01-Customer-churn_completed

June 25, 2019

1 Customer Churn

Photo by Louis Hansel

1.1 Context

Predict behavior to retain customers. You can analyze all relevant customer data and develop focused customer retention programs.

1.2 Content

Each row represents a customer, each column contains customer's attributes described on the column Metadata.

The data set includes information about:

- Customers who left within the last month – the column is called Churn
- Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies
- Customer account information – how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges
- Demographic info about customers – gender, age range, and if they have partners and dependents

1.3 Inspiration

To explore this type of models and learn more about the subject.

1.4 First insight

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split
```

In [3]:
```python
from sklearn.metrics import f1_score, classification_report

from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.svm import SVC, LinearSVC
```

In [4]:
```python
import lightgbm as lgbm
import xgboost as xgb
```

In [5]:
```python
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

pd.set_option('display.max_columns', 100)
```

In [6]:
```python
df = pd.read_csv('./input/Telco-Customer-Churn.csv')
df.head()
```

Out[6]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  No phone service             DSL             No          Yes
1                No             DSL            Yes           No
2                No             DSL            Yes          Yes
3  No phone service             DSL            Yes           No
4                No     Fiber optic             No           No

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No          No          No              No  Month-to-month
1              Yes          No          No              No        One year
2               No          No          No              No  Month-to-month
3              Yes         Yes          No              No        One year
4               No          No          No              No  Month-to-month

  PaperlessBilling              PaymentMethod  MonthlyCharges TotalCharges  \
0              Yes           Electronic check           29.85        29.85
1               No               Mailed check           56.95       1889.5
2              Yes               Mailed check           53.85       108.15
3               No  Bank transfer (automatic)           42.30      1840.75
4              Yes           Electronic check           70.70       151.65

  Churn
0    No
1    No
```

```
2    Yes
3     No
4    Yes
```

In [7]: df.shape

Out[7]: (7043, 21)

The dataset contains about 7000 customers with 19 features.

Features are the following: - `customerID`: a unique ID for each customer - `gender`: the gender of the customer - `SeniorCitizen`: whether the customer is a senior (i.e. older than 65) or not - `Partner`: whether the customer has a partner or not - `Dependents`: whether the customer has people to take care of or not - `tenure`: the number of months the customer has stayed - `PhoneService`: whether the customer has a phone service or not - `MultipleLines`: whether the customer has multiple telephonic lines or not - `InternetService`: the kind of internet services the customer has (DSL, Fiber optic, no) - `OnlineSecurity`: what online security the customer has (Yes, No, No internet service) - `OnlineBackup`: whether the customer has online backup file system (Yes, No, No internet service) - `DeviceProtection`: Whether the customer has device protection or not (Yes, No, No internet service) - `TechSupport`: whether the customer has tech support or not (Yes, No, No internet service) - `StreamingTV`: whether the customer has a streaming TV device (e.g. a TV box) or not (Yes, No, No internet service) - `StreamingMovies`: whether the customer uses streaming movies (e.g. VOD) or not (Yes, No, No internet service) - `Contract`: the contract term of the customer (Month-to-month, One year, Two year) - `PaperlessBilling`: Whether the customer has electronic billing or not (Yes, No) - `PaymentMethod`: payment method of the customer (Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic)) - `MonthlyCharges`: the amount charged to the customer monthly - `TotalCharges`: the total amount the customer paid

And the **Target** : - `Churn`: whether the customer left or not (Yes, No)

As you can see, many features are categorical with more than 2 values. You will have to handle this.

Take time to make a proper and complete EDA: this will help you build a better model.

---

2 Exploratory Data Analysisű

Global infos on the dataset (null values, types...)

In [8]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
customerID          7043 non-null object
gender              7043 non-null object
SeniorCitizen       7043 non-null int64
Partner             7043 non-null object
Dependents          7043 non-null object
tenure              7043 non-null int64
```

```
PhoneService        7043 non-null object
MultipleLines       7043 non-null object
InternetService     7043 non-null object
OnlineSecurity      7043 non-null object
OnlineBackup        7043 non-null object
DeviceProtection    7043 non-null object
TechSupport         7043 non-null object
StreamingTV         7043 non-null object
StreamingMovies     7043 non-null object
Contract            7043 non-null object
PaperlessBilling    7043 non-null object
PaymentMethod       7043 non-null object
MonthlyCharges      7043 non-null float64
TotalCharges        7043 non-null object
Churn               7043 non-null object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

Nb of each type

```
In [9]: df.dtypes.value_counts()
```

```
Out[9]: object     18
        int64       2
        float64     1
        dtype: int64
```

Nb of unique value for each type

```
In [10]: df.select_dtypes('object').apply(pd.Series.nunique, axis = 0)
```

```
Out[10]: customerID          7043
         gender                 2
         Partner                2
         Dependents             2
         PhoneService           2
         MultipleLines          3
         InternetService        3
         OnlineSecurity         3
         OnlineBackup           3
         DeviceProtection       3
         TechSupport            3
         StreamingTV            3
         StreamingMovies        3
         Contract               3
         PaperlessBilling       2
         PaymentMethod          4
         TotalCharges        6531
         Churn                  2
         dtype: int64
```

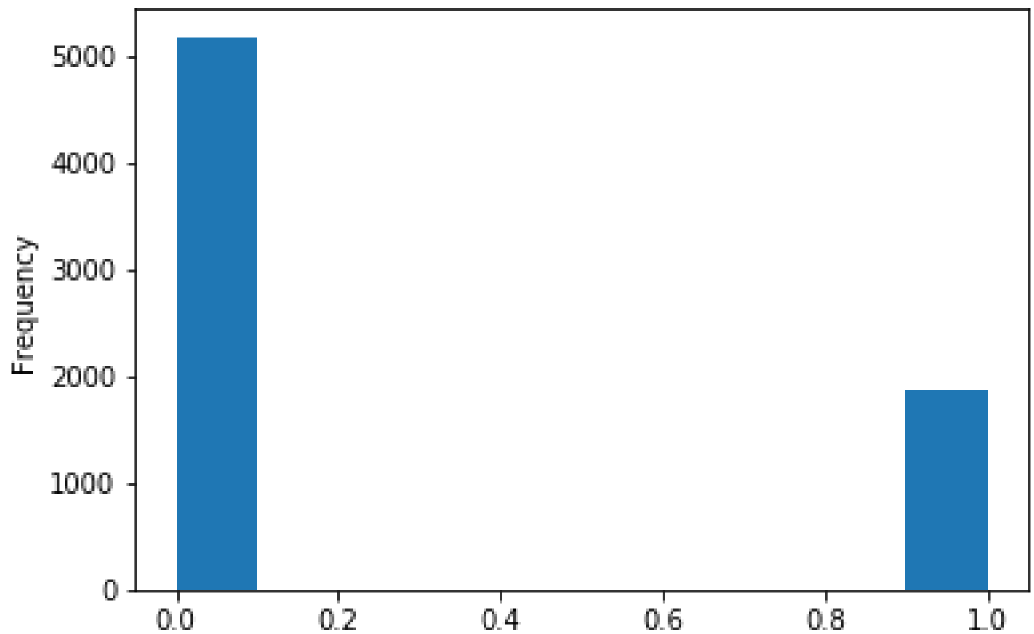
2.1 Target infos

```
In [11]: df['Churn'].value_counts()
```

```
Out[11]: No     5174
         Yes    1869
         Name: Churn, dtype: int64
```

```
In [12]: df['Churn'].str.replace('No', '0').str.replace('Yes', '1').astype(int).plot.hist()
```

```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4a41ebe438>
```



