

# Designing an end-to-end machine learning use case

END-TO-END MACHINE LEARNING



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# The case study

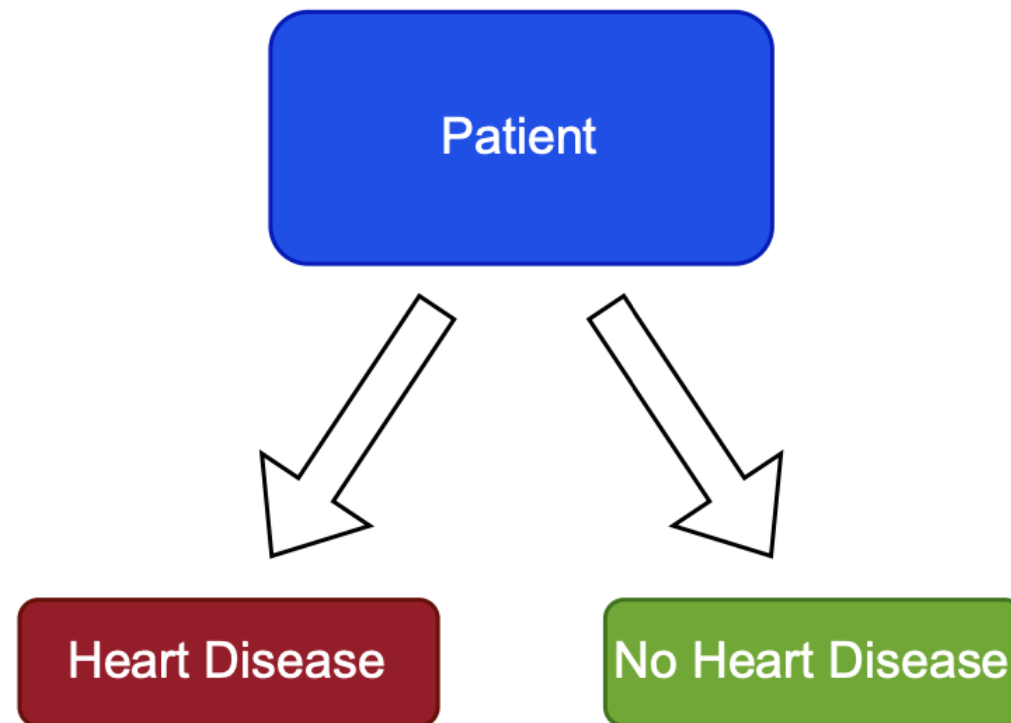
- Predicting heart disease
- Goal: inform decision-making of cardiologists



