edoardo_falchi_final_project_AEA1

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1 Applied Economics Analysis1 - Final Assignment

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2 Objective and motivation

As Garcia et al.(2016) affirm, globalization processes and market deregulation policies are rapidly changing the competitive environments of many economic sectors. The appearance of new competitors and technologies leads to an increase in competition and, with it, a growing preoccupation among service providing companies with creating stronger customer bonds.

"Churn" is the phenomenon where a customer switches from one service to a competitor's service (Tsai & Chen, 2009). Churn is a relevant issue because anticipating the customer's intention to abandon the provider becomes a competitive advantage for firms. Objective of the work is to analyze Churn phenomenon on data coming from Telco Sector and propose the best Target for a Retention Commercial Campaign.

The analysed dataset is taken from https://www.kaggle.com/blastchar/telco-customer-churn where each row represents a customer, each column contains customer's attributes. The raw data contains 7043 rows (customers) and 21 columns (features). The "Churn" column is the target.

Churn Phenomenon will be described through univariate and bivariate analysis, managing potential issues related to data like outliers and missing. I will estimate a Scoring Model through Logistic Regression in order to predict Churn Phenomenon, considering the variable Churn in the provided data set as dependent variable.

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3 Importing libraries and data

In [1]:
```
import pandas as pd
from IPython.display import display
pd.options.display.max_columns = None
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from scipy.spatial.distance import pdist, squareform
from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram
from sklearn.preprocessing import StandardScaler
import statsmodels.api as sm
import pylab as pl
import scikitplot as skplt
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples
from matplotlib import cm
%matplotlib inline
import os
from PIL import  Image
import io
import matplotlib.ticker as mtick
import scipy
```

In [2]:
```
import plotly.graph_objs as go
import plotly.offline as py
import plotly.tools as tls
import plotly.figure_factory as ff
py.init_notebook_mode(connected=True)
```

In [3]:
```
tcc = pd.read_csv("C:/Users/Utente/Desktop/studio/final assignment pyhton AEA1/tcc.csv")
```

In [4]:
```
tcc.head()
```

```
Out[4]:    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 [5]: # Hiding annoying warnings
        import warnings
        warnings.filterwarnings('ignore')
```

