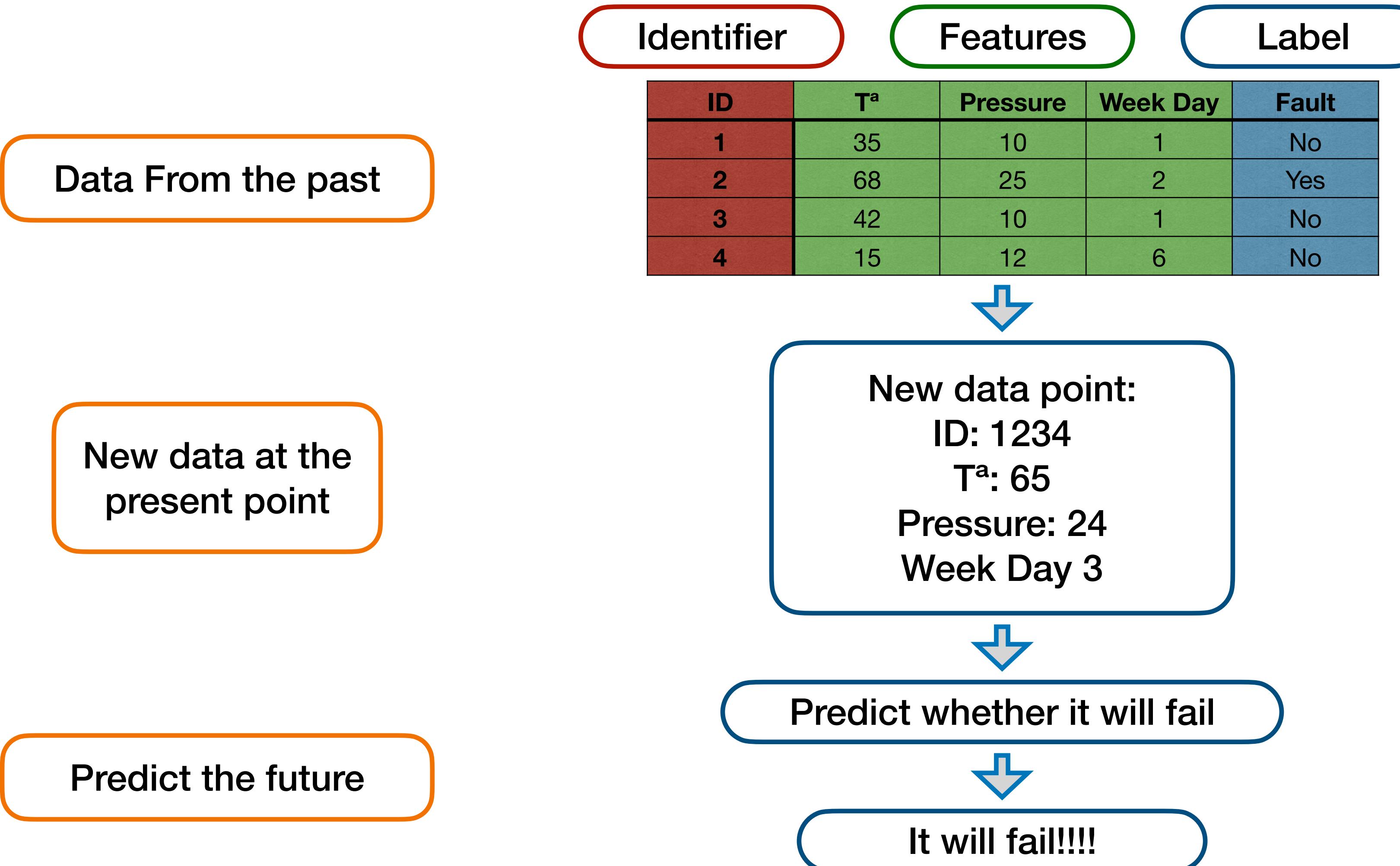
ID	#Bedrooms	#bathrooms	M2	Price(Euro)
1	3	2	120	190.000
2	3	3	150	250.000
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Predict House Prices