Basic stats on numerical cols

```
In [13]: df.describe()
```

```
Out[13]:        SeniorCitizen       tenure  MonthlyCharges
         count    7043.000000  7043.000000     7043.000000
         mean        0.162147    32.371149       64.761692
         std         0.368612    24.559481       30.090047
         min         0.000000     0.000000       18.250000
         25%         0.000000     9.000000       35.500000
         50%         0.000000    29.000000       70.350000
         75%         0.000000    55.000000       89.850000
         max         1.000000    72.000000      118.750000
```

2.2 Basic cleaning

```
In [14]: df.duplicated().sum()

Out[14]: 0

In [15]: df.isnull().sum()

Out[15]: customerID          0
         gender              0
         SeniorCitizen       0
         Partner             0
         Dependents          0
         tenure              0
         PhoneService        0
         MultipleLines       0
         InternetService     0
         OnlineSecurity      0
         OnlineBackup        0
         DeviceProtection    0
         TechSupport         0
         StreamingTV         0
         StreamingMovies     0
         Contract            0
         PaperlessBilling    0
         PaymentMethod       0
         MonthlyCharges      0
         TotalCharges        0
         Churn               0
         dtype: int64

In [16]: df = df.drop(columns=['customerID'])
```

No missing or duplicated rows. The customer ID is irrelevant and can be dropped.

2.3 Dealing with abnormal values

The 'TotalCharges' column has an object type, but it is supposed to contain only numerical values...Let's dig a little deeper:

```
In [17]: # example for the record strip non digit values
         #test = pd.Series(["U$ 192.01"])
         #test.str.replace('^[^\d]*', '').astype(float)

         #df.TotalCharges = df.TotalCharges.str.replace('^[^\d]*', '')

In [18]: df.iloc[0, df.columns.get_loc("TotalCharges")]

Out[18]: '29.85'
```

In [19]:
```python
float(df.iloc[0, df.columns.get_loc("TotalCharges")])
```

Out[19]: 29.85

In [20]:
```python
df.iloc[488, df.columns.get_loc("TotalCharges")]
```

Out[20]: ' '

In [21]:
```python
len(df[df['TotalCharges'] == ' '])
```

Out[21]: 11

Drop strange/missing values (the pandas method to_numeric could also has been used!):

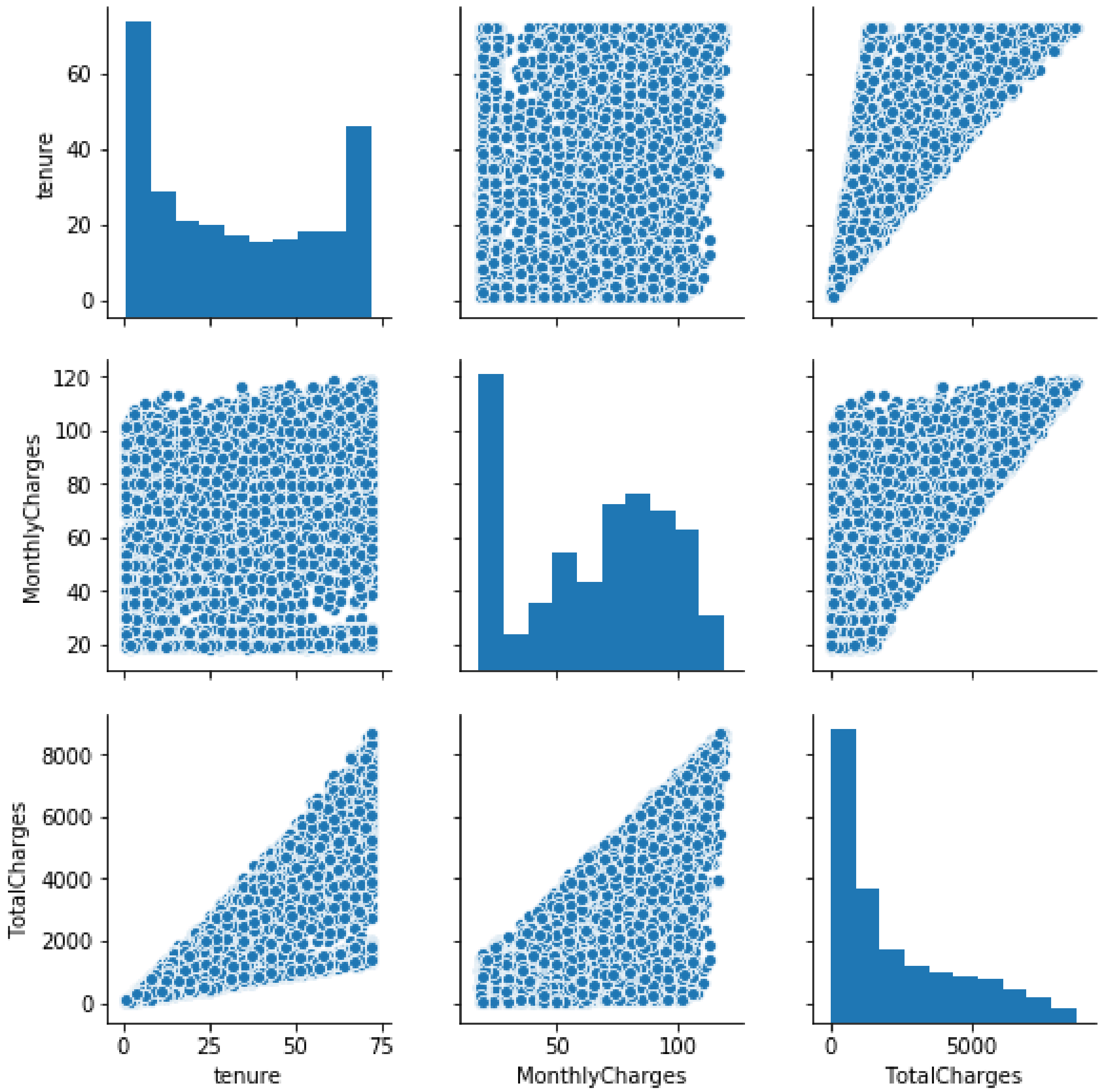
In [22]:
```python
# replace missing values by 0
df.TotalCharges = df.TotalCharges.replace(" ",np.nan)

# drop missing values - side note: it represents only 11 out of 7043 rows which is no
df = df.dropna()

# now we can convert the column type
df.TotalCharges = df.TotalCharges.astype('float')

df.shape
```