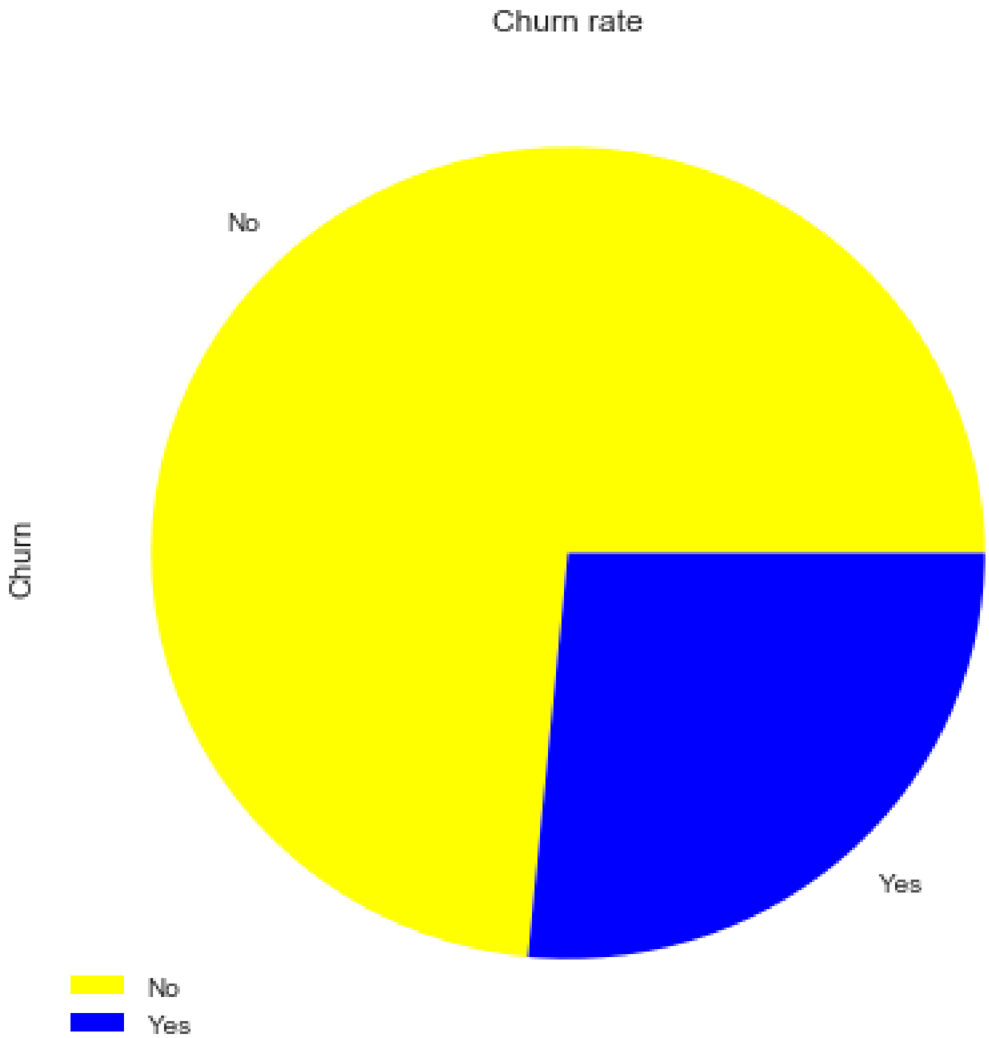
3.1 Univariate and Bivariate Analysis

3.1.1 Customer Churn

Let's first have a look at the churn rate.

```
In [6]: senior = (tcc['Churn'].value_counts()*100.0 /len(tcc)).plot(kind='pie',\
                labels = ['No', 'Yes'], figsize = (7,7) , colors = ['yellow','blue'])
```

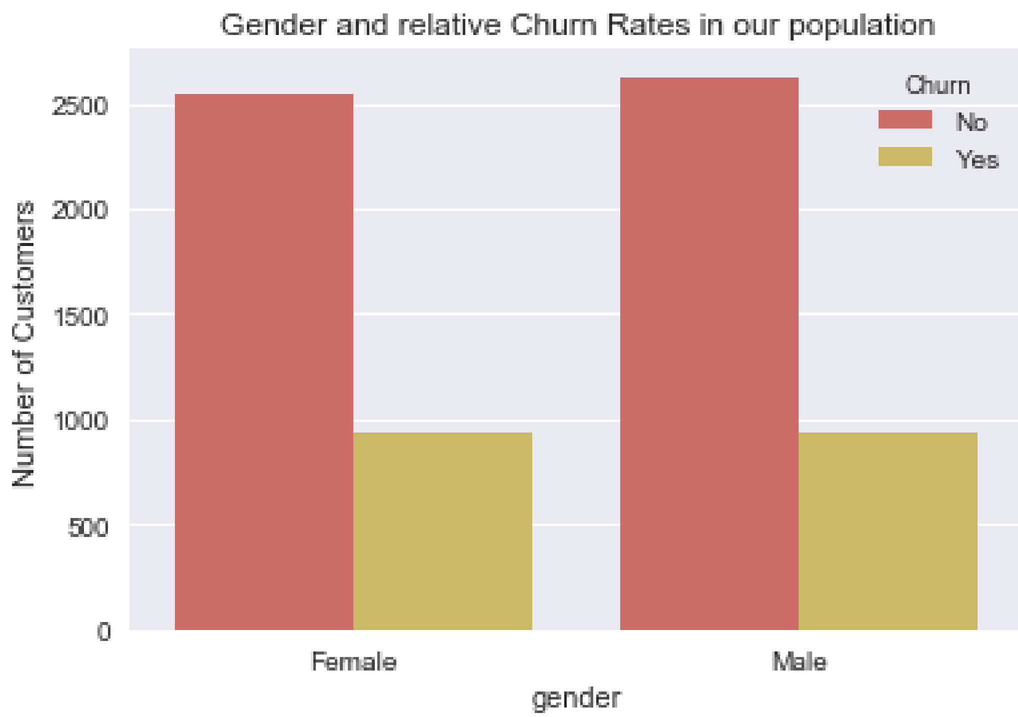
```
senior.set_title('Churn rate')
senior.legend(labels=['No','Yes']);
```



One customer over four churns.

