Customer Churn Prediction

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Defining the Problem

Customer Churn Prediction is critical for telecommunication companies as it can have a significant impact on the business's bottom line. When customers churn, they take their business with them, which means lost revenue. In addition, acquiring new customers can be expensive, so it's often more cost-effective to retain existing customers.

For this reason, large telecommunications corporations are seeking to develop models to predict which customers are more likely to change and take actions accordingly.

So, we build a model to predict how likely a customer will churn by analyzing its characteristics:

1. Demographic information
2. Account Information
3. Services Information

The objective is to obtain a data-driven solution that will allow us to reduce churn rates and, as a consequence, to increase customer satisfaction and corporation revenue.

Dataset

The data set used here is available in [Kaggle] and contains nineteen columns (independent variables) that indicate the characteristics of the clients of a fictional telecommunications corporation. The Churn column (response variable) indicates whether the customer departed within the last month or not. The class No includes the clients that did not leave the company last month, while the class Yes contains the clients that decided to terminate their relations with the company. The objective of the analysis is to obtain the relation between the customer's characteristics and the churn.

Project Steps :

1. Data Reading
2. Exploratory Data Analysis & Data Cleaning
3. Data Visualization
4. Feature Importance
5. Feature Engineering
6. Setting a baseline
7. Splitting the data into training and testing sets
8. Assessing multiple algorithms
9. Algorithm Fit
10. Hyperparameter Tuning
11. Model Performance
12. Conclusions — Summary

1.Data Reading

The first step of the analysis consists of reading and storing the data in a Pandas data frame using the `pandas.read_csv` function.

```
# import telecom dataset into a pandas data frame
df_telco = pd.read_csv('/content/telco_churn.csv')


# visualize column names
df_telco.columns
```

```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

```
# check unique values of each column
for column in df_telco.columns:
                print('Column:    {}    -    Unique    Values:    {}'.format(column,
df_telco[column].unique()))
```

```
Column: customerID - Unique Values: ['7590-VHVEG' '5575-GNVDE' '3668-QPYBK' ... '4801-JZAZL' '8361-LTMKD'
 '3186-AJIEK']
Column: gender - Unique Values: ['Female' 'Male']
Column: SeniorCitizen - Unique Values: [0 1]
Column: Partner - Unique Values: ['Yes' 'No']
Column: Dependents - Unique Values: ['No' 'Yes']
Column: tenure - Unique Values: [ 1 34  2 45  8 22 10 28 62 13 16 58 49 25 69 52 71 21 12 30 47 72 17 27
  5 46 11 70 63 43 15 60 18 66  9  3 31 50 64 56  7 42 35 48 29 65 38 68
 32 55 37 36 41  6  4 33 67 23 57 61 14 20 53 40 59 24 44 19 54 51 26  0
 39]
Column: PhoneService - Unique Values: ['No' 'Yes']
Column: MultipleLines - Unique Values: ['No phone service' 'No' 'Yes']
Column: InternetService - Unique Values: ['DSL' 'Fiber optic' 'No']
Column: OnlineSecurity - Unique Values: ['No' 'Yes' 'No internet service']
Column: OnlineBackup - Unique Values: ['Yes' 'No' 'No internet service']
Column: DeviceProtection - Unique Values: ['No' 'Yes' 'No internet service']
Column: TechSupport - Unique Values: ['No' 'Yes' 'No internet service']
Column: StreamingTV - Unique Values: ['No' 'Yes' 'No internet service']
Column: StreamingMovies - Unique Values: ['No' 'Yes' 'No internet service']
Column: Contract - Unique Values: ['Month-to-month' 'One year' 'Two year']
Column: PaperlessBilling - Unique Values: ['Yes' 'No']
Column: PaymentMethod - Unique Values: ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
Column: MonthlyCharges - Unique Values: [29.85 56.95 53.85 ... 63.1  44.2  78.7 ]
Column: TotalCharges - Unique Values: ['29.85' '1889.5' '108.15' ... '346.45' '306.6' '6844.5']
Column: Churn - Unique Values: ['No' 'Yes']
```

As shown above, the data set contains 19 independent variables, which can be classified into 3 groups:

(1) Demographic Information

- `gender`: Whether the client is a female or a male (`Female`, `Male`).
- `SeniorCitizen`: Whether the client is a senior citizen or not (`0`, `1`).
- `Partner`: Whether the client has a partner or not (`Yes`, `No`).
- `Dependents`: Whether the client has dependents or not (`Yes`, `No`).

(2) Customer Account Information

`tenure`: Number of months the customer has stayed with the company (Multiple different numeric values).
`Contract`: Indicates the customer's current contract type (`Month-to-Month`, `One year`, `Two year`).
`PaperlessBilling`: Whether the client has paperless billing or not (`Yes`,`No`).
`PaymentMethod`: The customer's payment method (`Electronic check`, `Mailed check`, `Bank transfer (automatic)`, `Credit Card (automatic)`).
`MonthlyCharges`: The amount charged to the customer monthly (Multiple different numeric values).
`TotalCharges`: The total amount charged to the customer (Multiple different numeric values).

(3) Services Information

`PhoneService`: Whether the client has a phone service or not (Yes, No).
`MultipleLines`: Whether the client has multiple lines or not (No phone service, No, Yes).
`InternetServices`: Whether the client is subscribed to Internet service with the company (DSL, Fiber optic, No)
`OnlineSecurity`: Whether the client has online security or not (No internet service, No, Yes).
`OnlineBackup`: Whether the client has online backup or not (No internet service, No, Yes).
`DeviceProtection`: Whether the client has device protection or not (No internet service, No, Yes).
`TechSupport`: Whether the client has tech support or not (No internet service, No, Yes).
`StreamingTV`: Whether the client has streaming TV or not (No internet service, No, Yes).
`StreamingMovies`: Whether the client has streaming movies or not (No internet service, No, Yes).

2. Exploratory Data Analysis & Data Cleaning

Exploratory data analysis consists of analyzing the main characteristics of a data set usually by means of visualization methods and summary statistics. The objective is to understand the data, discover patterns and anomalies, and check assumptions before performing further evaluations.

Missing values and data types
At the beginning of EDA, we want to know as much information as possible about the data, this is when the `pandas.DataFrame.info` method comes in handy. This method prints a concise summary of the data frame, including the column names and their data types, the number of non-null values, and the amount of memory used by the data frame.

```
# summary of the data frame
df_telco.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

As shown above, the data set contains **7043 observations** and **21 columns**. Apparently, there are no null values on the data set; however, we observe that the column `TotalCharges` was **wrongly detected as an object**. This column represents the total amount charged to the customer and it is, therefore, a numeric variable. For further analysis, we need to transform this column into a **numeric data type**. To do so, we can use the `pd.to_numeric` function. By default, this function raises an exception when it sees non-numeric data; however, we can use the argument `errors='coerce'` to skip those cases and replace them with a `NaN`.

```
# transform the column TotalCharges into a numeric data type
df_telco['TotalCharges'] = pd.to_numeric(df_telco['TotalCharges'], errors='coerce')
```

We can now observe that the column `TotalCharges` has 11 missing values.

```
# null observations of the TotalCharges column
df_telco[df_telco['TotalCharges'].isnull()]
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection
488	4472-LVYGI	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	...	Yes
753	3115-CZMZD	Male	0	No	Yes	0	Yes	No	No	No internet service	...	No internet service
936	5709-LVOEQ	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	...	Yes
1082	4367-NUYAO	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	...	No internet service
1340	1371-DWPAZ	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	...	Yes
3331	7644-OMVMY	Male	0	Yes	Yes	0	Yes	No	No	No internet service	...	No internet service
3826	3213-VVOLG	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	...	No internet service
4380	2520-SGTTA	Female	0	Yes	Yes	0	Yes	No	No	No internet service	...	No internet service
5218	2923-ARZLG	Male	0	Yes	Yes	0	Yes	No	No	No internet service	...	No internet service
6670	4075-WKNIU	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	...	Yes
6754	2775-SEFEE	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	...	No

11 rows × 21 columns

These observations also have a tenure of 0, even though `MontlyCharges` is not null for these entries. This information appeared to be contradictory, and therefore, we decided to remove those observations from the data set.

```
# drop observations with null values
df_telco.dropna(inplace=True)
```

Remove customerID column
The `customerID` column is useless to explain whether or not the customer will churn. Therefore, we drop this column from the data set.

```
# drop the customerID column from the dataset
df_telco.drop(columns='customerID', inplace=True)
```

Payment method denominations
As shown below, some payment method denominations contain in parenthesis the word automatic. These denominations are too long to be used as tick labels in further visualizations. Therefore, we remove this clarification in parenthesis from the entries of the `PaymentMethod` column.