Out[22]: (7032, 20)

In [23]:
```python
num_feat = df.select_dtypes(include=['float', 'int']).columns.tolist()
num_feat.remove('SeniorCitizen')    # SeniorCitizen is only a boolean
num_feat
```

Out[23]: ['tenure', 'MonthlyCharges', 'TotalCharges']

In [24]:
```python
sns.pairplot(data=df[num_feat])
plt.show()
```

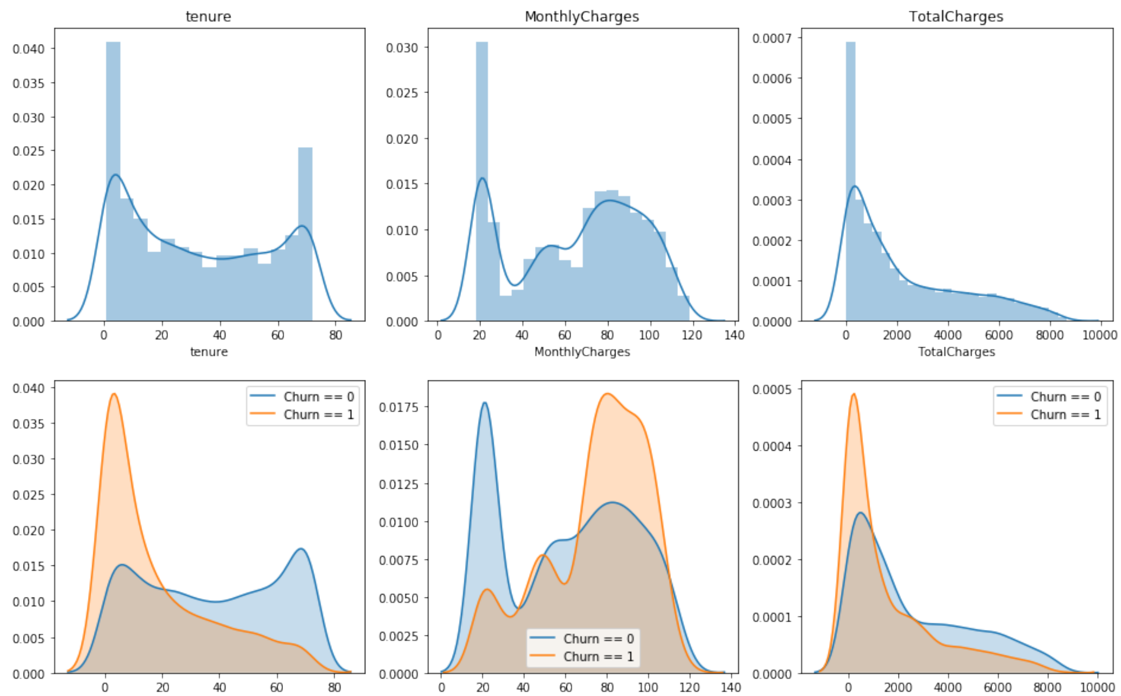


Plot distribution of those feat, w/ & w/o the distinction between the customers who churn

In [25]:
```
plt.figure(figsize=(16, 10))

plt.subplot(2, 3, 1)
sns.distplot(df['tenure'])
plt.title('tenure')

plt.subplot(2, 3, 2)
sns.distplot(df['MonthlyCharges'])
plt.title('MonthlyCharges')

plt.subplot(2, 3, 3)
sns.distplot(df['TotalCharges'])
```

```
plt.title('TotalCharges')

plt.subplot(2, 3, 4)
sns.kdeplot(df.loc[df['Churn'] == 'No', 'tenure'], shade=True,label = 'Churn == 0')
sns.kdeplot(df.loc[df['Churn'] == 'Yes', 'tenure'], shade=True,label = 'Churn == 1')

plt.subplot(2, 3, 5)
sns.kdeplot(df.loc[df['Churn'] == 'No', 'MonthlyCharges'], shade=True,label = 'Churn =
sns.kdeplot(df.loc[df['Churn'] == 'Yes', 'MonthlyCharges'], shade=True,label = 'Churn

plt.subplot(2, 3, 6)
sns.kdeplot(df.loc[df['Churn'] == 'No', 'TotalCharges'], shade=True,label = 'Churn ==
sns.kdeplot(df.loc[df['Churn'] == 'Yes', 'TotalCharges'], shade=True,label = 'Churn ==
```

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4a40662e10>



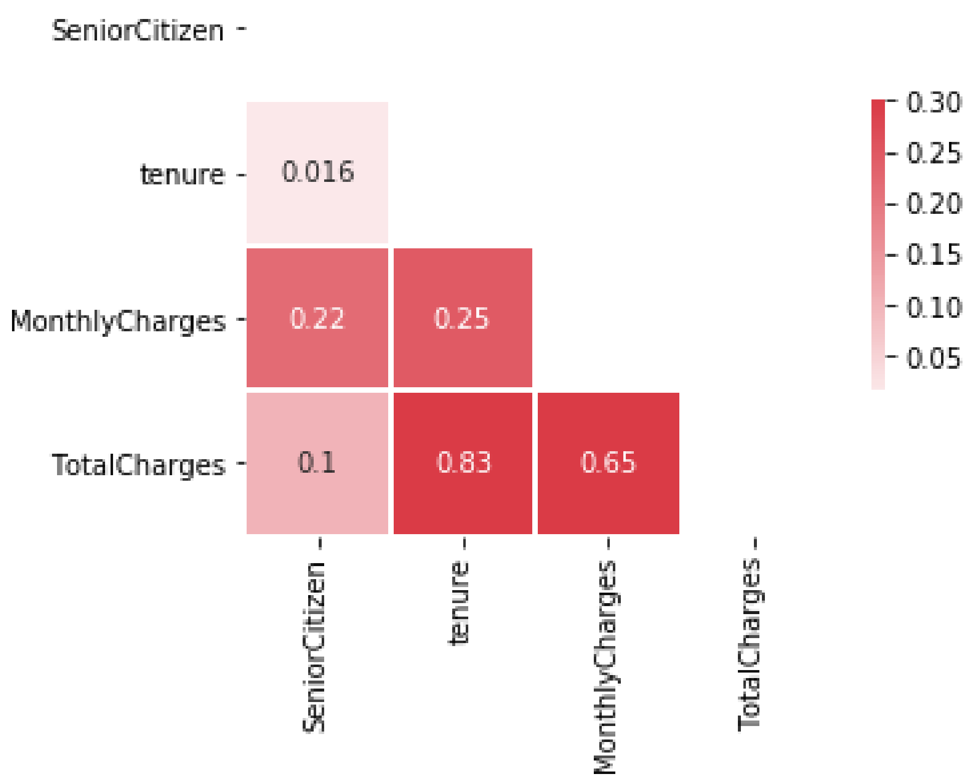
Are there any correlations ?