3.1.2 Gender distribution

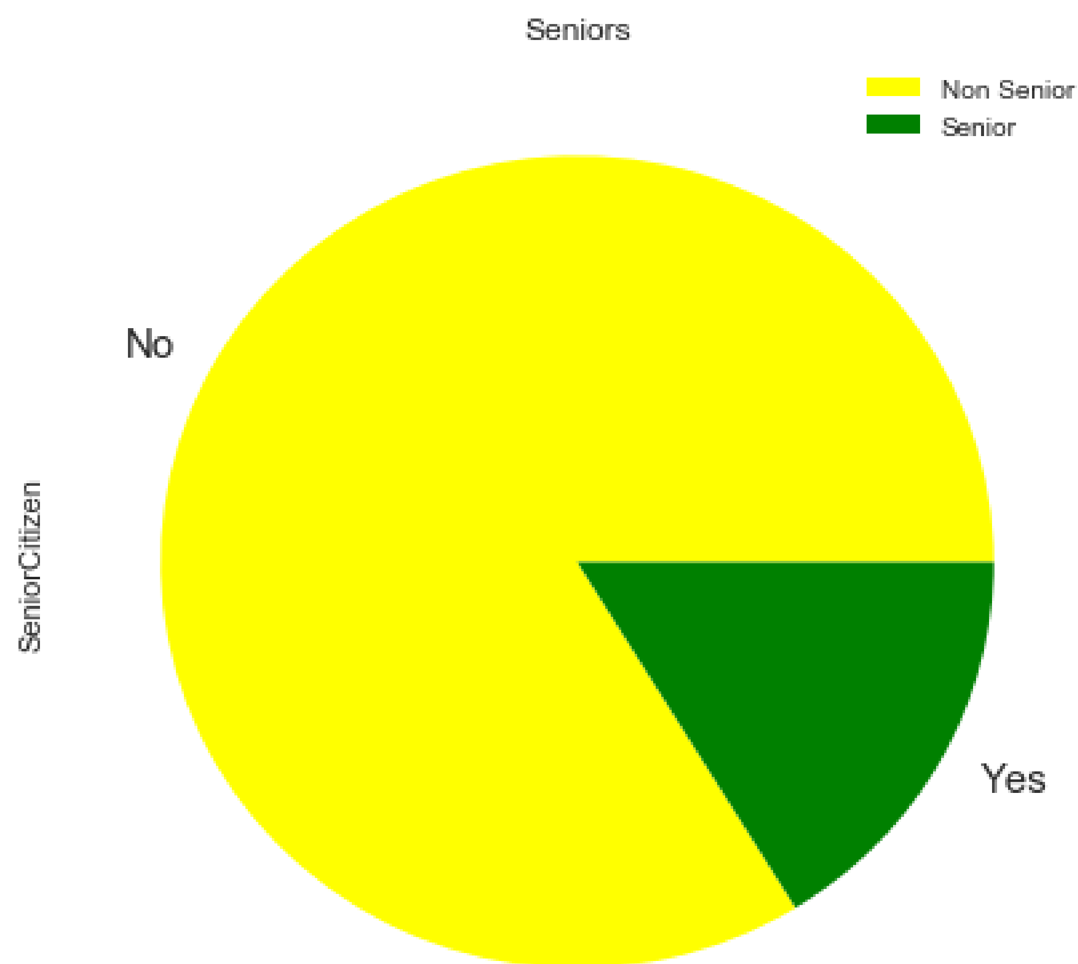
```
In [7]: gb = tcc.groupby("gender")["Churn"].value_counts().to_frame().rename({"Churn": "Number o
        sns.barplot(x = "gender", y = "Number of Customers", data = gb, hue = "Churn", palette =
```



Men and women are evenly distributed in the sample, and show the same proportions of Churn.