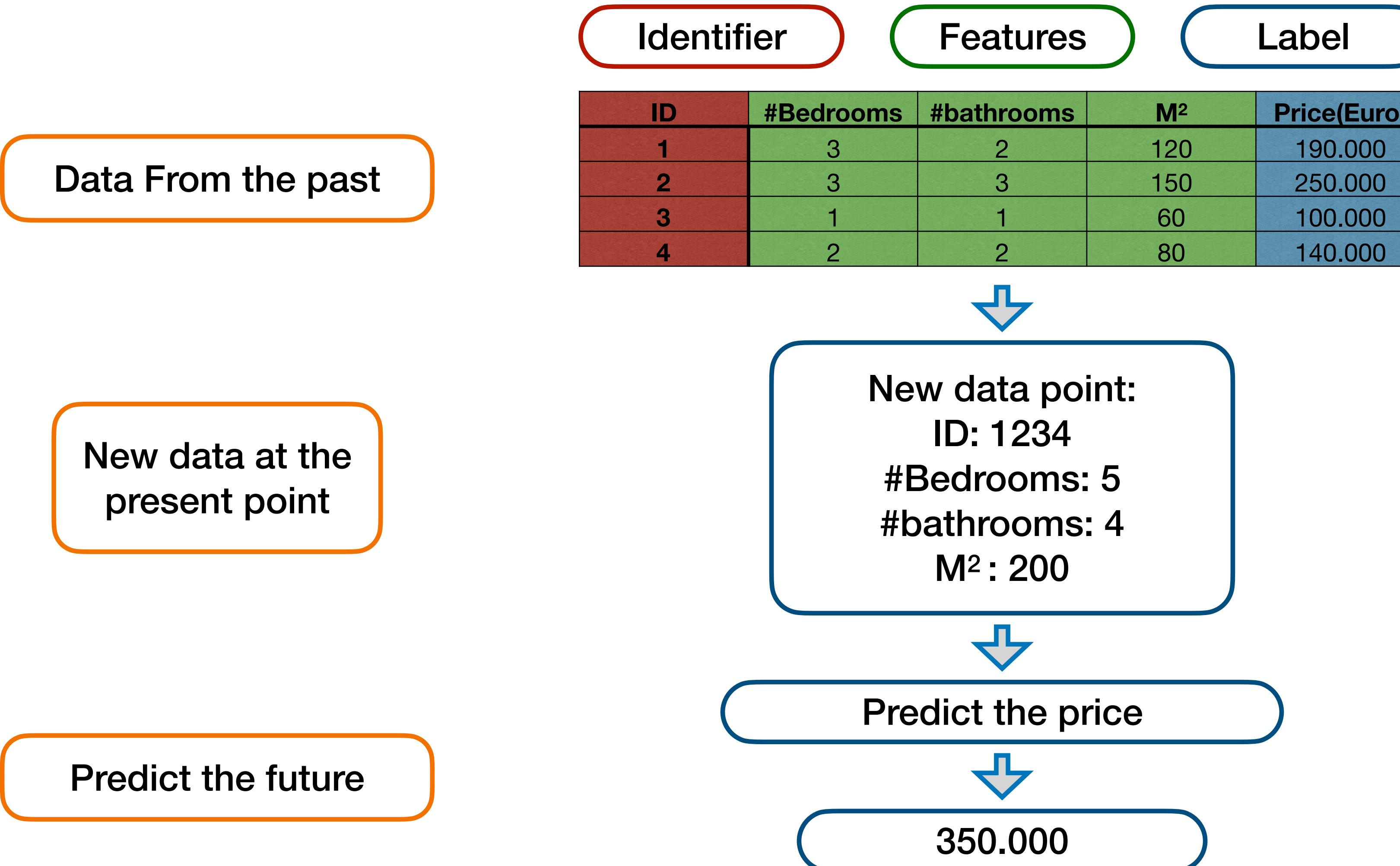
Name	MeanGrades	#PassedSubjects	Dropout
David	4	10	Yes
Evi	8	20	No
Fran	9	25	No
Encarna	7	18	No

Predict Student Dropout

# Learning from the past to predict the future



# Learning from the past to predict the future



# How do we learn from the past? We need something. A model

---

Data From the past

Identifier	Features	Label		
ID	#Bedrooms	#bathrooms	M <sup>2</sup>	Price(Euro)
1	3	2	120	190.000
2	3	3	150	250.000
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# How do we learn from the past? We need something. A model

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Predictive Model  
Black box

Train a model  
using the data  
from the past

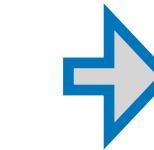
# How do we learn from the past? We need something. A model