In [26]:
```
corr = df.corr()
corr
```

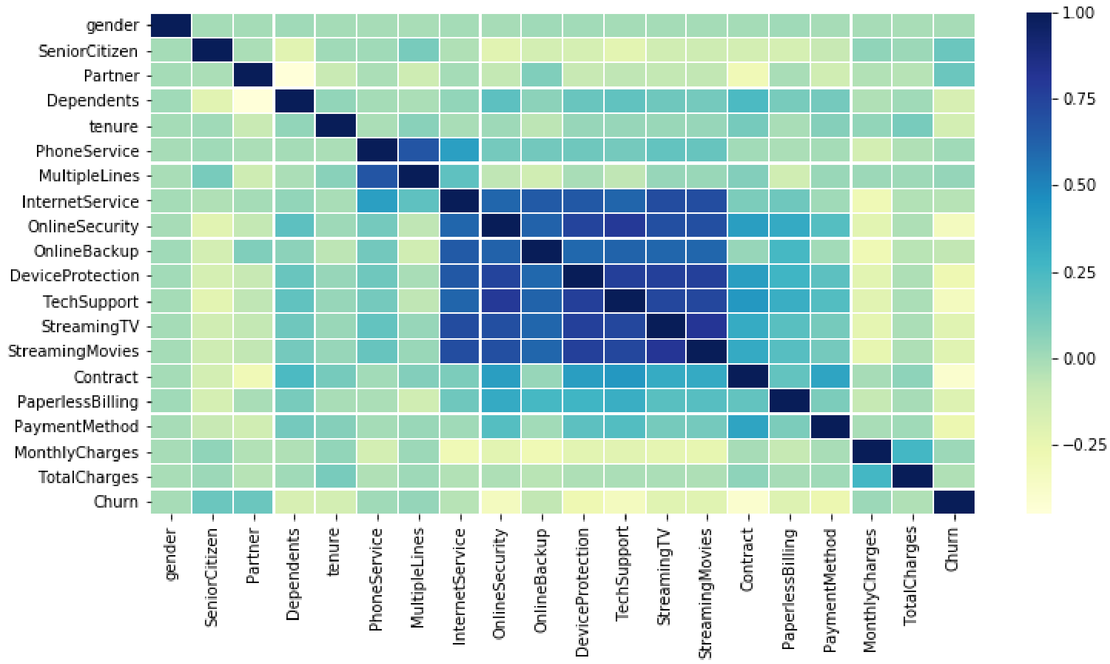
Out[26]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
SeniorCitizen	1.000000	0.015683	0.219874	0.102411
tenure	0.015683	1.000000	0.246862	0.825880
MonthlyCharges	0.219874	0.246862	1.000000	0.651065
TotalCharges	0.102411	0.825880	0.651065	1.000000

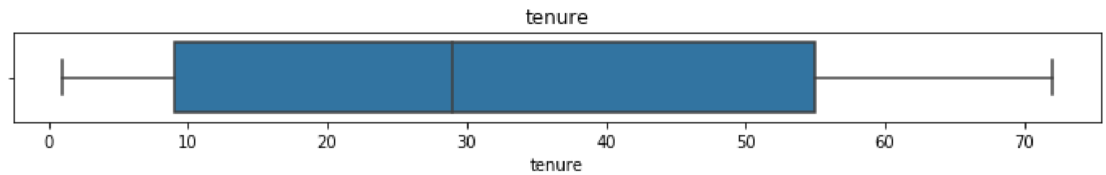
```
In [27]: # Generate a mask for the upper triangle
         mask = np.zeros_like(corr, dtype=np.bool)
         mask[np.triu_indices_from(mask)] = True

         # Set up the matplotlib figure
         f, ax = plt.subplots(figsize=(6, 4))

         # Generate a custom diverging colormap
         cmap = sns.diverging_palette(220, 10, as_cmap=True)

         # Draw the heatmap with the mask and correct aspect ratio
         sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
                     square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4a401d0da0>
```

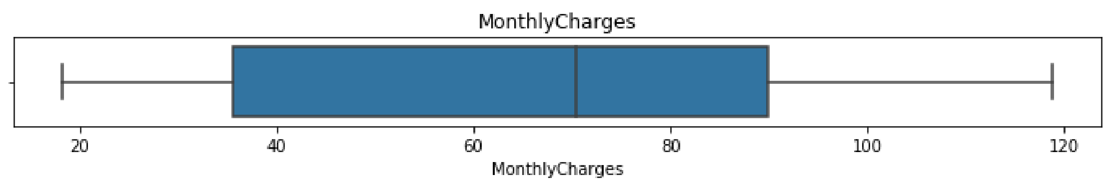


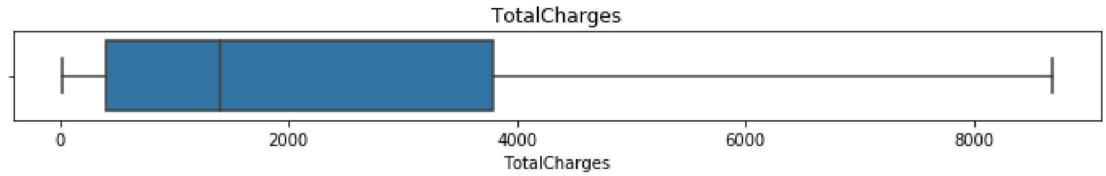

```
In [28]: plt.figure(figsize=(12, 6))

         corr = df.apply(lambda x: pd.factorize(x)[0]).corr()
         ax = sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns,
                          linewidths=.2, cmap="YlGnBu")
```



In [29]:
```python
for c in num_feat:
    plt.figure(figsize=(12, 1))
    sns.boxplot(df[c])
    plt.title(c)
    plt.show()
```