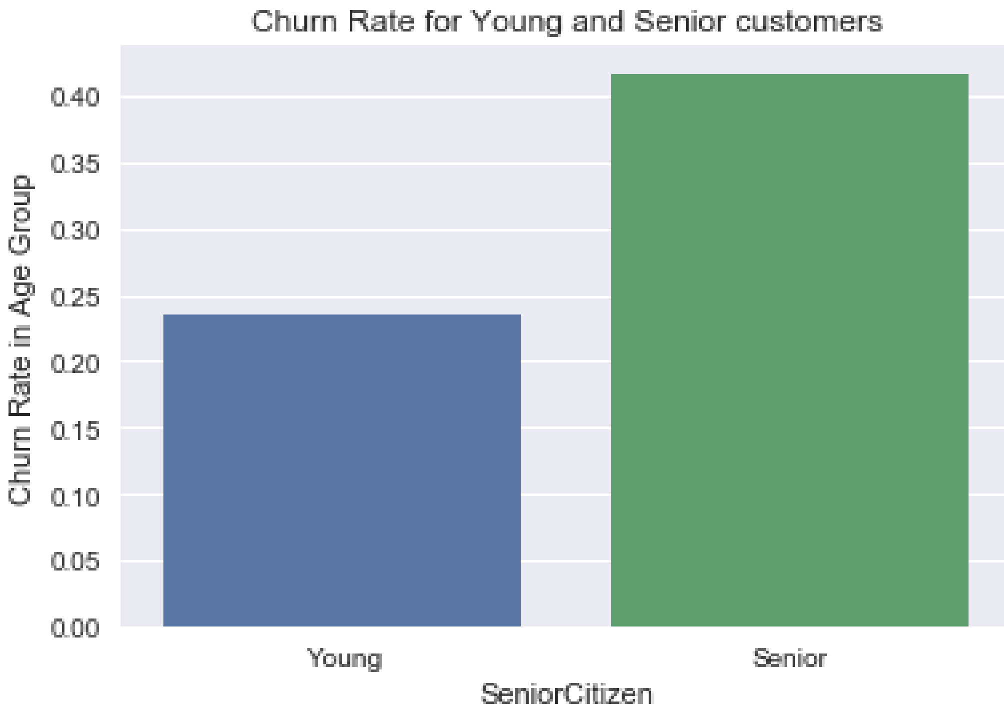
3.1.3 Age distribution

```
In [8]: senior = (tcc['SeniorCitizen'].value_counts()*100.0 /len(tcc)).plot(kind='pie',\
                labels = ['No', 'Yes'], figsize = (7,7) , colors = ['yellow','green'], fontsize

        senior.set_title('Seniors')
        senior.legend(labels=['Non Senior','Senior']);
```




```
In [9]: gb = tcc.groupby("SeniorCitizen")["Churn"].value_counts().to_frame().rename({"Churn": "N
        gb.replace([0, 1], ["Young", "Senior"], inplace = True)
        gb

Out[9]:   SeniorCitizen Churn  Number of Customers
        0         Young    No                 4508
        1         Young   Yes                 1393
        2        Senior    No                  666
        3        Senior   Yes                  476

In [10]: tp = gb.groupby("SeniorCitizen")["Number of Customers"].sum().to_frame().reset_index().
         gb = pd.merge(gb, tp, on = "SeniorCitizen")
         gb["Churn Rate in Age Group"] = gb["Number of Customers"]/gb["# Customers in Age Group"
         gb = gb[gb.Churn == "Yes"]
```

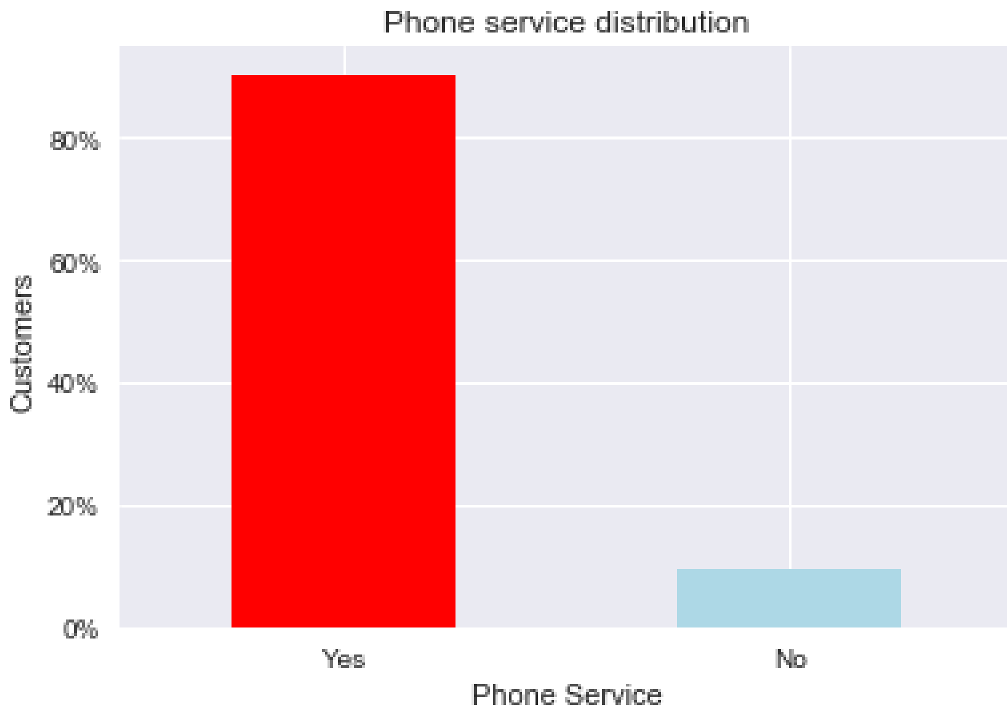
```
sns.barplot(x = "SeniorCitizen", y = "Churn Rate in Age Group", data = gb).set_title("C
```