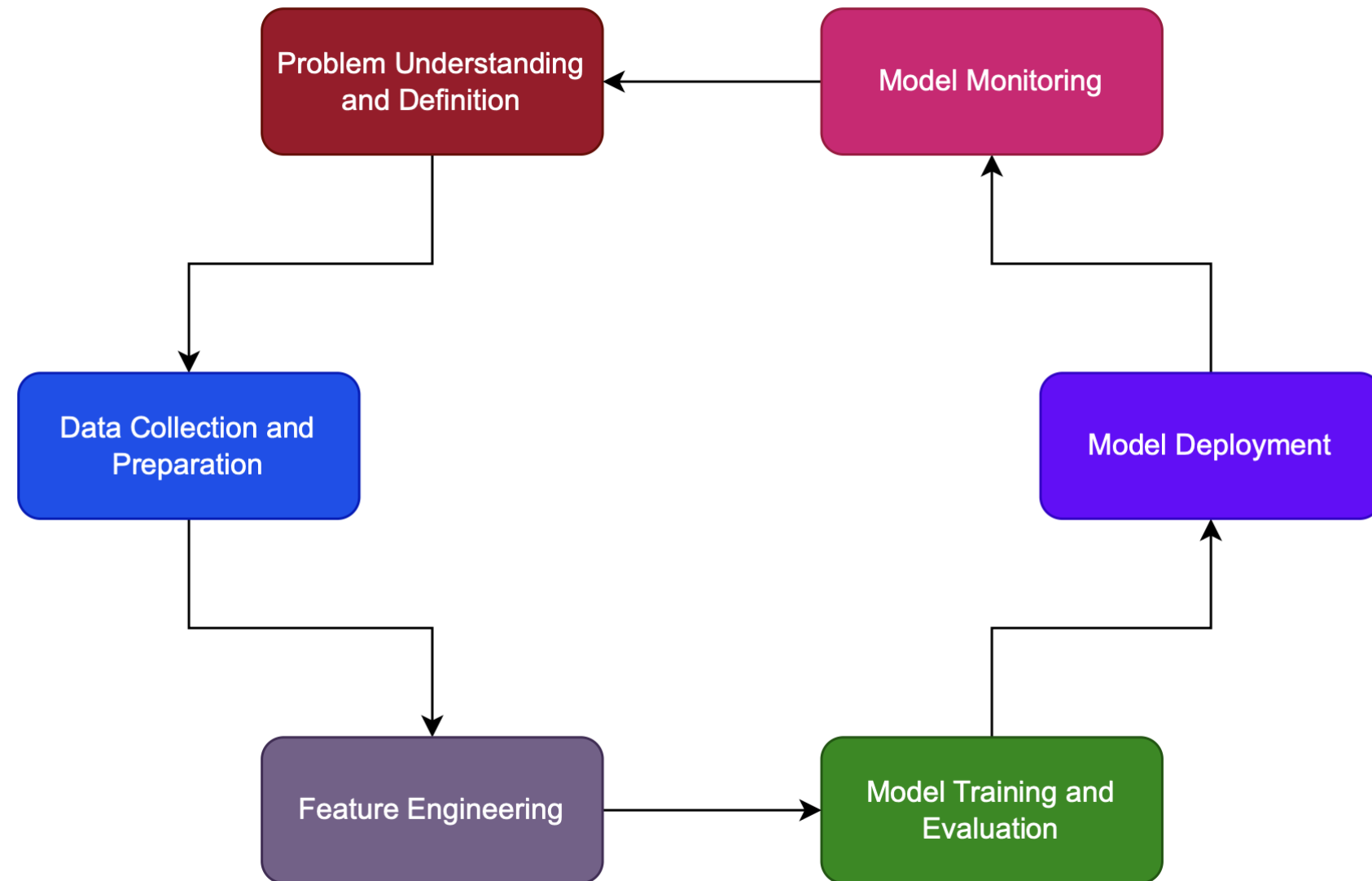
<sup>1</sup> Image source: <https://www.flaticon.com/free-icons/doctor>

# The model's role

- Models can **inform**, but should not **make** decisions
- Especially important in healthcare