```
# unique elements of the PaymentMethod column
df_telco.PaymentMethod.unique()
```

```
array(['Electronic check', 'Mailed check', 'Bank transfer (automatic)',
       'Credit card (automatic)'], dtype=object)
```

```
# remove (automatic) from payment method names
```

```
df_telco['PaymentMethod'] = df_telco['PaymentMethod'].str.replace(' (automatic)',
'', regex=False)
```

```
# unique elements of the PaymentMethod column after the modification
df_telco.PaymentMethod.unique()
```

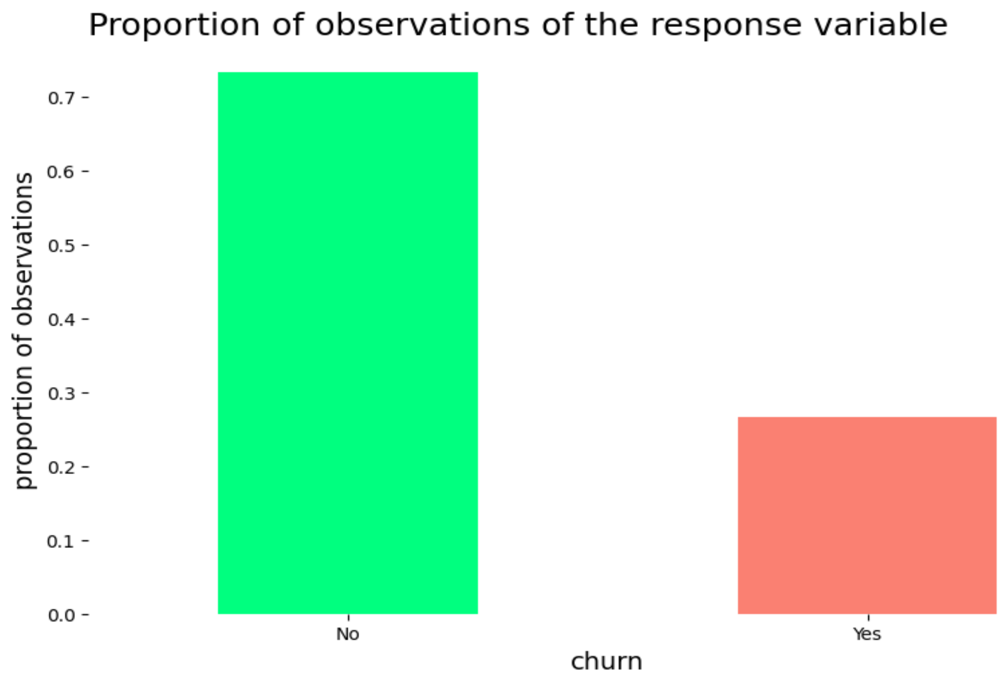
```
array(['Electronic check', 'Mailed check', 'Bank transfer', 'Credit card'],
      dtype=object)
```

3. Data Visualization

In this section, we analyze the data by using visualization.

Response Variable
The following bar plot shows the percentage of observations that correspond to each class of the response variable: no and yes. As shown below, this is an imbalanced data set because both classes are not equally distributed among all observations, being not the majority class (73.42%). When modeling, this imbalance will lead to a large number of false negatives, as we will see later.

```
# create a figure
fig = plt.figure(figsize=(10, 6))
ax = fig.add_subplot(111)

# proportion of observation of each class
prop_response = df_telco['Churn'].value_counts(normalize=True)

# create a bar plot showing the percentage of churn
prop_response.plot(kind='bar',
                   ax=ax,
                   color=['springgreen','salmon'])

# set title and labels
ax.set_title('Proportion of observations of the response variable',
             fontsize=18, loc='left')
ax.set_xlabel('churn',
              fontsize=14)
ax.set_ylabel('proportion of observations',
              fontsize=14)
ax.tick_params(rotation='auto')

# eliminate the frame from the plot
spine_names = ('top', 'right', 'bottom', 'left')
for spine_name in spine_names:
    ax.spines[spine_name].set_visible(False)
```



We are going to use **normalized stacked bar** plots to analyze the **influence of each independent categorical variable in the outcome**.

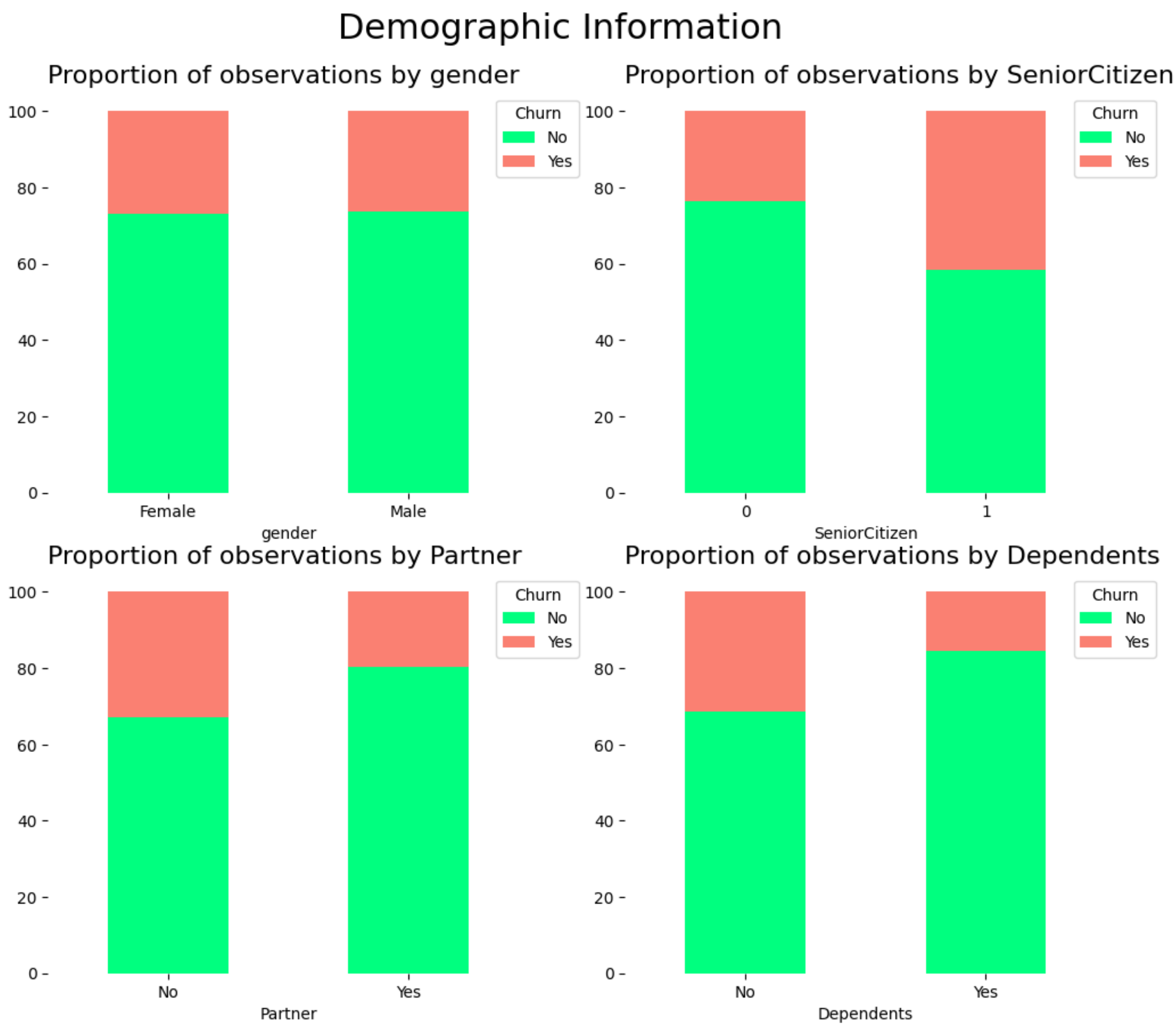
A **normalized stacked bar** plot makes each column the same height, so it is not useful for comparing total numbers; however, **it is perfect for comparing how the response variable varies across all groups of an independent variable**.
On the other hand, we use **histograms** to evaluate the **influence of each independent numeric variable in the outcome**. As mentioned before, the data set is imbalanced; therefore, we need to draw a probability density function of each class (`density=True`) to be able to compare both distributions properly.

Demographic Information
The following code creates a stacked percentage bar chart for each demographic attribute (`gender`, `SeniorCitizen`, `Partner`, `Dependents`), showing the percentage of `Churn` for each category of the attribute.

```
def percentage_stacked_plot(columns_to_plot, super_title):

    '''
    Prints a 100% stacked plot of the response variable for independent variable of
the list columns_to_plot.
            Parameters:
                        columns_to_plot (list of string): Names of the variables to
plot
                    super_title (string): Super title of the visualization
            Returns:
                    None
```

```
    '''

    number_of_columns = 2
    number_of_rows = math.ceil(len(columns_to_plot)/2)

    # create a figure
    fig = plt.figure(figsize=(12, 5 * number_of_rows))
    fig.suptitle(super_title, fontsize=22,  y=.95)


    # loop to each column name to create a subplot
    for index, column in enumerate(columns_to_plot, 1):

        # create the subplot
        ax = fig.add_subplot(number_of_rows, number_of_columns, index)

        # calculate the percentage of observations of the response variable for
each group of the independent variable
        # 100% stacked bar plot
        prop_by_independent = pd.crosstab(df_telco[column],
df_telco['Churn']).apply(lambda x: x/x.sum()*100, axis=1)

        prop_by_independent.plot(kind='bar', ax=ax, stacked=True,
                                 rot=0, color=['springgreen','salmon'])

        # set the legend in the upper right corner
        ax.legend(loc="upper right", bbox_to_anchor=(0.62, 0.5, 0.5, 0.5),
                  title='Churn', fancybox=True)

        # set title and labels
        ax.set_title('Proportion of observations by ' + column,
                     fontsize=16, loc='left')

        ax.tick_params(rotation='auto')