Data From the past

Identifier		Features			Label
ID	#Bedrooms	#bathrooms	M <sup>2</sup>	Price(Euro)	
1	3	2	120	190.000	
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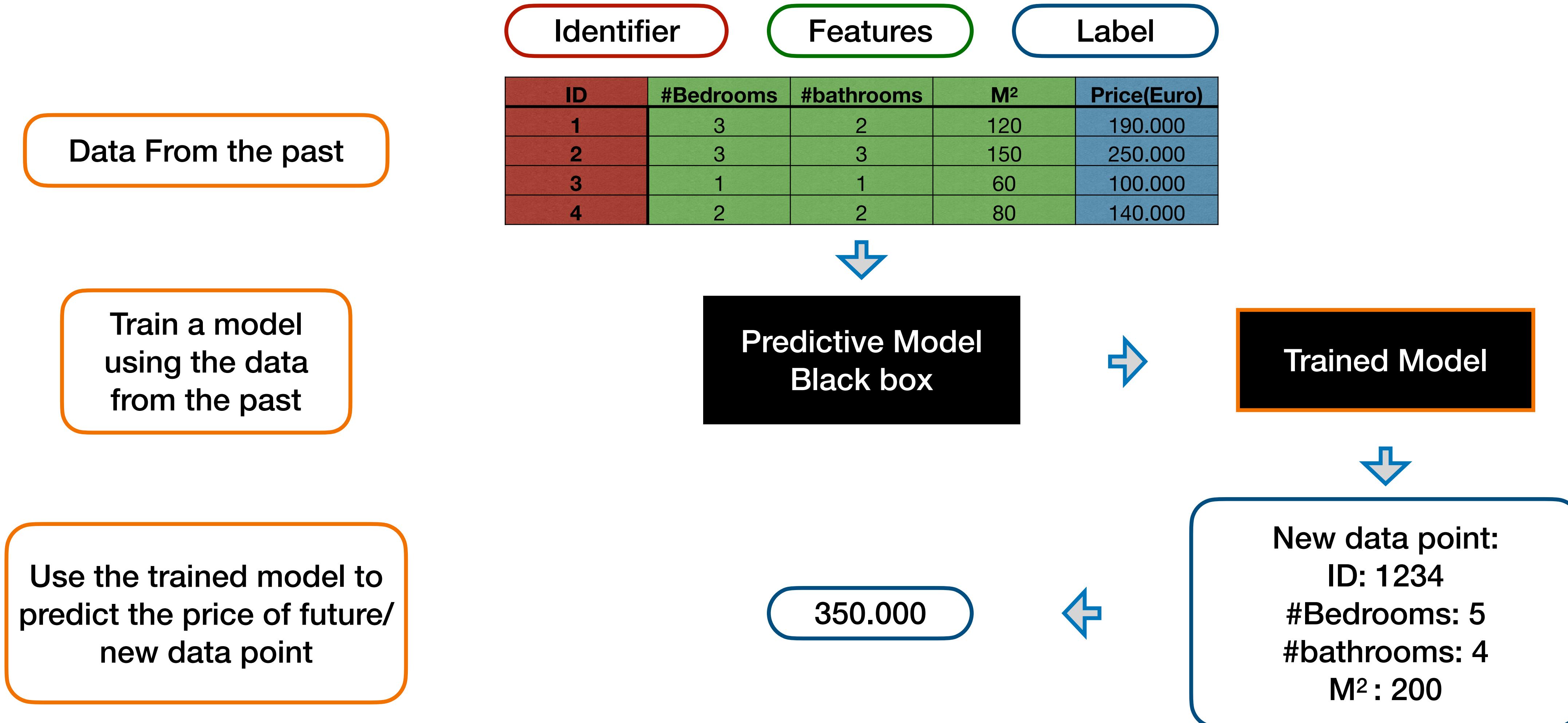
Train a model  
using the data  
from the past

Predictive Model  
Black box



Trained Model

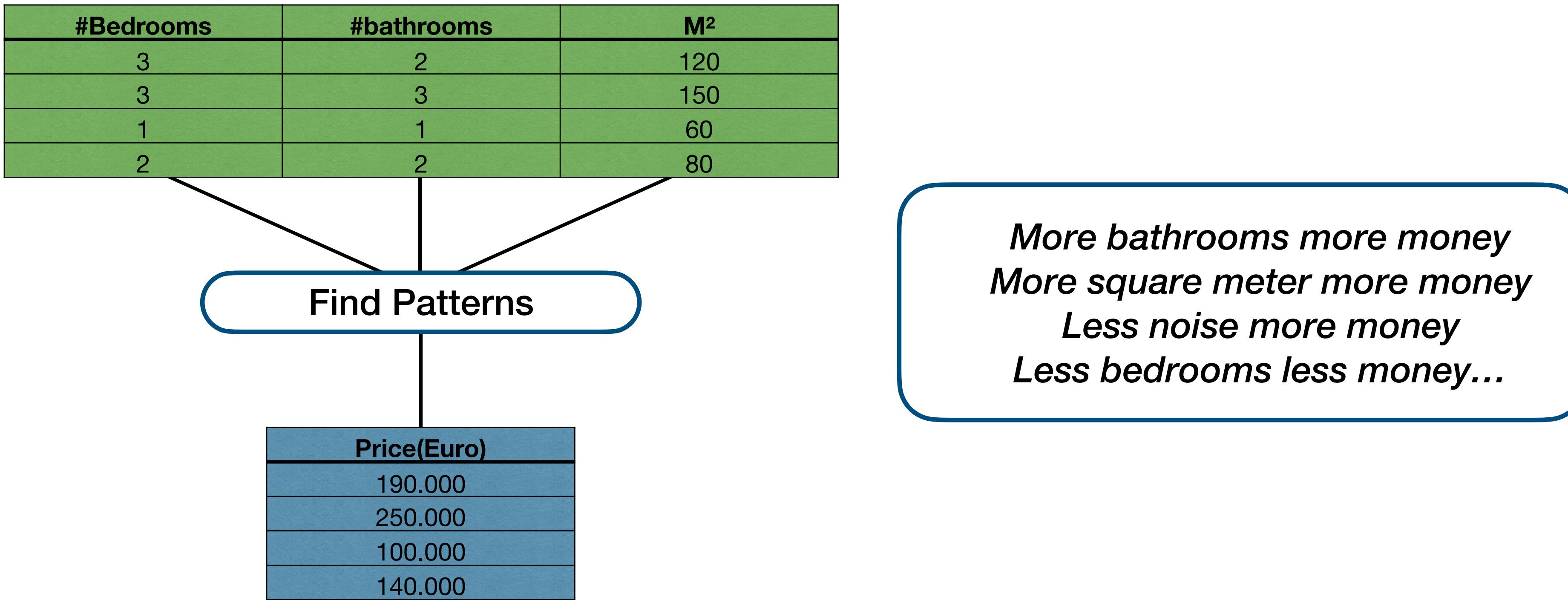
# How do we learn from the past? We need something. A model