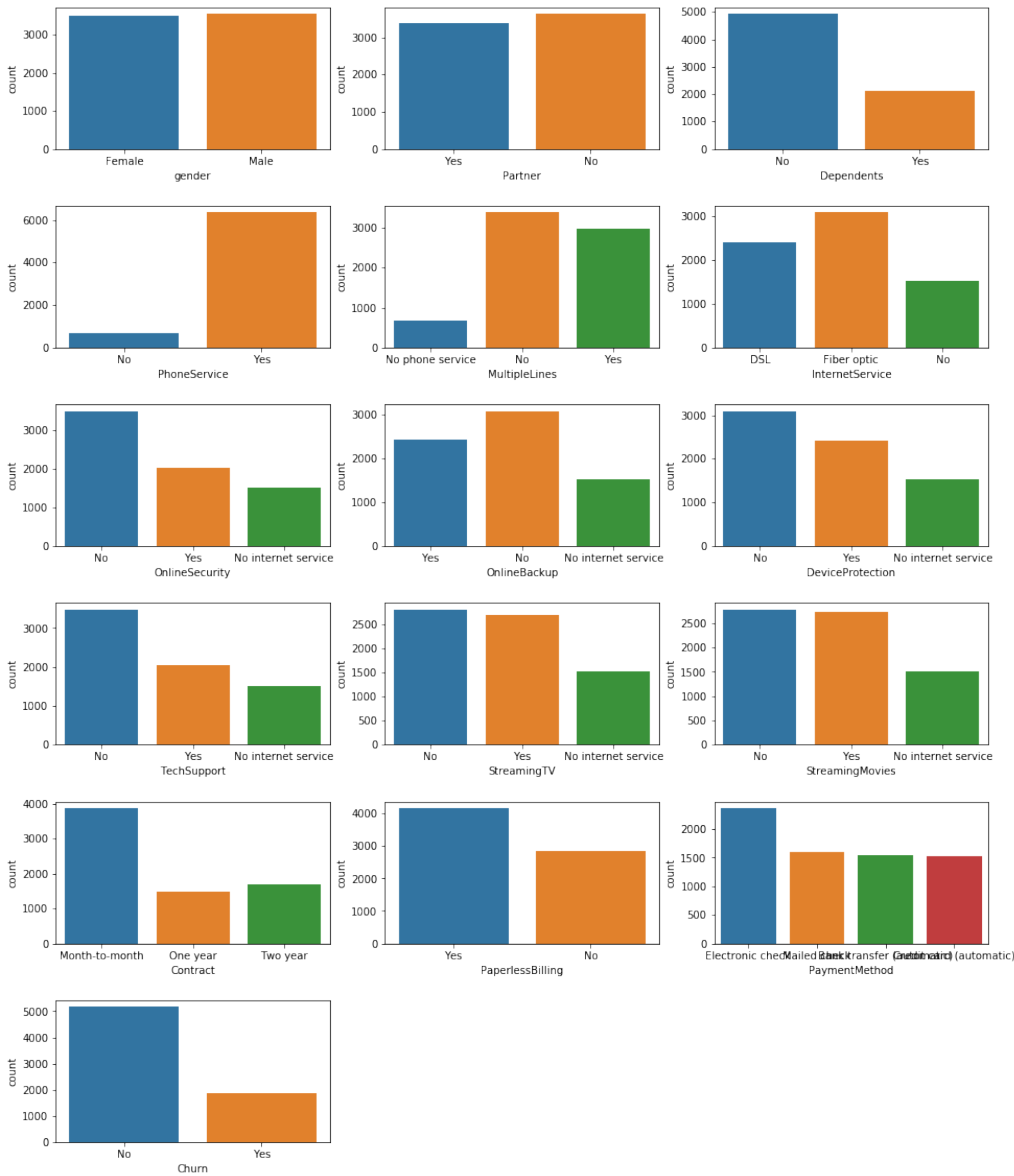



```
In [30]: cat_features = df.select_dtypes('object').columns.tolist()
         cat_features
```

```
Out[30]: ['gender',
          'Partner',
          'Dependents',
          'PhoneService',
          'MultipleLines',
          'InternetService',
          'OnlineSecurity',
          'OnlineBackup',
          'DeviceProtection',
          'TechSupport',
          'StreamingTV',
          'StreamingMovies',
          'Contract',
          'PaperlessBilling',
          'PaymentMethod',
          'Churn']
```

Plot the count of different categories for the other features (with text)

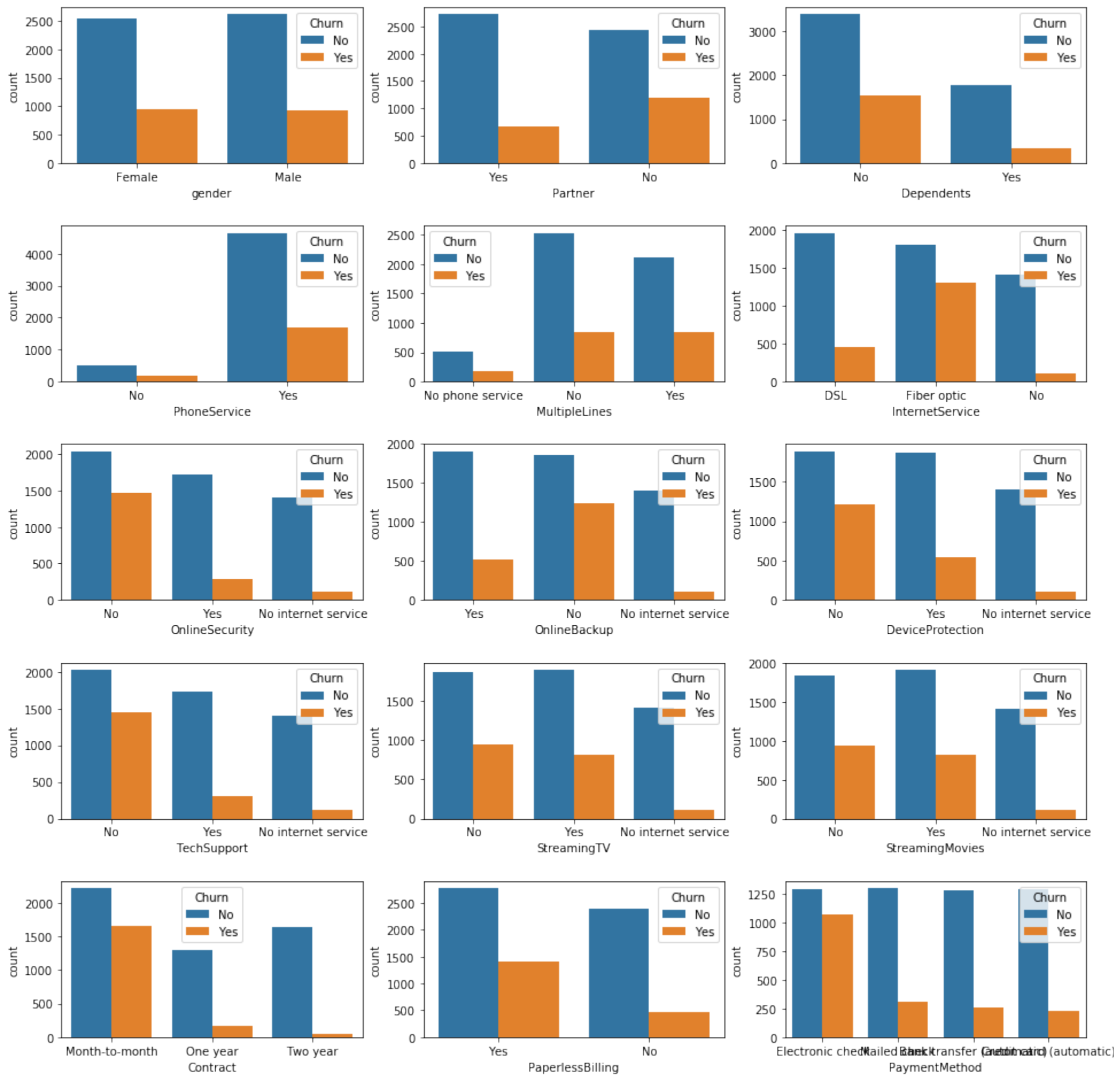
```
In [31]: plt.figure(figsize=(16, 20))
         plt.subplots_adjust(hspace=0.4)

         for i in range(len(cat_features)):
             plt.subplot(6, 3, i+1)
             sns.countplot(df[cat_features[i]])
             #plt.title(cat_features[i])

         plt.show()
```