        # eliminate the frame from the plot
        spine_names = ('top', 'right', 'bottom', 'left')
        for spine_name in spine_names:
            ax.spines[spine_name].set_visible(False)
```

```
# demographic column names
demographic_columns = ['gender', 'SeniorCitizen', 'Partner', 'Dependents']

# stacked plot of demographic columns
percentage_stacked_plot(demographic_columns, 'Demographic Information')
```



As shown above, each bar is a category of the independent variable, and it is subdivided to show the proportion of each response class (No and Yes).

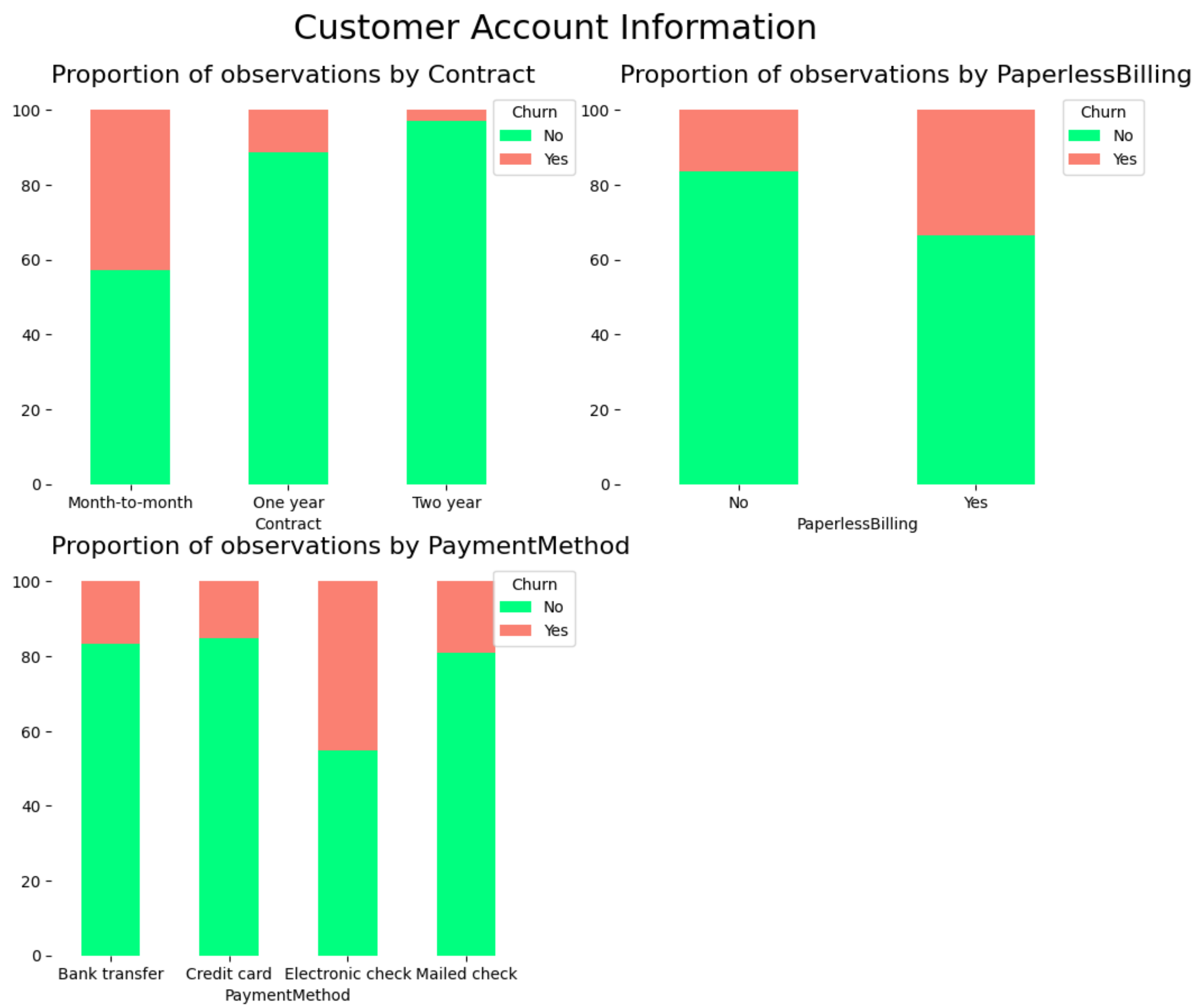
We can extract the **following conclusions** by analyzing **demographic attributes**:

- The churn rate of **senior citizens** is almost double that of **young citizens**.
- We do not expect **gender** to have significant predictive power. A similar percentage of churn is shown both when a customer is a man or a woman.
- Customers with a **partner** churn less than customers with no partner.

Customer Account Information — Categorical variables
As we did with demographic attributes, we evaluate the percentage of `Churn` for each category of the customer account attributes (`Contract`, `PaperlessBilling`, `PaymentMethod`).

```
# customer account column names
```

```
account_columns = ['Contract', 'PaperlessBilling', 'PaymentMethod']

# stacked plot of customer account columns
percentage_stacked_plot(account_columns, 'Customer Account Information')
```



We can extract the **following conclusions** by analyzing **customer account attributes**:

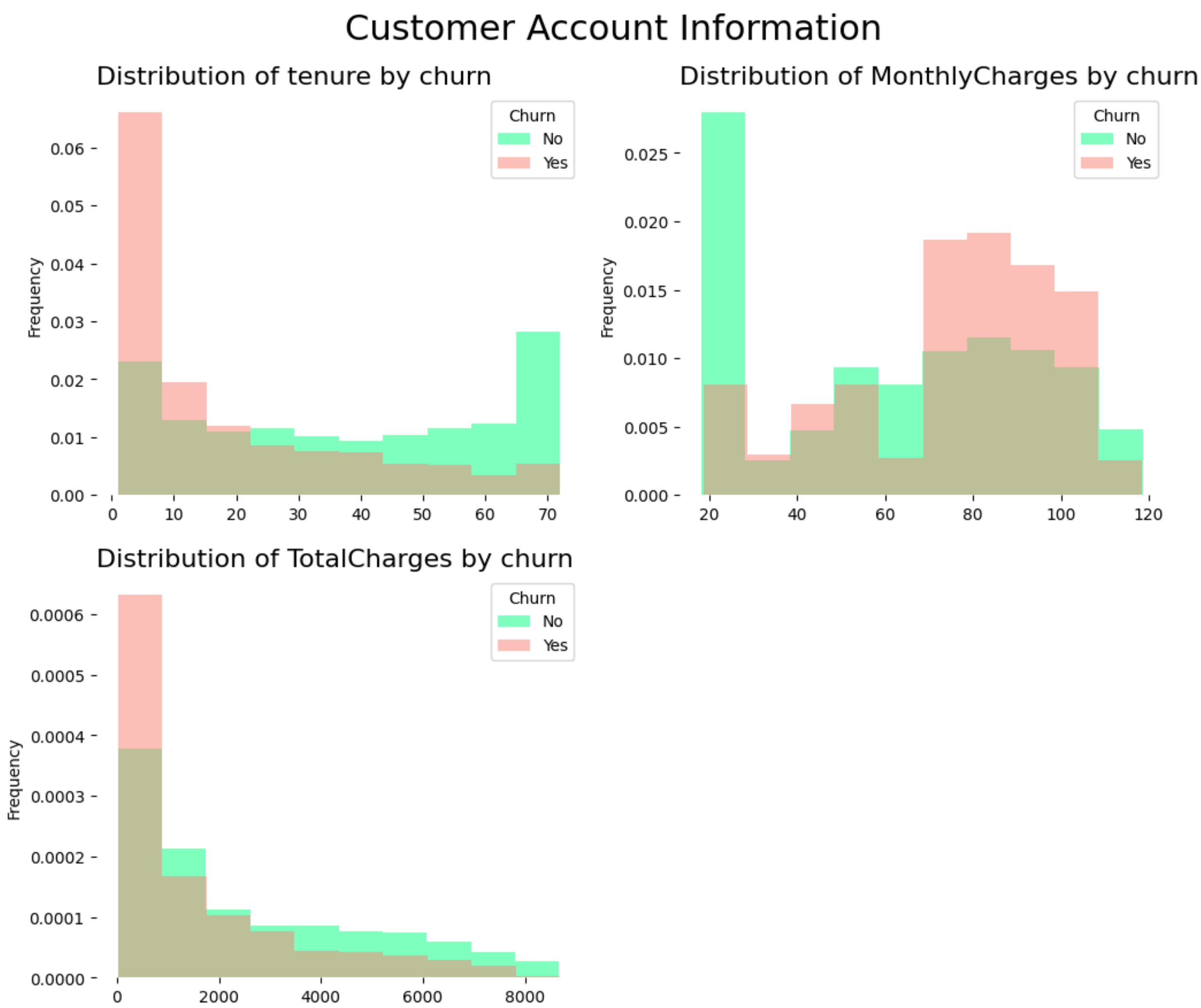
- Customers with **month-to-month contracts** have **higher churn rates** compared to clients with **yearly contracts**.
- Customers who opted for an **electronic check** as a paying method are more likely to leave the company.
- Customers subscribed to **paperless billing** churn more than those who are not subscribed.

Customer Account Information — Numerical variables

The following plots show the distribution of `tenure`, `MonthlyCharges`, `TotalCharges` by `Churn`. For all numeric attributes, the distributions of both classes (`No` and `Yes`) are different which suggests that all of the attributes will be useful to determine whether or not a customer churns.