# What is a model

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- Models are programs that can find patterns in the data that is fed to them

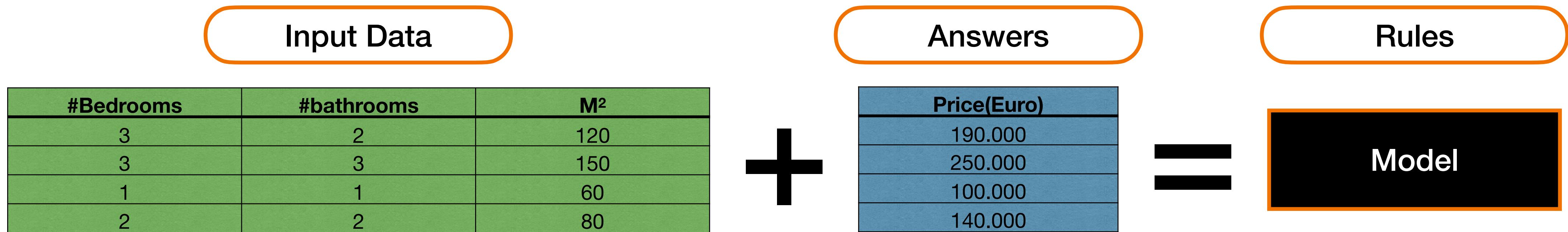


# Topic 5: Supervised vs. Unsupervised. Regression vs. Classification

# AI & Machine Learning

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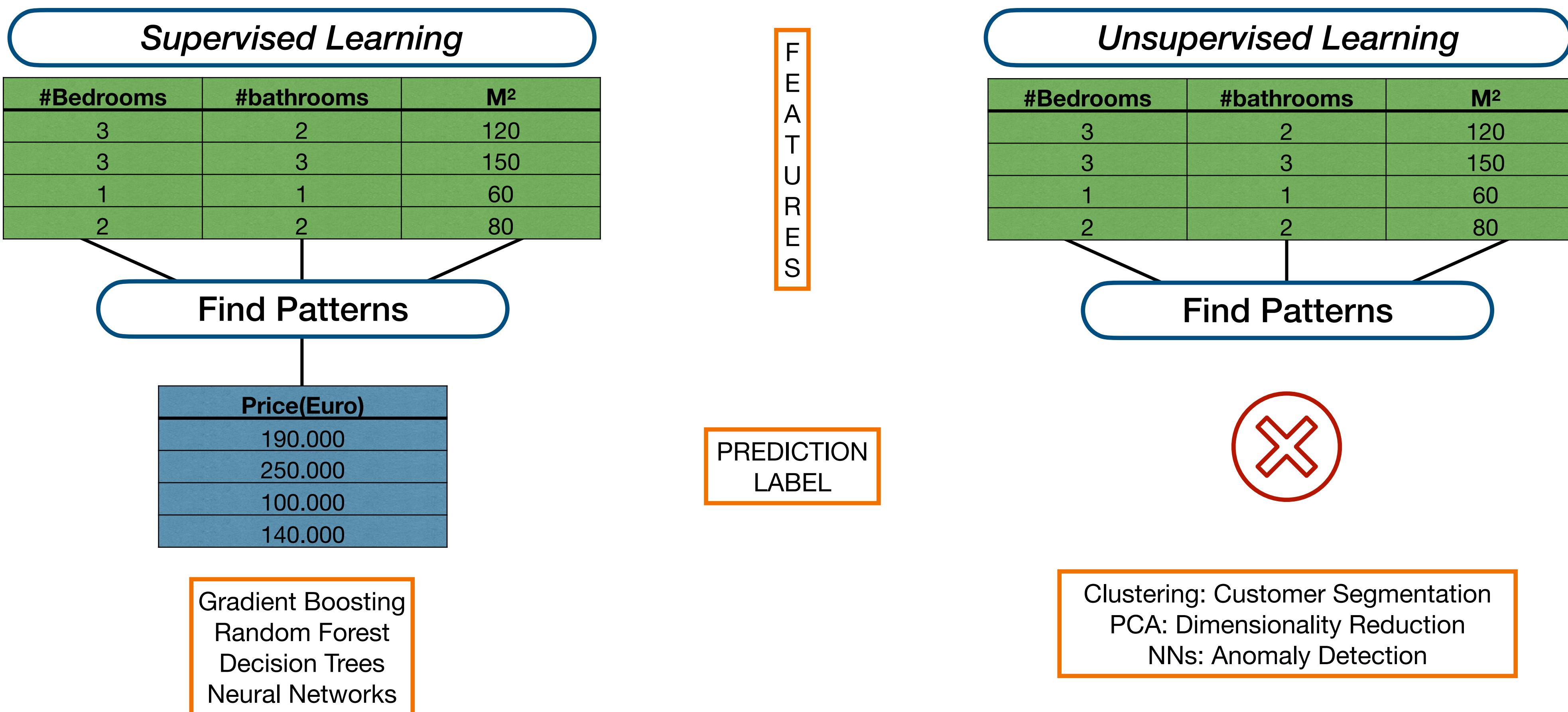
ML: Data (input) + Answers (predictive label) —> Rules (Model)