This sample is mainly composed by young people. Senior customers are more prone to churning.

3.1.4 Phone Service distribution

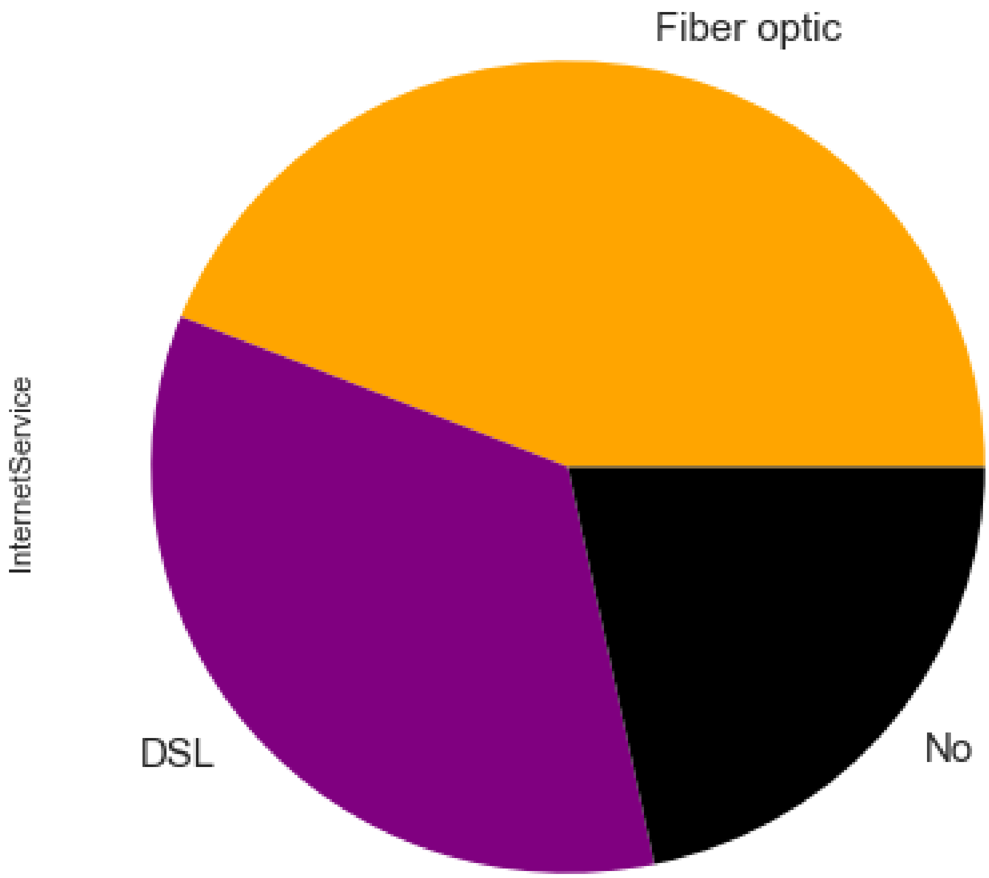
```
In [11]: phone = (tcc['PhoneService'].value_counts()*100.0 /len(tcc)).plot(kind='bar', stacked =
                                                               rot = 0, color = ['red','lightblue'])

         phone.yaxis.set_major_formatter(mtick.PercentFormatter())
         phone.set_ylabel('Customers')
         phone.set_xlabel('Phone Service')
         phone.set_ylabel('Customers')
         phone.set_title('Phone service distribution');
```



Just a little amount of people does not have phone service.