```
def histogram_plots(columns_to_plot, super_title):

    '''
     Prints a histogram for each independent variable of the list columns_to_plot.
            Parameters:
                        columns_to_plot (list of string): Names of the variables to
plot
                    super_title (string): Super title of the visualization
            Returns:
                    None
    '''
    # set number of rows and number of columns
    number_of_columns = 2
    number_of_rows = math.ceil(len(columns_to_plot)/2)

    # create a figure
    fig = plt.figure(figsize=(12, 5 * number_of_rows))
    fig.suptitle(super_title, fontsize=22,  y=.95)


    # loop to each demographic column name to create a subplot
    for index, column in enumerate(columns_to_plot, 1):

        # create the subplot
        ax = fig.add_subplot(number_of_rows, number_of_columns, index)

        # histograms for each class (normalized histogram)
                df_telco[df_telco['Churn']=='No'][column].plot(kind='hist',  ax=ax,
density=True,
                                                                         alpha=0.5,
color='springgreen', label='No')
               df_telco[df_telco['Churn']=='Yes'][column].plot(kind='hist',  ax=ax,
density=True,
                                                         alpha=0.5, color='salmon',
label='Yes')

        # set the legend in the upper right corner
        ax.legend(loc="upper right", bbox_to_anchor=(0.5, 0.5, 0.5, 0.5),
                  title='Churn', fancybox=True)

        # set title and labels
        ax.set_title('Distribution of ' + column + ' by churn',
                     fontsize=16, loc='left')

        ax.tick_params(rotation='auto')
```

```
        # eliminate the frame from the plot
        spine_names = ('top', 'right', 'bottom', 'left')
        for spine_name in spine_names:
            ax.spines[spine_name].set_visible(False)

# customer account column names
account_columns_numeric = ['tenure', 'MonthlyCharges', 'TotalCharges']
# histogram of customer account columns
histogram_plots(account_columns_numeric, 'Customer Account Information')
```



We can extract the **following conclusions** by analyzing the **histograms above**:

- The churn rate tends to be larger when **monthly charges** are high.
- New customers (low **tenure**) are more likely to churn.
- Clients with high **total charges** are less likely to leave the company.

Services Information
Lastly, we evaluate the percentage of the target for each category of the services columns with stacked bar plots.

```
# services column names
services_columns = ['PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
                    'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies']

# stacked plot of services columns
percentage_stacked_plot(services_columns, 'Services Information')
```

We can extract the **following conclusions** by evaluating **services attributes**:

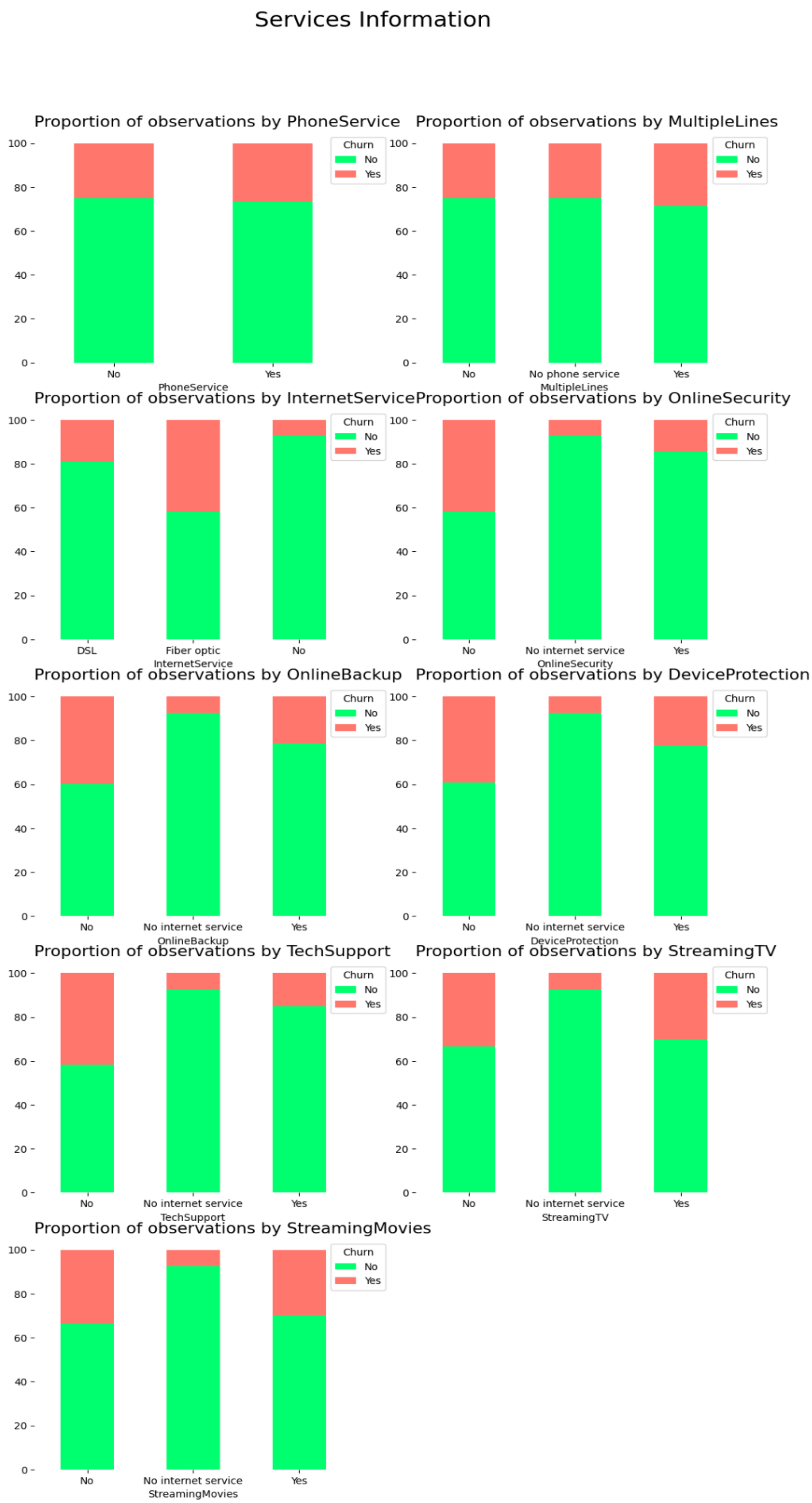
- We do not expect **phone attributes** (`PhoneService` and `MultipleLines`) to have significant predictive power. The percentage of churn for all classes in both independent variables is nearly the same.
- Clients with `online security` churn less than those without it.
- Customers with no `tech support` tend to churn more often than those with tech support.

By looking at the plots above, we can identify the **most relevant attributes for detecting churn**. We expect these attributes to be discriminative in our future models.

4. Feature Importance

Mutual information — analysis of linear and nonlinear relationships
Mutual information measures the mutual dependency between two variables based on entropy estimations. In machine learning, we are interested in **evaluating the degree of dependency between each independent variable and the response variable**. Higher values of mutual information show a higher degree of dependency which indicates that the independent variable will be useful for predicting the target.

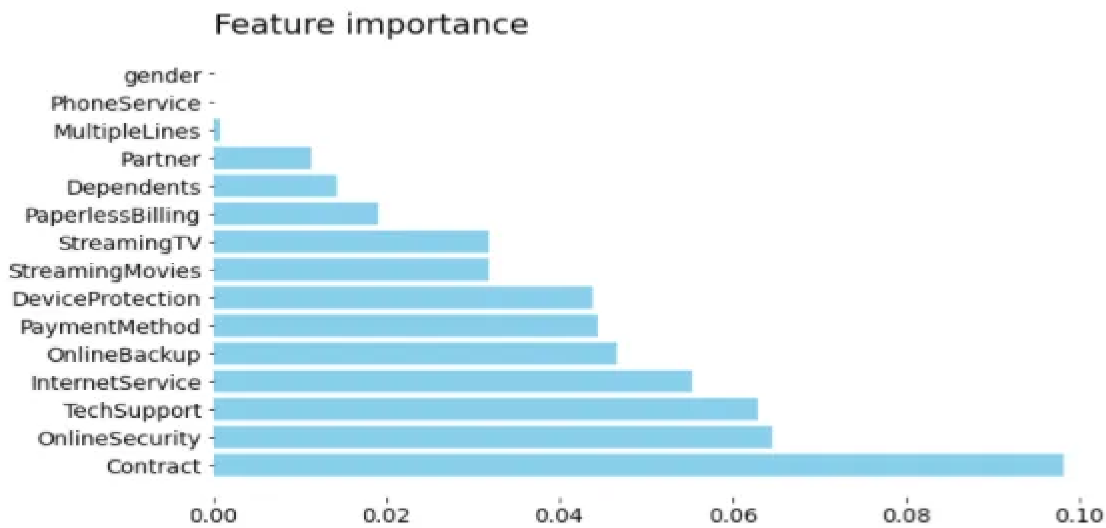
The Scikit-Learn library has implemented mutual information in the `metrics` package. The following code computes the mutual information score between each categorical variable of the data set and the `Churn` variable.


Services Information
Proportion of observations by PhoneService
Proportion of observations by MultipleLines
Proportion of observations by InternetService
Proportion of observations by OnlineSecurity
Proportion of observations by OnlineBackup
Proportion of observations by DeviceProtection
Proportion of observations by TechSupport
Proportion of observations by StreamingTV
Proportion of observations by StreamingMovies
Churn
No
Yes
0
20
40
60
80
100
No
Yes
No phone service
DSL
Fiber optic
No internet service
PhoneService
MultipleLines
InternetService
OnlineSecurity
OnlineBackup
DeviceProtection
TechSupport
StreamingTV
StreamingMovies