- Transform data into meaningful outputs  
(Learning from exposure to known examples)

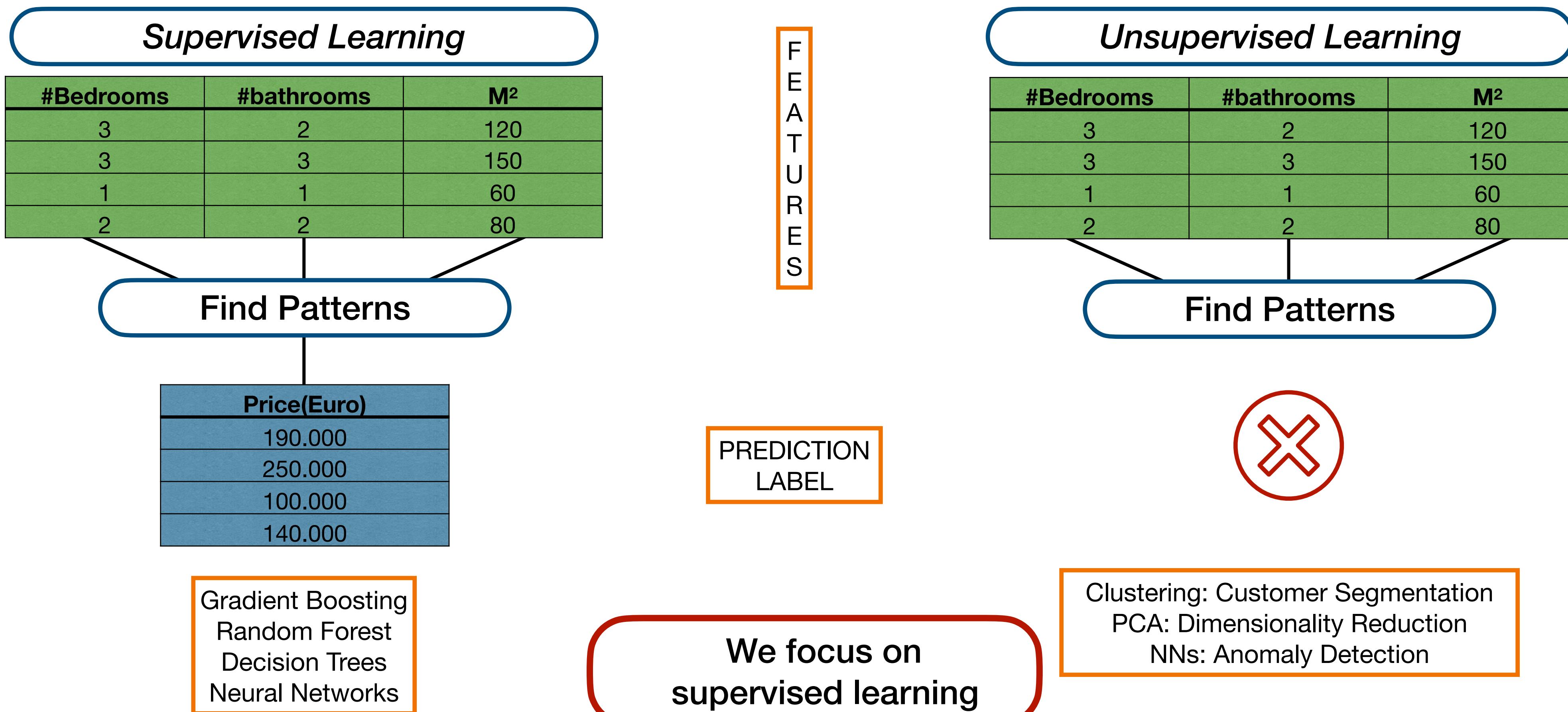
# Supervised vs. Unsupervised learning

- We distinguish between two types of models based on how they function and learn



# Supervised vs. Unsupervised learning

- We distinguish between two types of models based on how they function and learn



# Classification vs. Regression Problems

---

## Classification

ID	T <sup>a</sup>	Pressure	Week Day	Fault
1	35	10	1	No
2	68	25	2	Yes
3	42	10	1	No
4	15	12	6	No

