We will delve into the details of

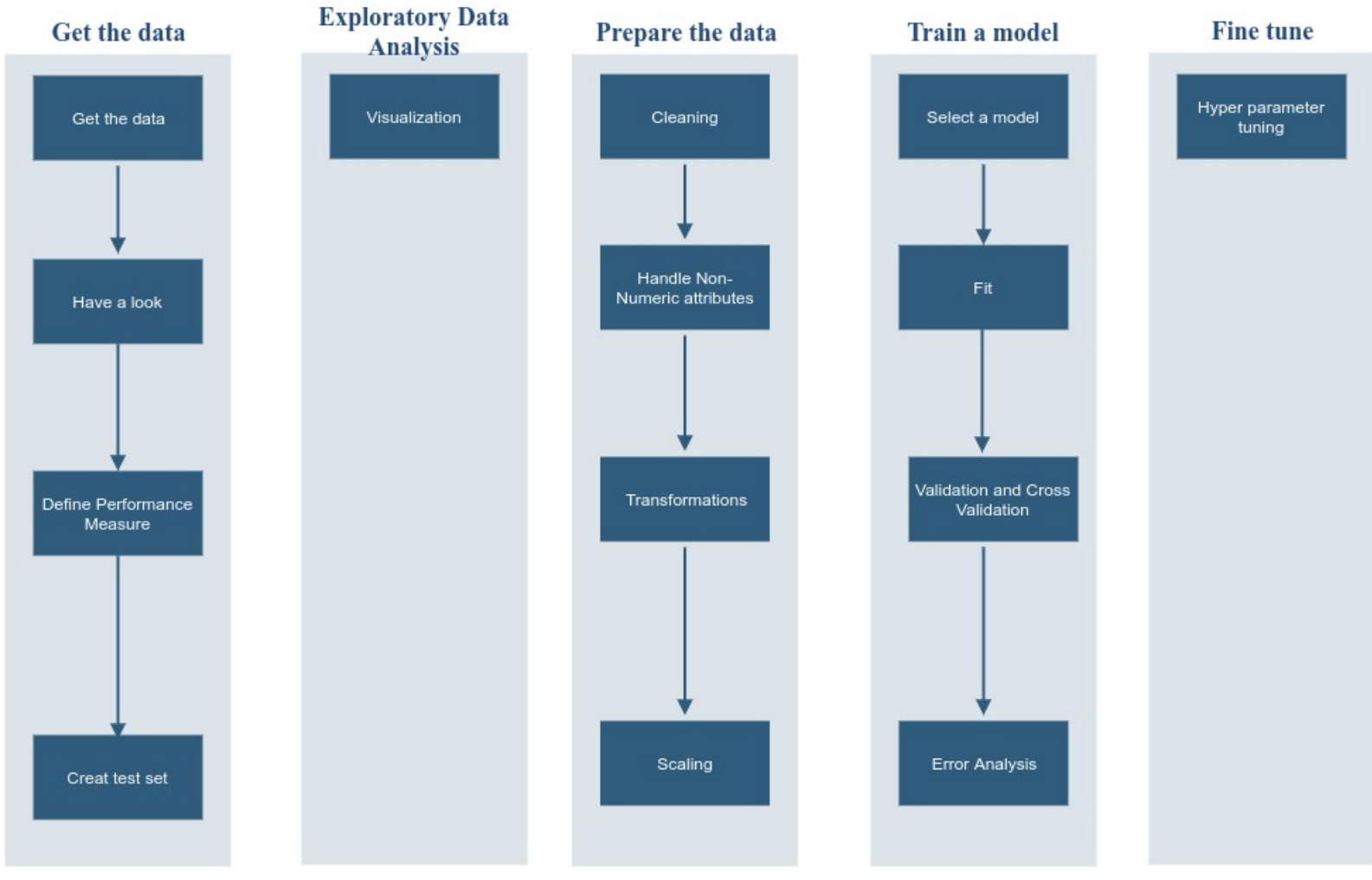
- Classification task
- Dealing with Non-numeric data

Recall: a Classification task has targets that are discrete values.