# The machine learning lifecycle



# Understanding end user requirements

Accuracy



Reliability



Security

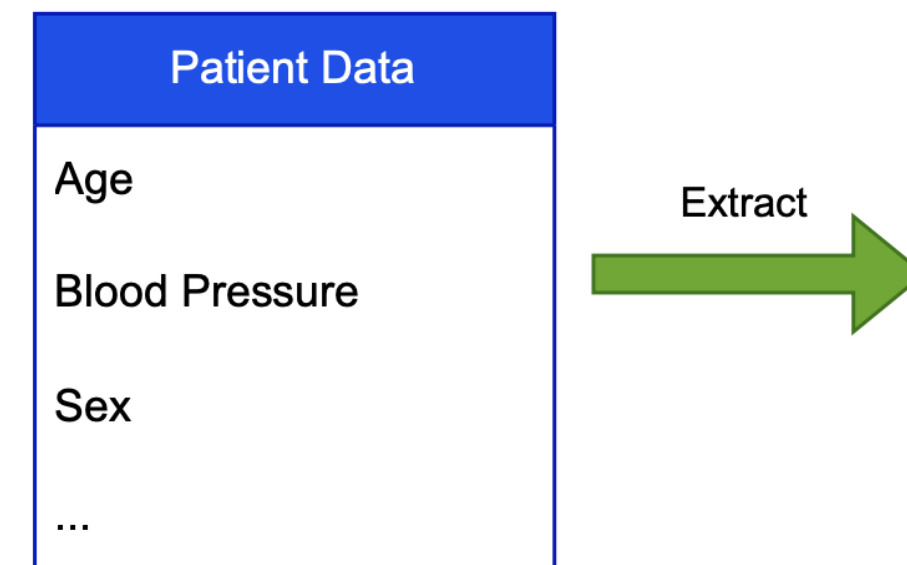


Interpretability



# Data collection

- Collect relevant data
  - Private dataset from company
  - Public dataset
- Understand data and context
  - Representation and measurement
  - Potential bias

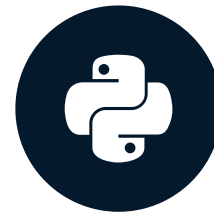


# Let's practice!

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# Exploratory Data Analysis

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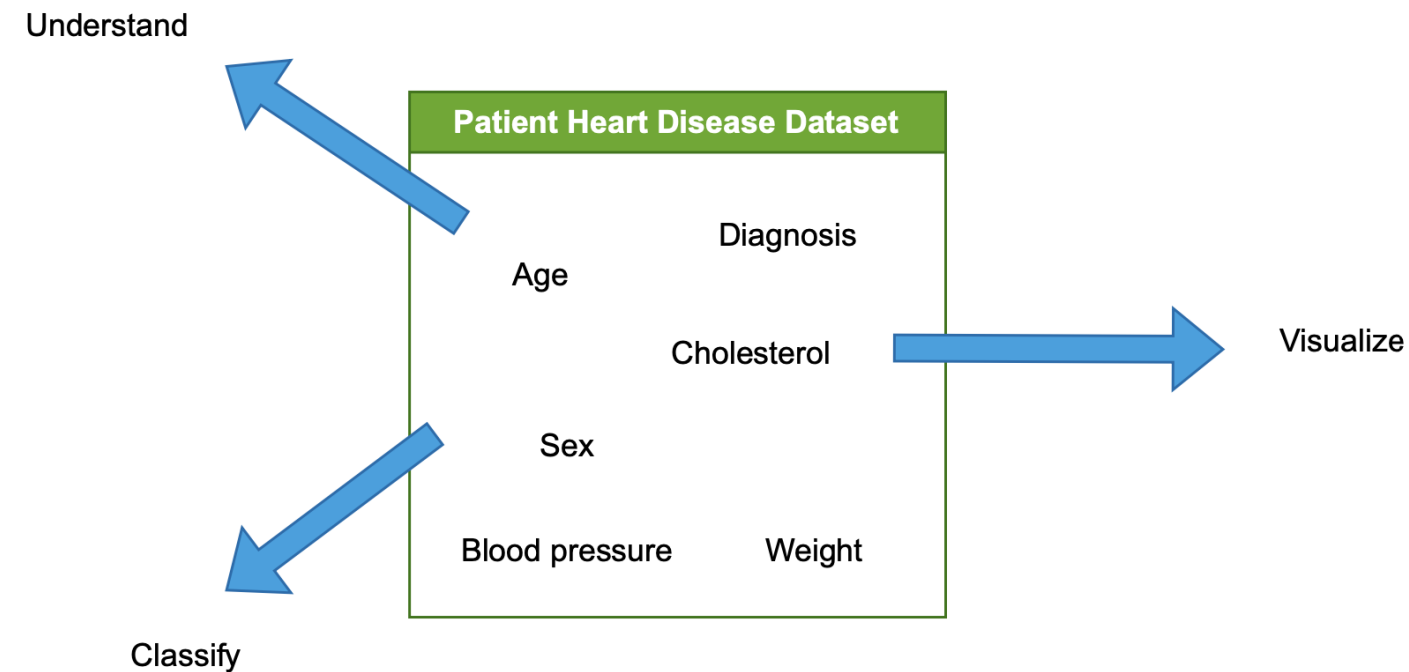