```python
from sklearn.metrics import mutual_info_score
def compute_mutual_information(categorical_serie):
    return mutual_info_score(categorical_serie, df_telco.Churn)

# select categorical variables excluding the response variable
categorical_variables = df_telco.select_dtypes(include=object).drop('Churn',
axis=1)

# compute the mutual information score between each categorical variable and the
target
feature_importance =
categorical_variables.apply(compute_mutual_information).sort_values(ascending=False
)

# visualize feature importance
print(feature_importance)
```

```
Contract            0.098182
OnlineSecurity      0.064528
TechSupport         0.062873
InternetService     0.055394
OnlineBackup        0.046659
PaymentMethod       0.044423
DeviceProtection    0.043784
StreamingMovies     0.031918
StreamingTV         0.031803
PaperlessBilling    0.019119
Dependents          0.014270
Partner             0.011383
MultipleLines       0.000798
PhoneService        0.000069
gender              0.000037
dtype: float64
```

Mutual information allows us not only to better understand our data but also to **identify the predictor variables that are completely independent of the target**. As shown above, `gender`, `PhoneService`, and `MultipleLines` have a mutual information score really **close to 0**, meaning those variables do not have a strong relationship with the target. This information is in line with the conclusions we have previously drawn by visualizing the data. In the following steps, we should consider removing those variables from the data set before training as they do not provide useful information for predicting the outcome.



The **mutual information** extends the notion of correlation to nonlinear relationships since, unlike Pearson's correlation coefficient, this method **is able to detect not only linear relationships but also nonlinear ones**.

5. Feature Engineering

Feature engineering is the process of **extracting features from the data and transforming them into a format that is suitable for the machine learning model**. In this project, we need to transform both numerical and categorical variables. Most machine learning algorithms require numerical values; therefore, **all categorical attributes available in the dataset should be encoded into numerical labels** before training the model. In addition, **we need to transform numeric columns into a common scale**. This will prevent columns with large values dominating the learning process. The techniques implemented in this project are described in more detail below. All transformations are implemented using only Pandas; however, we also provide an alternative implementation using Scikit-Learn.

No modification
The `SeniorCitizen` column is already a binary column and should not be modified.

Label Encoding
Label encoding is used to replace categorical values with numerical values. This encoding **replaces every category with a numerical label**. In this project, we use label encoding with the following binary variables: (1) `gender`, (2) `Partner`, (3) `Dependents`, (4)`PaperlessBilling`, (5)`PhoneService` , and (6)`Churn` .

```
df_telco_transformed = df_telco.copy()

# label encoding (binary variables)
label_encoding_columns = ['gender', 'Partner', 'Dependents', 'PaperlessBilling',
'PhoneService', 'Churn']

# encode categorical binary features using label encoding
for column in label_encoding_columns:
```

```
    if column == 'gender':
        df_telco_transformed[column] = df_telco_transformed[column].map({'Female': 1, 'Male': 0})
    else:
        df_telco_transformed[column] = df_telco_transformed[column].map({'Yes': 1, 'No': 0})
```

One-Hot Encoding
One-hot encoding creates a **new binary column for each level of the categorical variable**. The new column contains zeros and ones indicating the absence or presence of the category in the data. In this project, we apply one-hot encoding to the following categorical variables: (1) `Contract`, (2) `PaymentMethod`, (3) `MultipleLines`, (4) `InternetServices`, (5) `OnlineSecurity`, (6) `OnlineBackup`, (7) `TechSupport`, (8) TechSupport, (9) `StreamingTV`, and (10)`StreamingMovies`.

```
# one-hot encoding (categorical variables with more than two levels)
one_hot_encoding_columns = ['MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
                            'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract', 'PaymentMethod']

# encode categorical variables with more than two levels using one-hot encoding
df_telco_transformed = pd.get_dummies(df_telco_transformed, columns = one_hot_encoding_columns)
```

The main drawback of this encoding is the significant increase in the dimensionality of the dataset (**curse of dimensionality**); therefore, this method should be avoided when the categorical column has a large number of unique values.

Normalization
Data Normalization is a common practice in machine learning which consists of transforming **numeric columns** to a **common scale**. In machine learning, some feature values differ from others multiple times. The features with higher values will dominate the learning process; however, it does not mean those variables are more important to predict the target. **Data normalization** transforms multiscaled data to the same scale. After normalization, all variables have a **similar influence** on the model, improving the stability and performance of the learning algorithm.

There are multiple **normalization techniques** in statistics. In this project, we will use the min-max method to rescale the numeric columns (`tenure`, `MonthlyCharges`, and `TotalCharges`) to a common scale. The **min-max approach** (often called **normalization**) rescales the feature to a fixed range of [0,1] by subtracting the minimum value of the feature and then dividing by the range.

```
# min-max normalization (numeric variables)
min_max_columns = ['tenure', 'MonthlyCharges', 'TotalCharges']

# scale numerical variables using min max scaler
```

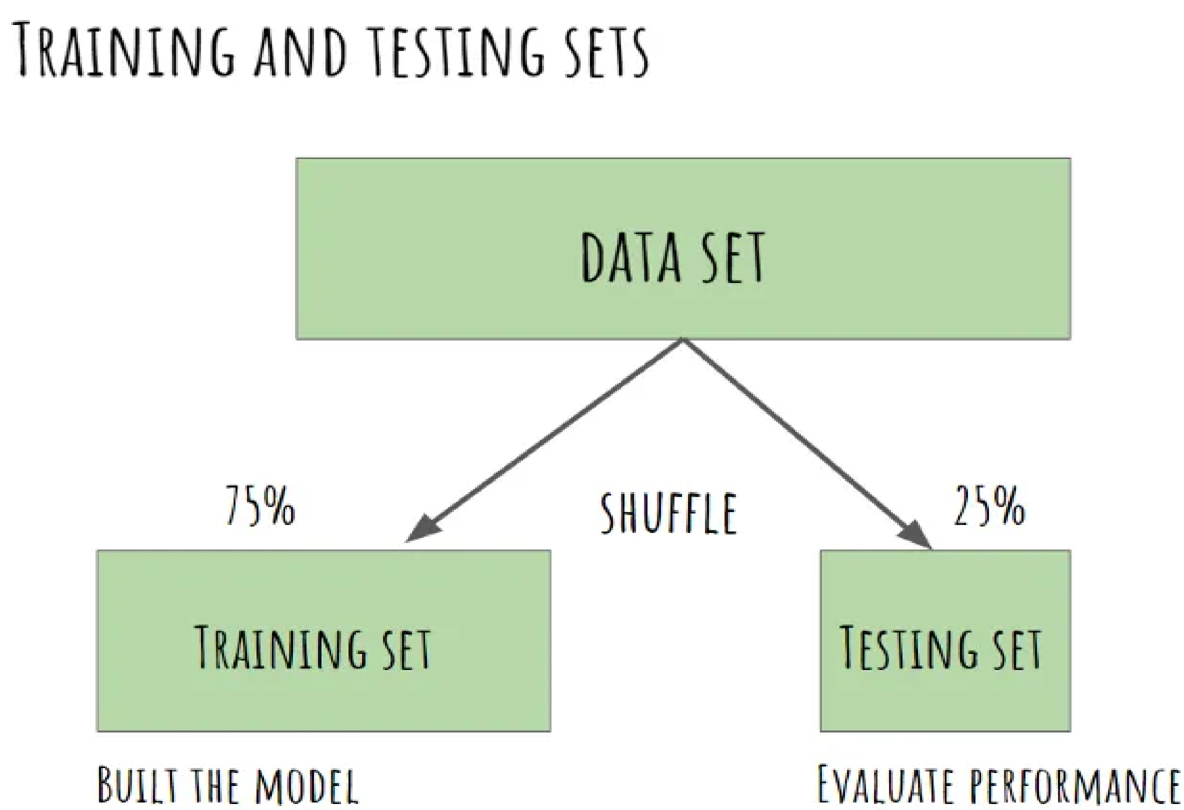
```
for column in min_max_columns:
        # minimum value of the column
        min_column = df_telco_transformed[column].min()
        # maximum value of the column
        max_column = df_telco_transformed[column].max()
        # min max scaler
         df_telco_transformed[column] = (df_telco_transformed[column] - min_column)
/ (max_column - min_column)
```

6. Setting a baseline

In machine learning, **we often use a simple classifier called baseline to evaluate the performance of a model**. In this classification problem, **the rate of customers that did not churn (most frequent class) can be used as a baseline** to evaluate the quality of the models generated. These models should outperform the baseline capabilities to be considered for future predictions.

7. Splitting the data in training and testing sets

The first step when building a model is to **split the data into two groups**, which are typically referred to as **training and testing sets**. The training set is used by the machine learning algorithm to build the model. The test set contains samples that are not part of the learning process and is used to evaluate the model's performance. It is important to assess the quality of the model using unseen data to guarantee an objective evaluation.



First, we create a variable `X` to store the **independent attributes** of the dataset. Additionally, we create a variable `y` to store only the target variable (`Churn`).