Same plot but with the distinction between customers who churn

```
In [32]: cat_features.remove('Churn')

         plt.figure(figsize=(16, 20))
         plt.subplots_adjust(hspace=0.4)

         for i in range(len(cat_features)):
             plt.subplot(6, 3, i+1)
```

```
        sns.countplot(df[cat_features[i]], hue=df['Churn'])
        #plt.title(cat_features[i])

    plt.show()
```



---

3 Data Preparation & Feature engineering

Target creation

```
In [33]: y = df.Churn.str.replace('No', '0').str.replace('Yes', '1').astype(int)
```

Label encoding of categorical features

In [34]:
```
X = pd.get_dummies(data=df, columns=cat_features, drop_first=True)
X = X.drop(columns=['Churn'])
```

In [35]:
```
X.shape, y.shape
```

Out[35]:
```
((7032, 30), (7032,))
```

Features creation

- In this case, it's complicated to add features from an other dataset because no information is provided with the CSV file we're using.
- All columns except the user_id are relevant, so all of them are kept.
- We can combine features to create new ones : by dividing TotalCharges with the tenure which provide a kind of charge average per month. This value compared to the Monthly charges can give an idea of the charges' evolution with time.

In [36]:
```
X['average_charges'] = X['TotalCharges'] / X['tenure']
X.loc[X['tenure'] == 0, 'average_charges'] = X['MonthlyCharges']
X.head()
```

Out[36]:
```
   SeniorCitizen  tenure  MonthlyCharges  TotalCharges  gender_Male  \
0              0       1           29.85         29.85            0
1              0      34           56.95       1889.50            1
2              0       2           53.85        108.15            1
3              0      45           42.30       1840.75            1
4              0       2           70.70        151.65            0

   Partner_Yes  Dependents_Yes  PhoneService_Yes  \
0            1               0                 0
1            0               0                 1
2            0               0                 1
3            0               0                 0
4            0               0                 1

   MultipleLines_No phone service  MultipleLines_Yes  \
0                               1                  0
1                               0                  0
2                               0                  0
3                               1                  0
4                               0                  0

   InternetService_Fiber optic  InternetService_No  \
0                            0                   0
1                            0                   0
2                            0                   0
3                            0                   0
4                            1                   0

   OnlineSecurity_No internet service  OnlineSecurity_Yes  \
```

```
0                                  0                   0
1                                  0                   1
2                                  0                   1
3                                  0                   1
4                                  0                   0

   OnlineBackup_No internet service  OnlineBackup_Yes  \
0                                 0                 1
1                                 0                 0
2                                 0                 1
3                                 0                 0
4                                 0                 0

   DeviceProtection_No internet service  DeviceProtection_Yes  \
0                                     0                     0
1                                     0                     1
2                                     0                     0
3                                     0                     1
4                                     0                     0

   TechSupport_No internet service  TechSupport_Yes  \
0                                0                0
1                                0                0
2                                0                0
3                                0                1
4                                0                0

   StreamingTV_No internet service  StreamingTV_Yes  \
0                                0                0
1                                0                0
2                                0                0
3                                0                0
4                                0                0

   StreamingMovies_No internet service  StreamingMovies_Yes  \
0                                    0                    0
1                                    0                    0
2                                    0                    0
3                                    0                    0
4                                    0                    0

   Contract_One year  Contract_Two year  PaperlessBilling_Yes  \
0                  0                  0                     1
1                  1                  0                     0
2                  0                  0                     1
3                  1                  0                     0
4                  0                  0                     1
```

```
   PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                      0                               1
1                                      0                               0
2                                      0                               0
3                                      0                               0
4                                      0                               1

   PaymentMethod_Mailed check  average_charges
0                           0        29.850000
1                           1        55.573529
2                           1        54.075000
3                           0        40.905556
4                           0        75.825000
```

Scaling data

```
In [37]: num_feat.append('average_charges')
         scaler = MinMaxScaler()
         X[num_feat] = scaler.fit_transform(X[num_feat])
```

```
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:323: DataCo
  return self.partial_fit(X, y)
```

```
In [38]: X.head()
```

```
Out[38]:    SeniorCitizen    tenure  MonthlyCharges  TotalCharges  gender_Male  \
         0              0  0.000000        0.115423      0.001275            0
         1              0  0.464789        0.385075      0.215867            1
         2              0  0.014085        0.354229      0.010310            1
         3              0  0.619718        0.239303      0.210241            1
         4              0  0.014085        0.521891      0.015330            0

            Partner_Yes  Dependents_Yes  PhoneService_Yes  \
         0            1               0                 0
         1            0               0                 1
         2            0               0                 1
         3            0               0                 0
         4            0               0                 1

            MultipleLines_No phone service  MultipleLines_Yes  \
         0                               1                  0
         1                               0                  0
         2                               0                  0
         3                               1                  0
         4                               0                  0

            InternetService_Fiber optic  InternetService_No  \
         0                            0                   0
```

```
1                          0               0
2                          0               0
3                          0               0
4                          1               0

   OnlineSecurity_No internet service  OnlineSecurity_Yes  \
0                                  0                   0
1                                  0                   1
2                                  0                   1
3                                  0                   1
4                                  0                   0

   OnlineBackup_No internet service  OnlineBackup_Yes  \
0                                0                 1
1                                0                 0
2                                0                 1
3                                0                 0
4                                0                 0

   DeviceProtection_No internet service  DeviceProtection_Yes  \
0                                    0                     0
1                                    0                     1
2                                    0                     0
3                                    0                     1
4                                    0                     0

   TechSupport_No internet service  TechSupport_Yes  \
0                               0                0
1                               0                0
2                               0                0
3                               0                1
4                               0                0

   StreamingTV_No internet service  StreamingTV_Yes  \
0                               0                0
1                               0                0
2                               0                0
3                               0                0
4                               0                0

   StreamingMovies_No internet service  StreamingMovies_Yes  \
0                                   0                    0
1                                   0                    0
2                                   0                    0
3                                   0                    0
4                                   0                    0

   Contract_One year  Contract_Two year  PaperlessBilling_Yes  \
```

```
0                  0                  0                      1
1                  1                  0                      0
2                  0                  0                      1
3                  1                  0                      0
4                  0                  0                      1

   PaymentMethod_Credit card (automatic)  PaymentMethod_Electronic check  \
0                                      0                               1
1                                      0                               0
2                                      0                               0
3                                      0                               0
4                                      0                               1

   PaymentMethod_Mailed check  average_charges
0                           0         0.149361
1                           1         0.388372
2                           1         0.374448
3                           0         0.252084
4                           0         0.576539
```