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# The EDA process

- Examine and analyse the dataset
- Understand the dataset
- Visualize the dataset
- Characterize / classify the dataset



# Understanding our data

```
df.head()
```

- Shows first rows of the dataset
- Provides snapshot of data's structure

```
# Print the first 5 columns  
print(heart_disease_df.head())
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0.0	125	212.0	0	1.0	168	0	NaN	2	2	3	0
1	53	1	0.0	140	203.0	1	0.0	155	1	NaN	0	0	3	0
2	70	1	0.0	145	174.0	0	1.0	125	1	NaN	0	0	3	0
3	61	1	0.0	148	203.0	0	1.0	161	0	NaN	2	1	3	0
4	62	0	0.0	138	294.0	1	1.0	106	0	NaN	1	3	2	0

```
df.info()
```

- Summarizes features
- Shows non-null entries and feature types

```
# Print out details  
print(heart_disease_df.info())
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 1076 entries, 0 to 1075  
Data columns (total 14 columns):  
#   Column      Non-Null Count  Dtype  
---  -  
0   age         1076 non-null   int64  
1   sex         1076 non-null   int64  
2   cp          1023 non-null   float64  
3   trestbps    1076 non-null   int64  
4   chol        1021 non-null   float64  
5   fbs         1076 non-null   int64  
6   restecg     1028 non-null   float64  
7   thalach     1076 non-null   int64  
8   exang       1076 non-null   int64  
9   oldpeak     0 non-null      float64  
10  slope       1076 non-null   int64  
11  ca          1076 non-null   int64  
12  thal        1076 non-null   int64  
13  target      1076 non-null   int64  
dtypes: float64(4), int64(10)  
memory usage: 117.8 KB
```

# Class (im)balance

```
df.value_counts()
```

- Counts number of unique occurrences of each class
- Class: binary presence of heart disease (1/0)
- Important for modeling

```
# print the class balance  
print(heart_disease_df['target'].value_counts(normalize=False))
```