## Regression

ID	#Bedrooms	#bathrooms	M <sup>2</sup>	Price(Euro)
1	3	2	120	190.000
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# Classification vs. Regression Problems

## Classification

ID	T <sup>a</sup>	Pressure	Week Day	Fault
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## Regression

ID	#Bedrooms	#bathrooms	M <sup>2</sup>	Price(Euro)
1	3	2	120	190.000
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*Classification is about predicting a label (Categorical) and regression is about predicting a quantity (Numerical)*

# Classification vs. Regression Problems

*Classification*

ID	T <sup>a</sup>	Pressure	Week Day	Fault
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2	68	25	2	Yes
3	42	10	1	No
4	15	12	6	No

*Regression*

ID	#Bedrooms	#bathrooms	M <sup>2</sup>	Price(Euro)
1	3	2	120	190.000
2	3	3	150	250.000
3	1	1	60	100.000
4	2	2	80	140.000

***Classification is about predicting a label (Categorical) and regression is about predicting a quantity (Numerical)***

- 1.- Spam email detection
- 2.- Sentiment analysis
- 3.- Image classification
- 4.- Fraud detection
- 5.- Disease diagnosis
- 6.- Customer churn prediction
- 7.- Handwritten digit recognition
- 8.- Intrusion detection in network security
- 9.- Document classification

- 1.- Predicting house prices
2. -Estimating the sales volume of a product
- 3.- Forecasting stock market prices
- 4.- Predicting a student's GPA
- 5.- Estimating the energy consumption of a building
- 6.- Predicting the lifespan of a mechanical component
- 7.- Forecasting the demand for a particular product
- 8.- Estimating the price of a used car
- 9.- Predicting the success rate of a marketing campaign

# Topic 6: Arranging data for models - Data Preparation

# Computers only understand numbers!

---

Categorical Features		Numerical Features	
Gender	Parent Education	Age	Grade
Male	College	21	8
Female	High School	22	9
Male	None	20	6
Female	College	21	5

Computers need to code the categorical features/columns as numbers. How do we do it?

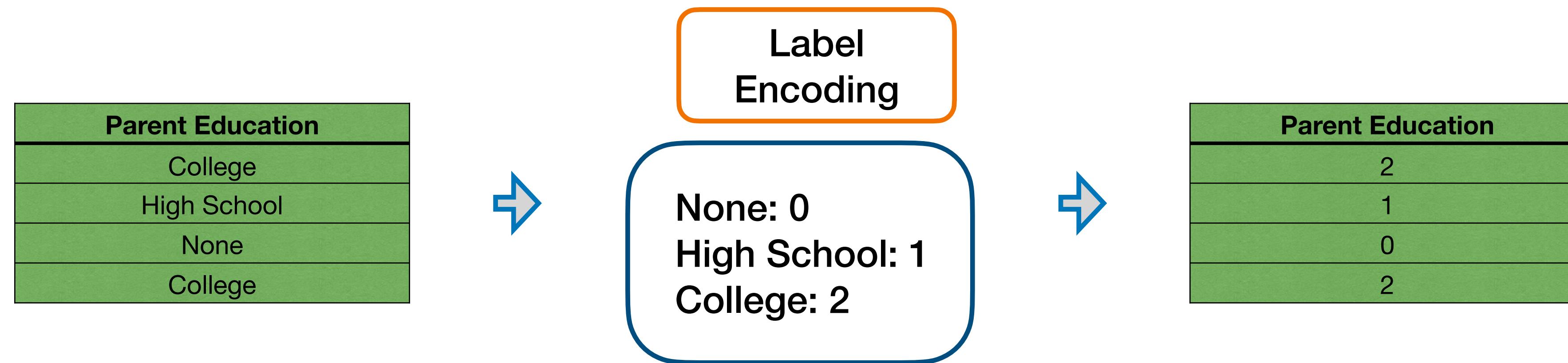
We have two main approaches:

- Label Encoding
- One Hot Encoding

# Label Encoding

---

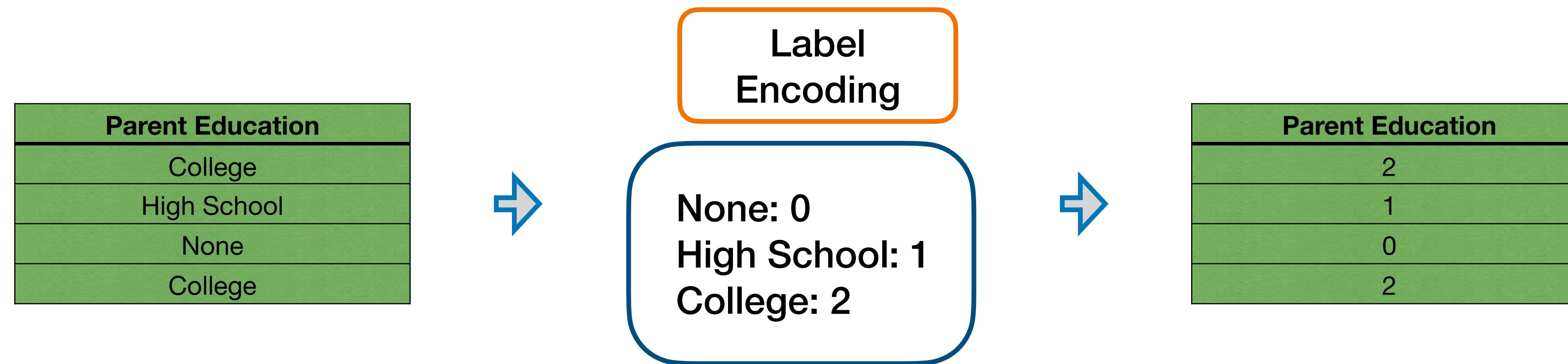
Process of converting the labels into a numeric form so as to convert them into the machine-readable form