3.1.5 Internet service distribution

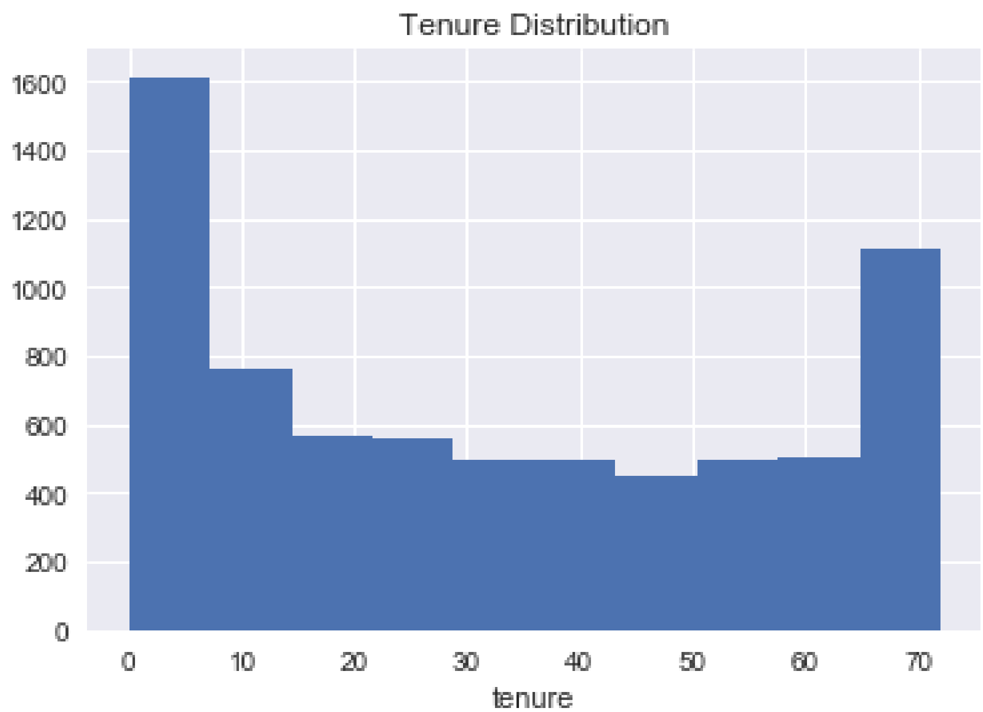
```
In [12]: internet = (tcc['InternetService'].value_counts()*100.0 /len(tcc)).plot(kind='pie',\
                   labels = ['Fiber optic', 'DSL', 'No'], figsize = (7,7) , colors = ['orange','pu

         senior.set_title('Seniors')
         senior.legend(labels=['Non Senior','Senior']);
```



Among the ones that have internet service, DSL and Fiber optic are almost equally distributed (the fraction of people having Fiber optic is slightly greater). Less than one fourth of the members of our sample has no internet service.

3.1.6 Tenure distribution

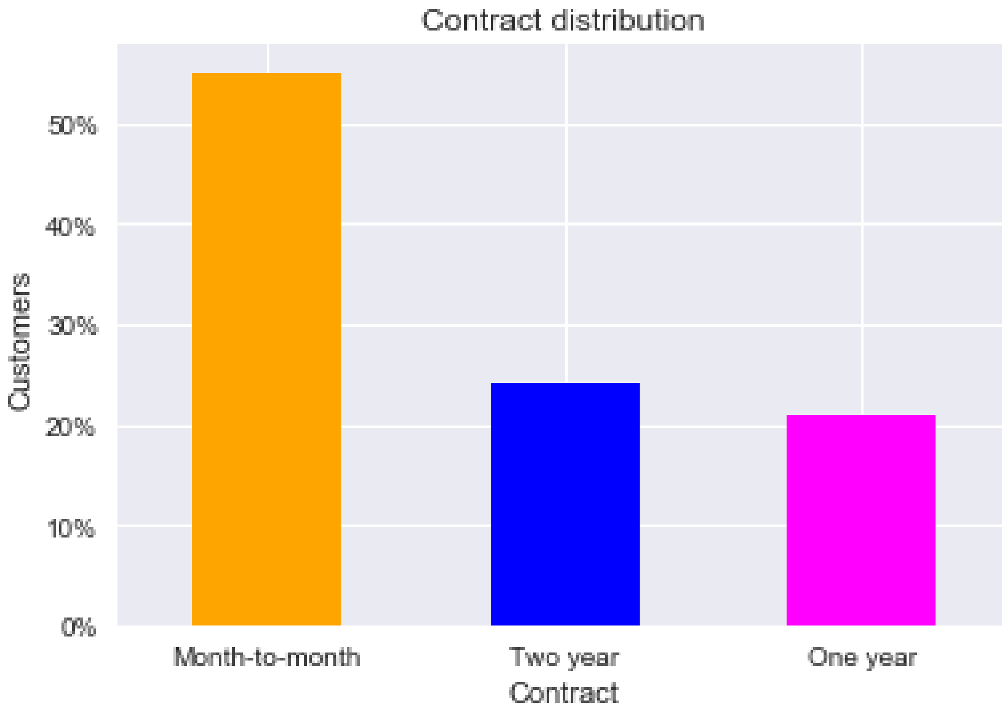
```
In [13]: plt.hist(tcc.tenure)
         plt.xlabel('tenure')
         plt.title("Tenure Distribution");
```