Splitting train and test sets

In [39]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

Features importances

In [40]:
```
rnd_clf = RandomForestClassifier(n_estimators=500, n_jobs=-1)
rnd_clf.fit(X, y)
```

Out[40]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=500, n_jobs=-1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

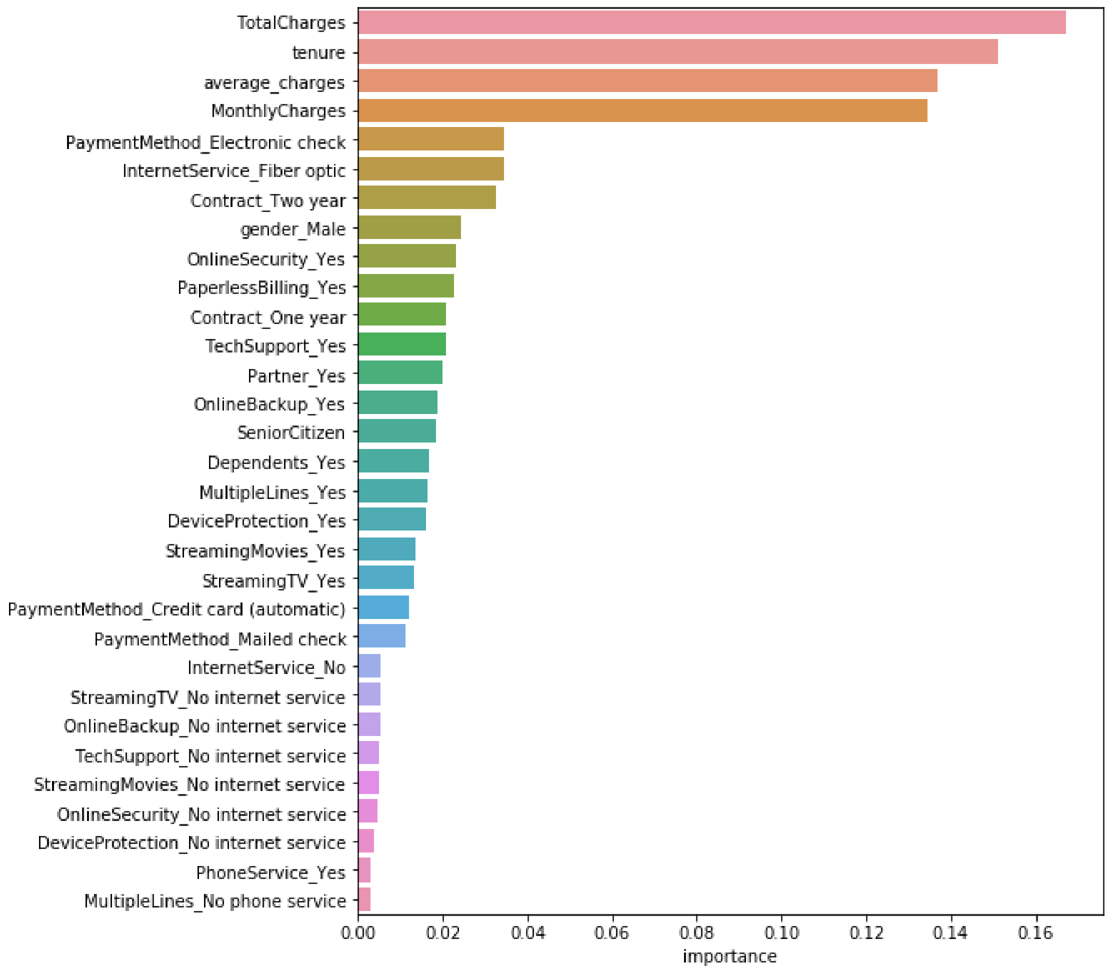
In [41]:
```
feature_importances = pd.DataFrame(rnd_clf.feature_importances_, index = X.columns,
                                    columns=['importance']).sort_values('importance',
feature_importances[:10]
```

Out[41]:

	importance
TotalCharges	0.167416
tenure	0.150908
average_charges	0.137030
MonthlyCharges	0.134679
PaymentMethod_Electronic check	0.034640
InternetService_Fiber optic	0.034376
Contract_Two year	0.032602

```
gender_Male                     0.024216
OnlineSecurity_Yes              0.022954
PaperlessBilling_Yes            0.022600
```

In [42]:
```
plt.figure(figsize=(8, 10))
sns.barplot(x="importance", y=feature_importances.index, data=feature_importances)
plt.show()
```



---

4 Baselines

In [43]:
```
# f1_score binary by default
def get_f1_scores(clf, model_name):
    y_train_pred, y_pred = clf.predict(X_train), clf.predict(X_test)
    print(model_name, f'\t - Training F1 score = {f1_score(y_train, y_train_pred) * 10
```

```
In [44]: model_list = [RandomForestClassifier(),
              LogisticRegression(),
              SVC(),
              LinearSVC(),
              SGDClassifier(),
              lgbm.LGBMClassifier(),
              xgb.XGBClassifier()
                       ]
```

```
In [45]: model_names = [str(m)[:str(m).index('(')] for m in model_list]
```

```
In [46]: for model, name in zip(model_list, model_names):
             model.fit(X_train, y_train)
             get_f1_scores(model, name)
```

```
RandomForestClassifier          - Training F1 score = 95.88% / Test F1 score = 51.62%
LogisticRegression          - Training F1 score = 60.45% / Test F1 score = 56.12%
SVC          - Training F1 score = 58.92% / Test F1 score = 54.46%
LinearSVC          - Training F1 score = 59.91% / Test F1 score = 56.36%
SGDClassifier          - Training F1 score = 40.85% / Test F1 score = 36.83%
LGBMClassifier          - Training F1 score = 76.50% / Test F1 score = 57.02%
XGBClassifier          - Training F1 score = 62.61% / Test F1 score = 58.36%
```

The 1st model - RandomForrest Clf - is clearly overfitting the train dataset and can't generalize. The others models don't have good results and are probably underfitting. So let's tuned them !