# Label Encoding

---

Process of converting the labels into a numeric form so as to convert them into the machine-readable form

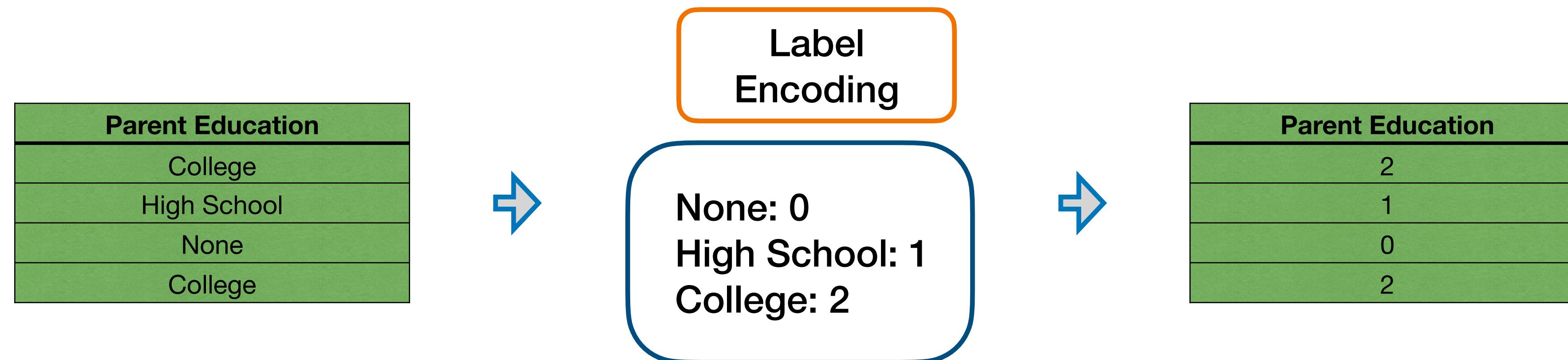


## Limitations / Disadvantages

Numeric values can be “misinterpreted” by the algorithms. For example, the value of 0 is obviously less than the value of 4 but is that so?

# Label Encoding

Process of converting the labels into a numeric form so as to convert them into the machine-readable form



## Limitations / Disadvantages

Numeric values can be “misinterpreted” by the algorithms. For example, the value of 0 is obviously less than the value of 4 but is that so?

## Python Code

```
df['parent_ed_cat_encode'] = df['parental level of education']\n    .astype('category').cat.codes
```

```
df[['parental level of education', 'parent_ed_cat_encode']].head()
```

	parental level of education	parent_ed_cat_encode
0	high school	2
1	some college	4
2	high school	2
3	associate's degree	0
4	high school	2

# Exercise

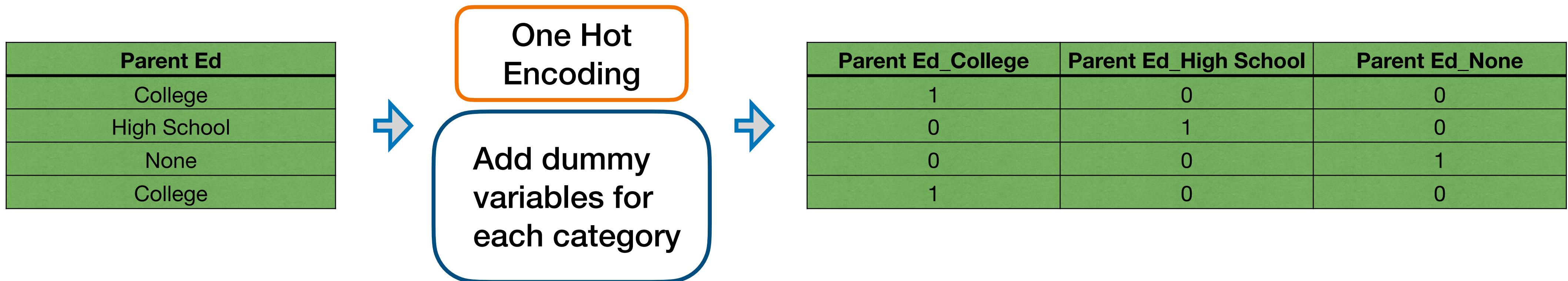
---

- Test label encoding to the column race/ethnicity. You can use pandas or scikitlearn
- Delete the new column when done or do not modify the source dataframe.
- Does label encoding makes sense here?