```
1      551  
0      525  
Name: target, dtype: int64
```

# Missing values

- Can lead to errors
- Unrepresentative, biased results

Use `df.isnull()`

- Checks for null/empty/missing values
- Applied to column or collection of columns

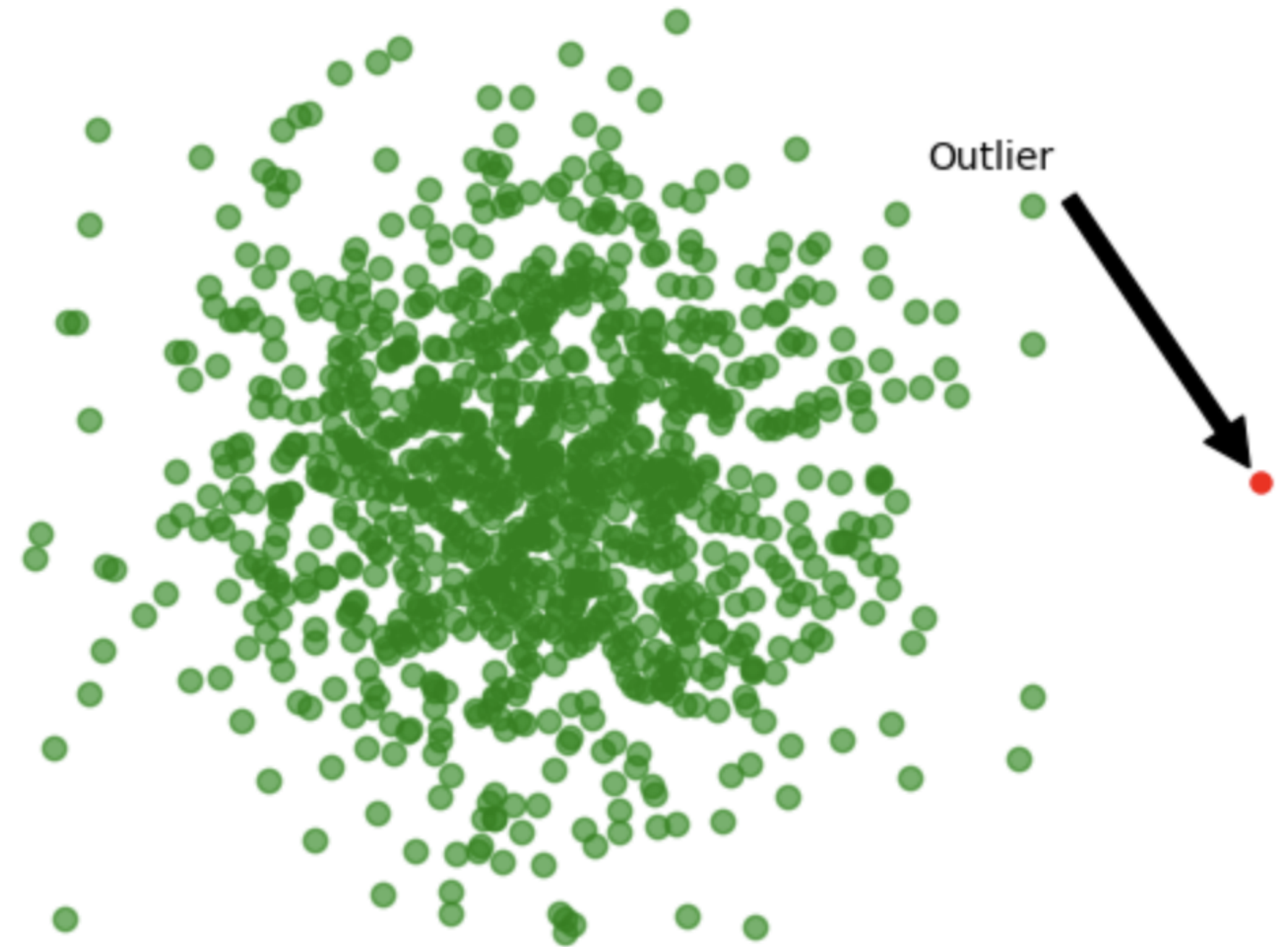
## Usage

```
# check whether all values in a column are null
print(heart_disease_df['oldpeak'].isnull().all())
```

True

# Outliers

- Anomalous values
  - Measurement errors
  - Data entry errors
  - Rare events
- Can skew model performance
  - Model learns based on extreme values
  - Doesn't capture general data trend
- Sometimes can be useful:
  - Rare values
  - Detection: use boxplot, or IQR



# Visualizing our data

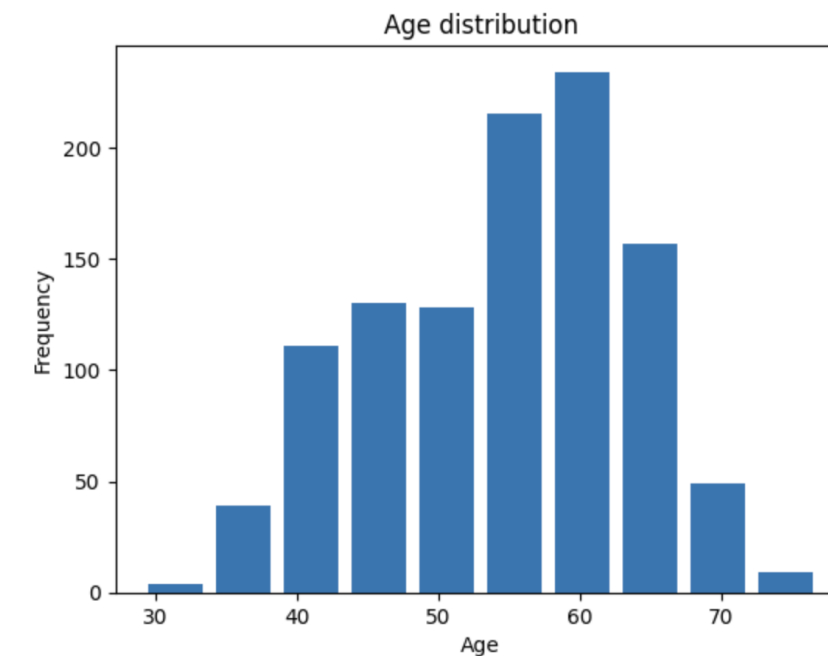
Visualizations show:

- General trends
- Missing values and outliers

Other types of visualizations:

- Kernel density estimation
- Empirical cumulative distributions
- Bivariate distributions