```
# select independent variables
X = df_telco_transformed.drop(columns='Churn')

# select dependent variables
y = df_telco_transformed.loc[:, 'Churn']

# prove that the variables were selected correctly
print(X.columns)

# prove that the variables were selected correctly
print(y.name)
```

```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'PaperlessBilling', 'MonthlyCharges', 'TotalCharges',
       'MultipleLines_No', 'MultipleLines_No phone service',
       'MultipleLines_Yes', 'InternetService_DSL',
       'InternetService_Fiber optic', 'InternetService_No',
       'OnlineSecurity_No', 'OnlineSecurity_No internet service',
       'OnlineSecurity_Yes', 'OnlineBackup_No',
       'OnlineBackup_No internet service', 'OnlineBackup_Yes',
       'DeviceProtection_No', 'DeviceProtection_No internet service',
       'DeviceProtection_Yes', 'TechSupport_No',
       'TechSupport_No internet service', 'TechSupport_Yes', 'StreamingTV_No',
       'StreamingTV_No internet service', 'StreamingTV_Yes',
       'StreamingMovies_No', 'StreamingMovies_No internet service',
       'StreamingMovies_Yes', 'Contract_Month-to-month', 'Contract_One year',
       'Contract_Two year', 'PaymentMethod_Bank transfer',
       'PaymentMethod_Credit card', 'PaymentMethod_Electronic check',
       'PaymentMethod_Mailed check'],
      dtype='object')
Churn
```

Then, we can use the `train_test_split` function from the `sklearn.model_selection` package to create both the training and testing sets.

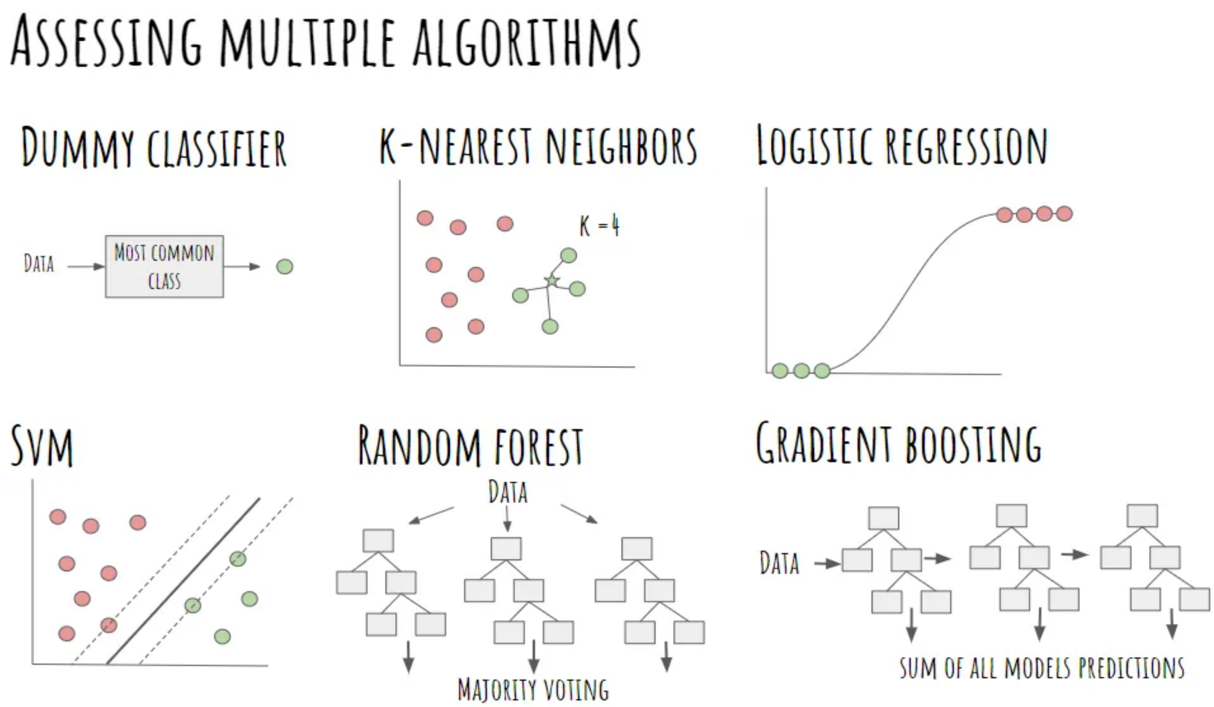
```
# split the data in training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
                                                    random_state=40, shuffle=True)
```

8. Assessing multiple algorithms

Algorithm selection is a key challenge in any machine learning project since there is not an algorithm that is the best across all projects. Generally, we need to evaluate a set of potential candidates and select for further evaluation those that provide better performance.

In this project, we compare **6 different algorithms**, all of them already implemented in Scikit-Learn.

- **Dummy classifier (baseline)**
- **K Nearest Neighbours**
- **Logistic Regression**
- **Support Vector Machines**
- **Random Forest**
- **Gradient Boosting**



As shown below, **all models outperform the dummy classifier model** in terms of prediction accuracy. Therefore, we can affirm that **machine learning is applicable to our problem** because we observe an improvement over the baseline.

```
from sklearn.dummy import DummyClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier

def create_models(seed=2):
    '''
    Create a list of machine learning models.
            Parameters:
                    seed (integer): random seed of the models
            Returns:
```

```python
                    models (list): list containing the models
    '''

    models = []
            models.append(('dummy_classifier',   DummyClassifier(random_state=seed,
strategy='most_frequent')))
    models.append(('k_nearest_neighbors', KNeighborsClassifier()))
    models.append(('logistic_regression', LogisticRegression(random_state=seed)))
    models.append(('support_vector_machines', svm.SVC(random_state=seed)))
    models.append(('random_forest', RandomForestClassifier(random_state=seed)))
                                                models.append(('gradient_boosting',
GradientBoostingClassifier(random_state=seed)))

    return models

# create a list with all the algorithms we are going to assess
models = create_models()
```

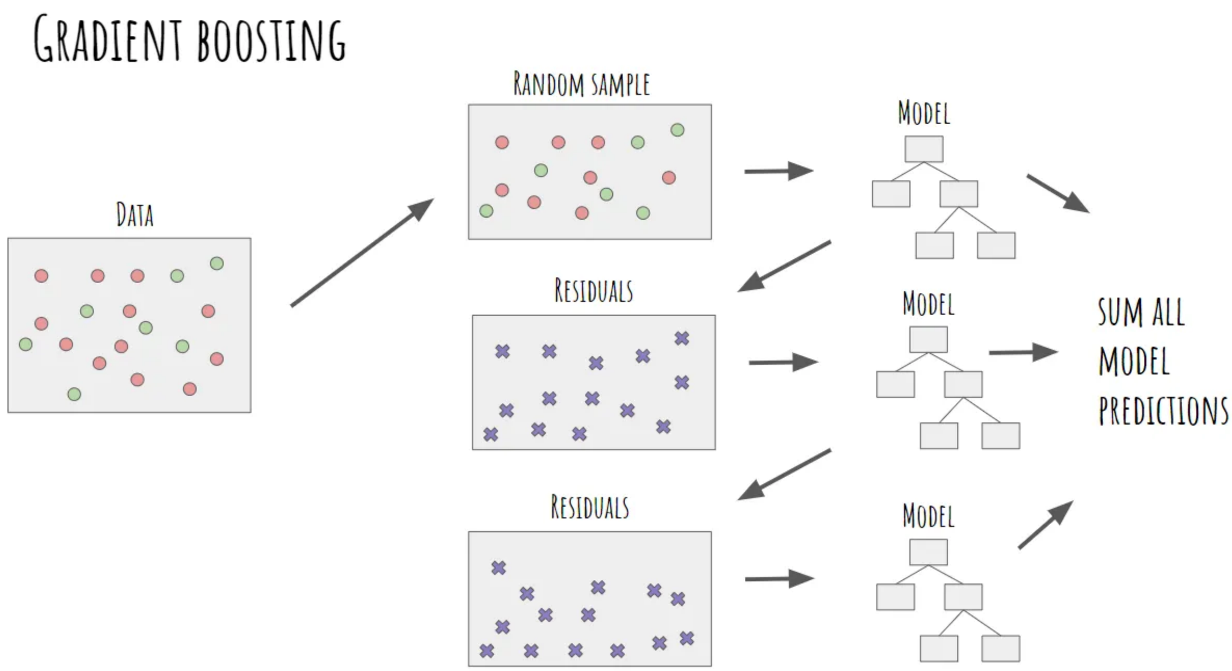
```python
# test the accuracy of each model using default hyperparameters
from sklearn.metrics import accuracy_score

results = []
names = []
scoring = 'accuracy'
for name, model in models:
    # fit the model with the training data
    model.fit(X_train, y_train).predict(X_test)
    # make predictions with the testing data
    predictions = model.predict(X_test)
    # calculate accuracy
    accuracy = accuracy_score(y_test, predictions)
    # append the model name and the accuracy to the lists
    results.append(accuracy)
    names.append(name)
    # print classifier accuracy
    print('Classifier: {}, Accuracy: {})'.format(name, accuracy))
```