# One hot encoding

---

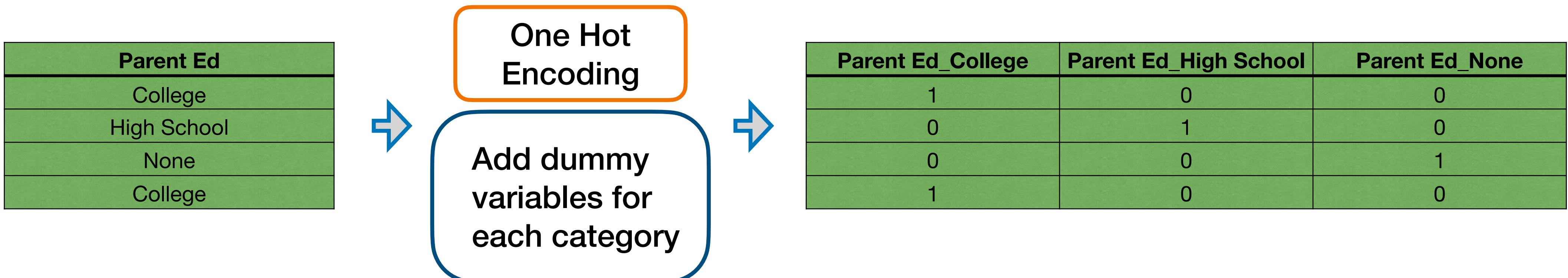
Convert each category value into a new column and assigns a 1 or 0 (True/False) value to the column.



# One hot encoding

---

Convert each category value into a new column and assigns a 1 or 0 (True/False) value to the column.



## Limitations / Disadvantages

It has the benefit of not weighting a value improperly but does have the downside of adding more columns to the data set.

# One hot encoding

Convert each category value into a new column and assigns a 1 or 0 (True/False) value to the column.

Parent Ed
College
High School
None
College

One Hot Encoding

Add dummy variables for each category

Parent Ed_College	Parent Ed_High School	Parent Ed_None
1	0	0
0	1	0
0	0	1
1	0	0

Limitations / Disadvantages

It has the benefit of not weighting a value improperly but does have the downside of adding more columns to the data set.

Python Code

```
pd.get_dummies(df['gender'], columns=['gender']).head()
```

	female	male
0	0	1
1	0	1
2	0	1
3	0	1
4	1	0

# Exercise

---

- Do one-hot encoding of all categorical columns

# Data Normalisation

---

- Normalization techniques can be used to change a continuous feature to fall within a specified range while maintaining the relative differences between the values for the feature.
- The simplest approach to normalization is **range normalization**,
- Range normalization performs a linear scaling of the original values of the continuous feature into a given range ([0, 1]).

$$x_{inorm} = \frac{x_i - X_{min}}{X_{max} - X_{min}} \cdot (range_{max} - range_{min}) + range_{min}$$

# Data Normalisation Practice

---

$$x_{inorm} = \frac{x_i - X_{min}}{X_{max} - X_{min}} \cdot (range_{max} - range_{min}) + range_{min}$$

Age
10
25
53
42

# Data Normalisation Practice

---

$$x_{inorm} = \frac{x_i - X_{min}}{X_{max} - X_{min}} \cdot (range_{max} - range_{min}) + range_{min}$$

Age
10
25
53
42

Age_norm
0
0.35
1
0.74

# Exercise

---

- Write a function that normalizes any column that you input in the range [0, 1] and test it.
- Check that your output is correct using MinMaxScaler from scikit learn

# Train & Test sets. Why are they necessary?

---

**Overfitting:** The model is not good on never seen data

**Underfitting:** The model is bad everywhere

The reason to have a separate train and test set is to avoid overfitting of the model to the data

# Train & Test sets. Why are they necessary?

---

Overfitting: The model is not good on never seen data

Underfitting: The model is bad everywhere

The reason to have a separate train and test set is to avoid overfitting of the model to the data

Training Set

Gender	Parent Education	Age	Grade
Male	College	21	8
Female	High School	22	9

Test Set

Gender	Parent Education	Age	Grade
Male	None	20	6
Female	College	21	5

To train the model. Can represent up to 90 % of the data

To test how the model generalizes to never seen data

# Documentation

# Datacamp Courses

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## Python Fundamentals

Are you ready to gain the foundational skills you need to become a Python programmer? In this track, you'll learn the Python basics you need to start on your programming journey, including how to clean real-world data ready for analysis, use data visualization libraries, and even how to write your own Python functions.

Your instructor Hugo will introduce you to how companies worldwide use Python to gain a competitive edge. Through hands-on coding exercises you'll then learn how to store, manipulate, and explore data using NumPy. Then it's time to level-up as you learn how to visualize your data using Matplotlib, manipulate DataFrames and dictionaries using pandas, and write your own functions and list comprehension. Start this track to add these essential Python skills to your data science toolbox.

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