---

5 Training more accurately other models

5.1 Randomforest with weighted classes

```
In [47]: rfc = RandomForestClassifier()
         rfc.fit(X_train, y_train)
         get_f1_scores(rfc, 'RandomForest')
```

```
RandomForest          - Training F1 score = 96.83% / Test F1 score = 48.52%
```

```
In [48]: y.sum(), len(y) - y.sum()
```

```
Out[48]: (1869, 5163)
```

```
In [49]: rfc = RandomForestClassifier(class_weight={1:1869, 0:5174})
         rfc.fit(X_train, y_train)
         get_f1_scores(rfc, 'RandomForest weighted')
```

```
RandomForest weighted          - Training F1 score = 96.35% / Test F1 score = 51.89%
```

The improvement is not significant...

5.2 LGBM with weighted classes

```
In [50]: lgbm_w = lgbm.LGBMClassifier(n_jobs = -1, class_weight={0:1869, 1:5174})
         lgbm_w.fit(X_train, y_train)
         get_f1_scores(lgbm_w, 'LGBM weighted')
```

```
LGBM weighted          - Training F1 score = 78.76% / Test F1 score = 63.03%
```

5.3 XGB with ratio

```
In [51]: ratio = ((len(y) - y.sum()) - y.sum()) / y.sum()
         ratio
```

```
Out[51]: 1.7624398073836276
```

```
In [52]: xgb_model = xgb.XGBClassifier(objective="binary:logistic", scale_pos_weight=ratio)
         xgb_model.fit(X_train, y_train)
         get_f1_scores(xgb_model, 'XGB with ratio')
```

```
XGB with ratio          - Training F1 score = 66.48% / Test F1 score = 63.47%
```

That's a little better.

5.4 Adaboost

```
In [53]: abc = AdaBoostClassifier()
         abc.fit(X_train, y_train)
         get_f1_scores(abc, 'Adaboost')
```

```
Adaboost          - Training F1 score = 60.75% / Test F1 score = 58.05%
```

---

6 Using GridsearchCV & Combining the best models

With XGB

```
In [54]: print(classification_report(y_test, xgb_model.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.87      0.81      0.84      1018
           1       0.58      0.70      0.63       389

   micro avg       0.78      0.78      0.78      1407
   macro avg       0.73      0.75      0.74      1407
weighted avg       0.79      0.78      0.78      1407
```

Let's use a GridSearch with 5 cross validation to tuned the hyperparameters

```
In [55]: from sklearn.model_selection import GridSearchCV
```

```
In [56]: params = {'learning_rate':[0.175, 0.167, 0.165, 0.163, 0.17],
                   'max_depth':[1, 2, 3],
                   'scale_pos_weight':[1.70, 1.73, 1.76, 1.79]}
         clf_grid = GridSearchCV(xgb.XGBClassifier(), param_grid=params, cv=5, scoring='f1', n_
         clf_grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:   10.3s
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:   16.2s finished
```

```
Out[56]: GridSearchCV(cv=5, error_score='raise-deprecating',
                estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
                max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
                n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
                reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
                silent=True, subsample=1),
                fit_params=None, iid='warn', n_jobs=-1,
                param_grid={'learning_rate': [0.175, 0.167, 0.165, 0.163, 0.17], 'max_depth':
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring='f1', verbose=1)
```

```
In [57]: clf_grid.best_score_
```

```
Out[57]: 0.635398553168061
```

```
In [58]: clf_grid.best_params_
```

```
Out[58]: {'learning_rate': 0.163, 'max_depth': 1, 'scale_pos_weight': 1.76}
```

With a LogisticRegression

```
In [59]: lr = LogisticRegression(C=10, class_weight={0:0.26, 1:0.74})
```

```
In [60]: lr.fit(X_train, y_train)
         get_f1_scores(lr, 'Logistic Reg')
```

```
Logistic Reg          - Training F1 score = 62.82% / Test F1 score = 64.88%
```

Now we can try to combine the best models

```
In [61]: xgb_model = xgb.XGBClassifier(objective="binary:logistic", learning_rate=0.167, max_de
         xgb_model.fit(X_train, y_train)
         get_f1_scores(xgb_model, 'XGB with ratio')
```

```
XGB with ratio          - Training F1 score = 66.17% / Test F1 score = 63.93%
```

```
In [62]: y_pred_lr = lr.predict_proba(X_test)
```

```
In [63]: lgbm_w = lgbm.LGBMClassifier(n_jobs = -1, class_weight={0:1869, 1:5174})
         lgbm_w.fit(X_train, y_train)
         y_pred_lgbm = lgbm_w.predict_proba(X_test)
```

```
In [65]: # y_pred with predict_proba returns 2 cols, one for each class
         y_pred_xgb = xgb_model.predict_proba(X_test)
         y_pred_xgb[:5, 1]
```

```
Out[65]: array([0.66343373, 0.6869538 , 0.031379  , 0.49967214, 0.06845096],
               dtype=float32)
```

```
In [66]: y_pred_lgbm[:5, 1]
```

```
Out[66]: array([0.65824753, 0.73075217, 0.06651954, 0.50086417, 0.0424213 ])
```

```
In [67]: test = np.vstack((y_pred_lgbm[:5, 1], y_pred_xgb[:5, 1]))
         test
```

```
Out[67]: array([[0.65824753, 0.73075217, 0.06651954, 0.50086417, 0.0424213 ],
                [0.66343373, 0.68695378, 0.031379  , 0.49967214, 0.06845096]])
```

```
In [68]: np.mean(test, axis=0)
```

```
Out[68]: array([0.66084063, 0.70885298, 0.04894927, 0.50026816, 0.05543613])
```

```
In [69]: y_pred_mean = np.mean(np.vstack((y_pred_lgbm[:, 1], y_pred_xgb[:, 1])), axis=0)
         y_pred_mean[:5]
```

```
Out[69]: array([0.66084063, 0.70885298, 0.04894927, 0.50026816, 0.05543613])
```

```
In [70]: y_pred_mean[y_pred_mean < 0.5] = 0
         y_pred_mean[y_pred_mean > 0.5] = 1
         y_pred_mean[:5]
```

```
Out[70]: array([1., 1., 0., 1., 0.])
```

```
In [71]: print(f'F1 score of models combined on the test dataset = {f1_score(y_test, y_pred_mea
```

```
F1 score of models combined on the test dataset = 63.59%
```

Despite combining model, the best F1 score is still obtained by XGB with tuned hyperparameters.

```
In [ ]:
```