```
Classifier: dummy_classifier, Accuracy: 0.745164960182025)
Classifier: k_nearest_neighbors, Accuracy: 0.7531285551763367)
Classifier: logistic_regression, Accuracy: 0.7923777019340159)
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
Classifier: support_vector_machines, Accuracy: 0.7878270762229806)
Classifier: random_forest, Accuracy: 0.7713310580204779)
Classifier: gradient_boosting, Accuracy: 0.7963594994311718)
```

It is important to bear in mind that we have **trained all the algorithms using the default hyperparameters**. The accuracy of many machine learning algorithms is highly sensitive to the hyperparameters chosen for training the model. A more in-depth analysis will include an evaluation of a wider range of hyperparameters (not only default values) before choosing a model (or models) for hyperparameter tuning. Nonetheless, this is out of the scope of this article. In this example, we will only further evaluate the model that presents higher accuracy using the default hyperparameters. As shown above, this corresponds to the **gradient boosting model** which shows an accuracy of nearly 80%.

9. Algorithm Fit : Gradient Boosting

Gradient Boosting is a very popular machine learning **ensemble method** based on a **sequential training** of multiple models to make predictions. In Gradient Boosting, first, you make a model using a random sample of your original data. After fitting the model, you make predictions and compute the residuals of your model. **The residuals** are the difference **between the actual values and the predictions of the model**. Then, you train a new tree based on the residuals of the previous tree, calculating again the residuals of this new model. We repeat this process until we reach a threshold (residual close to 0), meaning there is a very low difference between the actual and predicted values. Finally, **you take a sum of all model forecasts** (prediction of the data and predictions of the error) to make a final prediction.



We can easily build a **gradient boosting classifier** with Scikit-Learn using the `GradientBoostingClassifier` class from the `sklearn.ensemble` module. After creating the model, we need to train it (using the `.fit` method) and test its performance by comparing the predictions (`.predict` method) with the actual class values, as you can see in the code above.

The GradientBoostingClassifier has multiple hyperparameters; some of them are listed below:

`learning_rate`: the contribution of each tree to the final prediction.

`n_estimators`: the number of decision trees to perform (boosting stages).
`max_depth`: the maximum depth of the individual regression estimators.
`max_features`: the number of features to consider when looking for the best split.
`min_samples_split:` the minimum number of samples required to split an internal node.

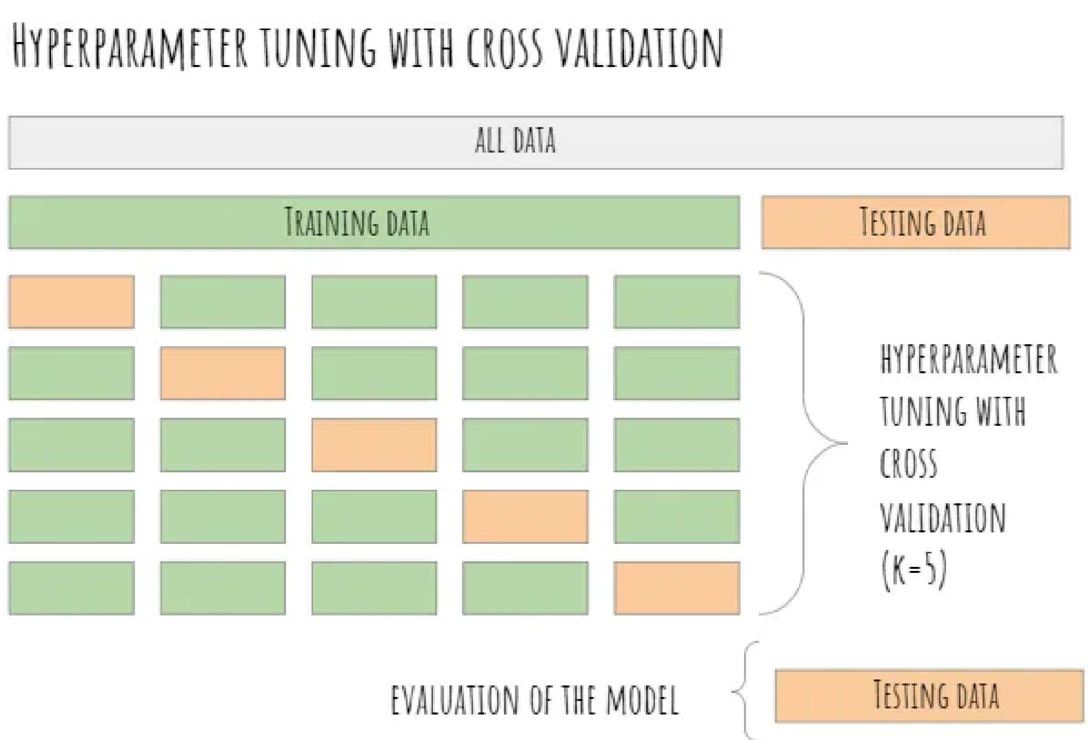
The next step consists of finding the combination of hyperparameters that leads to the best classification of our data. This process is called hyperparameter tuning.

10. Hyperparameter Tuning

Thus far we have split our data into a **training set** for **learning the parameters of the model**, and a **testing set for evaluating its performance**. The next step in the machine learning process is to perform hyperparameter tuning. The **selection of hyperparameters** consists of testing the performance of the model against different combinations of hyperparameters, selecting those that perform best according to **a chosen metric** and a **validation method**.

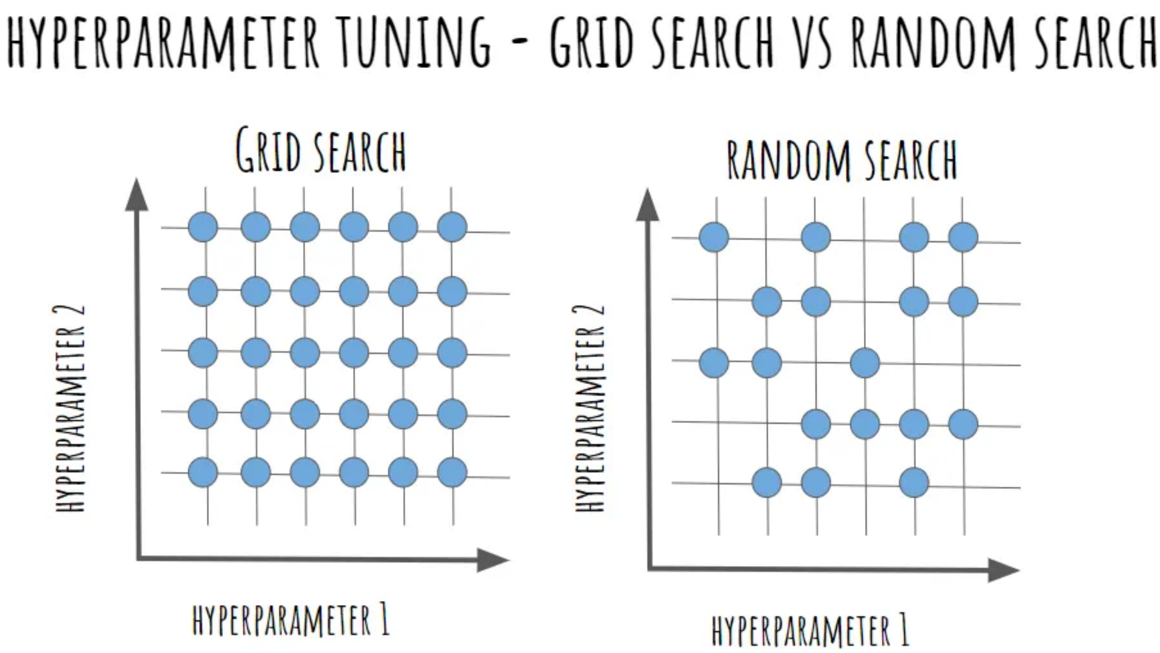
For hyperparameter tuning, **we need to split our training data again into a set for training and a set for testing** the hyperparameters (often called validation set). It is a very common practice to use **k-fold cross-validation for hyperparameter tuning**. The training set is divided again into **k equal-sized** samples, 1 sample is used for testing and the remaining k-1 samples are used for training the model, repeating the process k times. Then, the k evaluation metrics (in this case the accuracy) are averaged to produce a single estimator.

It is important to stress that **the validation set is used for hyperparameter selection and not for evaluating the final performance of our model**, as shown in the image below.



There are multiple techniques to find the best hyperparameters for a model. The most popular methods are (1) **grid search**, (2) **random search**, and (3) **bayesian optimization**. **Grid search tests all combinations of hyperparameters** and selects the best performing one. It is a really time-consuming method, particularly when the number of hyperparameters and values to try are really high.

In **random search**, you specify a grid of hyperparameters, and **random combinations are selected** where each combination of hyperparameters has an equal chance of being sampled. We do not analyze all combinations of hyperparameters, but only random samples of those combinations. This approach is much more computationally efficient than trying all combinations; however, it also has some disadvantages. The main drawback of **random search** is that **not all areas of the grid are evenly covered**, especially when the number of combinations selected from the grid is low.



We can implement **random search** in Scikit-learn using the `RandomSearchCV` class from the `sklearn.model_selection` package.

First of all, we specify the grid of hyperparameter values using a dictionary (`grid_parameters`) where the **keys** represent the **hyperparameters** and the **values** are the **set of options** we want to evaluate. Then, we define the `RandomizedSearchCV` object for trying different random combinations from this grid. The number of hyperparameter combinations that are sampled is defined in the `n_iter` parameter. Naturally, increasing `n_iter` will lead in most cases to more accurate results, since more combinations are sampled; however, on many occasions, the improvement in performance won't be significant.