```
df['age'].plot(kind='hist')  
plt.xlabel('Age')  
plt.ylabel('Frequency')  
plt.show()
```



<sup>1</sup> <https://seaborn.pydata.org/tutorial/distributions.html>, <https://app.datacamp.com/learn/courses/intermediate-data-visualization-with-seaborn>

# Goals of EDA

## Understand the data

- Are there any patterns?
- Eg: do men have higher rate of heart disease?

## Formulate hypotheses

- What should we expect from the data?

## Detect outliers

- Does any data fall outside what is acceptable?
- Are there incorrect or missing values?

## Check assumptions

- Does what we expect line up with reality?

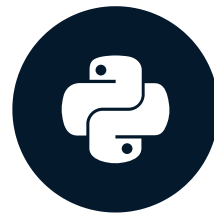
# Let's practice!

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# Data preparation

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# Data preparation steps

Dataset has:

- Missing values
- Outliers
- Imbalances
- Empty columns
- Duplicates

Data preparation:

- Based on insights from EDA
- Critical for model performance downstream

# Null / empty values

- Drop missing or sparse rows/columns
- Null values can break model
- Use `df.drop()` for columns
- Use `df.dropna(how='all')` for rows

```
# count missing values
print(df['oldpeak'].isnull().sum())

# Drop empty column(s) and row(s)
columns_dropped = heart_disease_df.drop(['oldpeak'], axis='columns')
rows_and_columns_dropped = columns_dropped.dropna(how='all')
```

# Dealing with null / empty values

- Data cleaning / dropping values depends on EDA findings
- If given column has too many missing values:
  - Drop column
- If target column has missing values:
  - Drop rows with missing targets
  - Or treat as separate category

# Imputation

What to do when there are only a few missing values?

- Imputation:
  - Fill missing values with substitutes
- Strategies
  - Fill with mean or median
  - Use constant or previous value

```
# Calculate the mean cholesterol value
mean_value = heart_disease_df['chol'].mean()

# Fill missing cholesterol values with the mean
heart_disease_df['chol'].fillna(mean_value, inplace=True)
```

# Advanced imputation

Advanced techniques:

- K-nearest neighbors
- SMOTE (synthetic minority oversampling technique)

```
from sklearn.impute import KNNImputer

# Initialize KNNImputer
imputer = KNNImputer(n_neighbors=2, weights="uniform")

# Perform the imputation on your DataFrame
df_imputed['oldpeak'] = imputer.fit_transform(df['oldpeak'])
```

# Dropping duplicates

- Data must be clean, concise, and rich
- Redundancies are unhelpful
- Duplicates can bias or confuse model
- Look at unique identifiers as a criteria for dropping records / rows.

```
# Drop duplicate rows
heart_disease_duplicates_dropped = heart_disease_column_dropped.drop_duplicates()
```

# Let's practice!

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