We will begin with the simple Binary Classification task in which the targets have only two possible values

- Positive
- Negative

We will explore an example in depth, following our Recipe for Machine Learning.


Get the data
Get the data
Have a look
Define Performance Measure
Creat test set
Exploratory Data Analysis
Visualization
Prepare the data
Cleaning
Handle Non-Numeric attributes
Transformations
Scaling
Train a model
Select a model
Fit
Validation and Cross Validation
Error Analysis
Fine tune
Hyper parameter tuning

# Get the data

## Frame the problem

We will introduce the Classification task using an historical event: the sinking of the Titanic.

(Also the subject of a famous movies)

Our task: given attributes of a passenger on the ship, predict whether the passenger survived.

Let's visit the notebook section Get the data (Classification_and_Non_Numerical_Data.ipynb#Frame-the-problem) and perform the following steps

- Frame the problem
- Get the data
- Have a look at the data

# Define a Performance Measure

# Create a test set

For Regression (continous variable as target), RMSE was our Performance Measure.

What is an appropriate measure for a *discrete* target ?

Let's visit the notebook section Define a Performance Measure (Classification_and_Non_Numerical_Data.ipynb#Recipe-A.3:-Select-a-performance-measure) and perform the following steps

- Define a performance measure
- Create a test set

# Recipe Step B: Exploratory Data Analysis (EDA)

There are quite a few features available.

Exploratory Data Analysis can help us

- Understand each feature in isolation (e.g., distribution)
    - May cause us to transform the feature, e.g., scaling
- Understand a possible relationship between target (survival) and each feature
    - Is this feature useful for predicting survival ?
- Understand possible relationships between features
- Possibly suggest creating new, synthetic features that alter or combine raw features

# Visualize Data to gain insights

Let's visit the notebook section Visualize Data (Classification_and_Non_Numerical_Data.ipynb#Recipe-Step-B:-Exploratory-Data-Analysis-(EDA))

# Prepare the data

Time to get our data ready. The steps we will perform include:

- Cleaning
- Handling non-numeric attributes
- Transformations

We will begin by discussing our plans for each step.

Let's visit the notebook section Prepare the data (Classification_and_Non_Numerical_Data.ipynb#Recipe-Step-C:-Prepare-the-data)

## Code for Prepare the Data

We will use an `sklearn` Pipeline to implement the Prepare the Data Step

- One Pipeline devoted to numeric features
- One Pipeline devoted to categorical features
- a `FeatureUnion` Pipeline that combines the numeric and categorical pipelines

Let's return to the notebook section Using a Pipeline (Classification_and_Non_Numerical_Data.ipynb#Recipe-Step-C--using-a-sophisticated-pipeline) to see the code.

# Train a model

We will perform the following steps

- Select a model
- Fit
- Cross Validation

The main classification model we will discuss is Logistic Regression.

But, it turns out:

- It is no harder to train *several* models than it is to just train one !
- So we will train a number of classification models, even before we formally introduce them
- This is the power of `sklearn` and similar toolkits for Machine Learning
    - All models have a consistent API: `fit`, `transform`, `predict`

So, after today's lecture: it will no longer be about the code

- The code to use most models is nearly identical, thanks to the consistent API
- My notebooks will be less "code-heavy"
    - The code will be isolated into separate modules, which you can examine
    - You just won't see the body in the notebook

If our goal was to learn an API, we'd be done.

But our goal is to pursue a systematic approach to problem solving in Machine Learning, with an emphasis

- On process
- Understanding concepts, loss functions, etc.
- Diagnosing problems with models and improving them

Let's return to the notebook section Train a model (Classification_and_Non_Numerical_Data.ipynb#Recipe-Step-D:-Train-a-model)

# Error Analysis

Let's introduce some concepts relevant to analyzing errors for the Classification task.

We will be very brief, for now. We will explore this topic in depth in a dedicated module on Error Analysis.

Let's return to the notebook section Error Analysis (Classification_and_Non_Numerical_Data.ipynb#Recipe-D.4:--Error-analysis)

In [1]:
```
print("Done")
```

```
Done
```