```
# define the parameter grid
from sklearn.model_selection import RandomizedSearchCV

grid_parameters = {'n_estimators': [80, 90, 100, 110, 115, 120],
```

```
                    'max_depth': [3, 4, 5, 6],
                    'max_features': [None, 'auto', 'sqrt', 'log2'],
                    'min_samples_split': [2, 3, 4, 5]}


# define the RandomizedSearchCV class for trying different parameter combinations
random_search = RandomizedSearchCV(estimator=GradientBoostingClassifier(),
                                   param_distributions=grid_parameters,
                                   cv=5,
                                   n_iter=150,
                                   n_jobs=-1)

# fitting the model for random search
random_search.fit(X_train, y_train)

# print best parameter after tuning
print(random_search.best_params_)
```

```
{'n_estimators': 100, 'min_samples_split': 3, 'max_features': 'log2', 'max_depth': 3}
```

After fitting the grid object, we can obtain the **best hyperparameters** using `best_params_` attribute. As you can see above, the best hyperparameters are: {'**n_estimators': 100, 'min_samples_split': 3, 'max_features': 'log2', 'max_depth': 3**}.

11. Model Performance

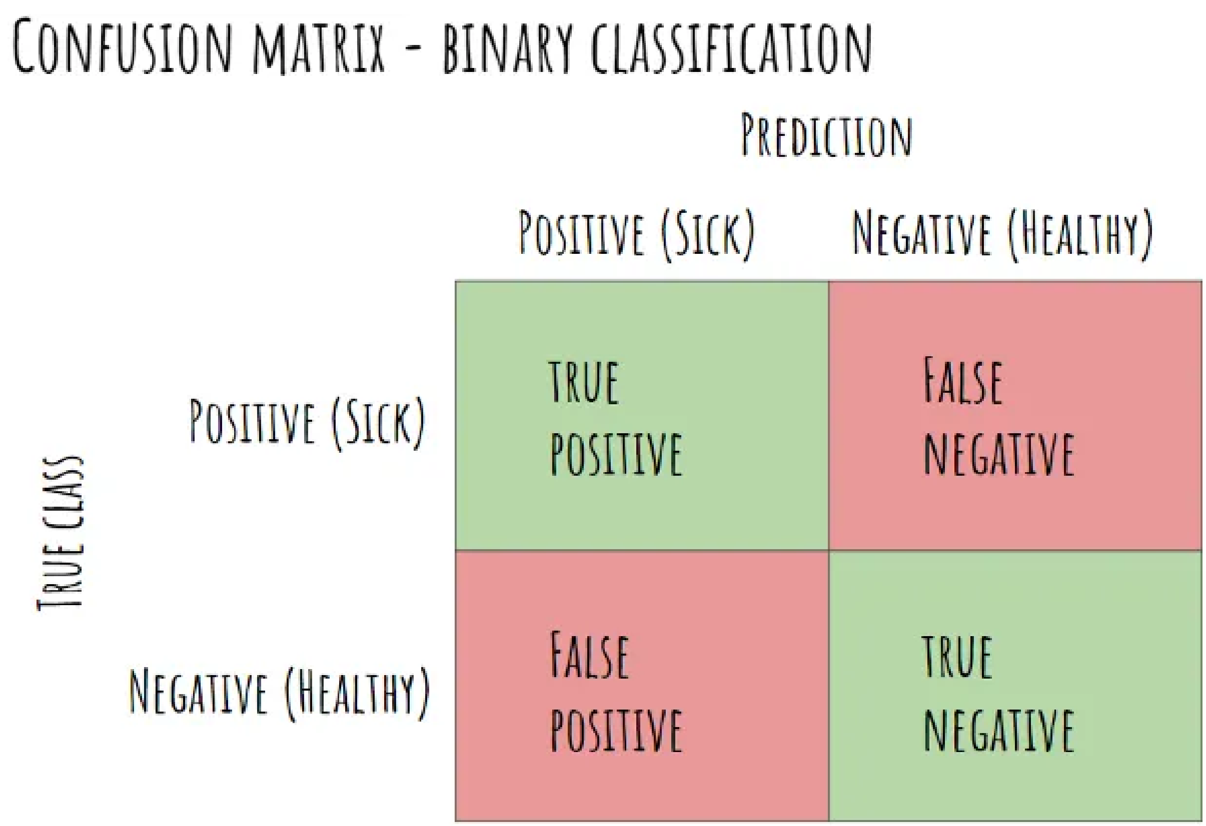
The last step of the **machine learning process** is to **check the performance of the model** (best hyperparameters) by using the confusion matrix and some evaluation metrics.

Confusion matrix

The **confusion matrix**, also known as the error matrix, is used to **evaluate the performance of a machine learning model** by examining the number of observations that are correctly and incorrectly classified. **Each column of the matrix contains the predicted classes while each row represents the actual classes or vice versa**. In a perfect classification, the confusion matrix will be all zeros except for the diagonal. **All the elements out of the main diagonal represent misclassifications**. It is important to bear in mind that the confusion matrix allows us to observe patterns of misclassification (which classes and to which extent they were incorrectly classified).

In **binary classification problems**, the **confusion matrix** is a 2-by-2 matrix composed of 4 elements:

- **TP (True Positive):** number of patients with spine problems that are correctly classified as sick.
- **TN (True Negative):** number of patients without pathologies who are correctly classified as healthy.
- **FP (False Positive):** number of healthy patients that are wrongly classified as sick.
- **FN (False Negative):** number of patients with spine diseases that are misclassified as healthy.



Now that the model is trained, it is time to evaluate its performance using the testing set. First, we use the previous model (gradient boosting classifier with best hyperparameters) to predict the class labels of the testing data (with the `predict` method). Then, we construct the confusion matrix using the confusion_matrix function from the `sklearn.metrics` package to check which observations were properly classified. The output is a NumPy array **where the rows represent the true values and the columns the predicted classes**.

```
# make the predictions
random_search_predictions = random_search.predict(X_test)

# construct the confusion matrix
confusion_matrix = confusion_matrix(y_test, random_search_predictions)

# visualize the confusion matrix
confusion_matrix
```

```
array([[1154,  156],
       [ 196,  252]])
```

As shown above, 1402 observations of the testing data were correctly classified by the model (1154 true negatives and 252 true positives). On the contrary, we can observe 354 misclassifications (156 false positives and 196 false negatives).

Evaluation metrics
Evaluating the quality of the model is a fundamental part of the machine learning process. The most used **performance evaluation metrics** are calculated based on the elements of the confusion matrix.

- **Accuracy:** It represents the proportion of predictions that were correctly classified. Accuracy is the most commonly used evaluation metric; however, it is important to bear in mind that accuracy can be misleading when working with imbalanced datasets.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Sensitivity:** It represents the proportion of positive samples (diseased patients) that are identified as such.

$$Sensitivity = \frac{TP}{TP + FN}$$

- **Specificity:** It represents the proportion of negative samples (healthy patients) that are identified as such.

$$Specificity = \frac{TN}{TN + FP}$$

- **Precision:** It represents the proportion of positive predictions that are actually correct.

$$Precision = \frac{TP}{TP + FP}$$

We can calculate the evaluation metrics manually using the numbers of the confusion matrix. Alternatively, Scikit-learn has already implemented the function `classification_report` that provides a **summary of the key evaluation metrics**. The classification report contains the precision, sensitivity, f1-score, and support (number of samples) achieved for each class.

```
# print classification report
print(classification_report(y_test, random_search_predictions))
```

```
              precision    recall  f1-score   support

           0       0.85      0.88      0.87      1310
           1       0.62      0.56      0.59       448

    accuracy                           0.80      1758
   macro avg       0.74      0.72      0.73      1758
weighted avg       0.79      0.80      0.80      1758
```

As shown above, we obtain a **sensitivity** of 0.56 (252/(196+252)) and a specificity of 0.88 (1154/(1154+156)). The model obtained predicts more accurately customers that do not churn. This should not surprise us at all, since **gradient boosting classifiers are usually biased toward the classes with more observations**.

As we may have noticed, the previous summary does not contain the accuracy of the classification. However, this can be easily calculated using the function `accuracy_score` from the `metrics` module.

```
# print the accuracy of the model
accuracy_score(y_test, random_search_predictions)
```

```
0.7997724687144482
```

As we can observe, hyperparameter tuning has barely increased the accuracy of the model.

12. Conclusions — Summary

In this post, we have walked through a complete end-to-end machine learning project using the **Telco Customer Churn** dataset. We started by cleaning the data and analyzing it with visualization. Then, to be able to build a machine learning model, we transformed the categorical data into numeric variables (feature engineering). After transforming the data, we tried 6 different machine learning algorithms using default parameters. Finally, we tuned the hyperparameters of the **Gradient Boosting Classifier** (best performance model) for model optimization, obtaining an **accuracy of nearly 80%** (close to 6% higher than the baseline).

It is important to stress that the **exact steps of a machine learning task vary by project**. Although in this project, we followed a linear process, machine learning **projects tend to be iterative rather than linear processes**, where previous steps are often revisited as we learn more about the problem we try to solve.