The majority of the customers in the sample are new clients. There is also a high number of people with a tenure around 70 months. Most likely the company is not older than 72 months, and there either was a strong incentive for subscription (like a competitive launch offer, which could explain the high number through efficient retention rates) or there was some form of selection bias (the offers were unique on the market and highly valued by a group of customers, leading to fast market saturation, which could explain the high number by keeping the retention rate constant and leveraging high sales volumes). These are the only two reasons that can explain such a sharp kickstart in the number of subscriptions and their sudden drop.

3.1.7 Contract distribution

```
In [14]: contract = (tcc['Contract'].value_counts()*100.0 /len(tcc)).plot(kind='bar', stacked =
                                                                 rot = 0, color = ['orange','blue','mage

         contract.yaxis.set_major_formatter(mtick.PercentFormatter())
         contract.set_ylabel('Customers')
         contract.set_xlabel('Contract')
         contract.set_ylabel('Customers')
         contract.set_title('Contract distribution');
```



More than half customers have a month-to-month contract.

```
In [15]: tcc.columns
```

```
Out[15]: Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
                'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
                'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
                'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
                'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
               dtype='object')
```

3.2 Dealing with Missing Values

```
In [16]: missing_values = []
         for col in tcc.columns:
             missing_values.append(tcc[col].isna().any())

         missing_values = pd.DataFrame(np.array(missing_values).reshape(1, 21))
         missing_values.columns = tcc.columns
         missing_values_table   = tcc.append(missing_values).tail(1)
         missing_values_table   = missing_values_table.astype(bool)
         missing_values_table   = missing_values_table.transpose()
         missing_values_table.columns = ["Missing?"]

         missing_values_table["dtype"] = tcc.dtypes
         missing_values_table
```

```
Out[16]:                    Missing?    dtype
         customerID            False   object
         gender                False   object
         SeniorCitizen         False    int64
         Partner               False   object
         Dependents            False   object
         tenure                False    int64
         PhoneService          False   object
         MultipleLines         False   object
         InternetService       False   object
         OnlineSecurity        False   object
         OnlineBackup          False   object
         DeviceProtection      False   object
         TechSupport           False   object
         StreamingTV           False   object
         StreamingMovies       False   object
         Contract              False   object
         PaperlessBilling      False   object
         PaymentMethod         False   object
         MonthlyCharges        False  float64
         TotalCharges          False   object
         Churn                 False   object
```

The dtypes are not coherent with logic. There's no point in encoding TotalCharges as a string and MonthlyCharges as a float, or PhoneService as Yes/No and SeniorCitizen as a 0/1 dummy. Let's fix that.

```
In [17]: try:
             tcc.TotalCharges.astype("float64")
         except ValueError:
             print("We can't convert this column to floats, there must be some non-convertible v

We can't convert this column to floats, there must be some non-convertible values
```

```
In [18]: print(tcc.TotalCharges.value_counts().head())
         print("")
         print("We have 11 observations that take an empty string value. Let's drop that. The st
         tcc.TotalCharges.value_counts().index[1]

         11
20.2     11
19.75     9
19.9      8
20.05     8
Name: TotalCharges, dtype: int64

We have 11 observations that take an empty string value. Let's drop that. The string we want to
```

Out[18]: '20.2'

Let's drop the observations with empty values, reset the index and now I should be able to convert the TotalCharges column to float:

```
In [19]: tcc.drop(tcc[tcc.TotalCharges == " "].index, axis = 0, inplace = True)
         tcc.reset_index(drop = True, inplace = True)
```

```
In [20]: tcc.TotalCharges = tcc.TotalCharges.astype("float64")
```

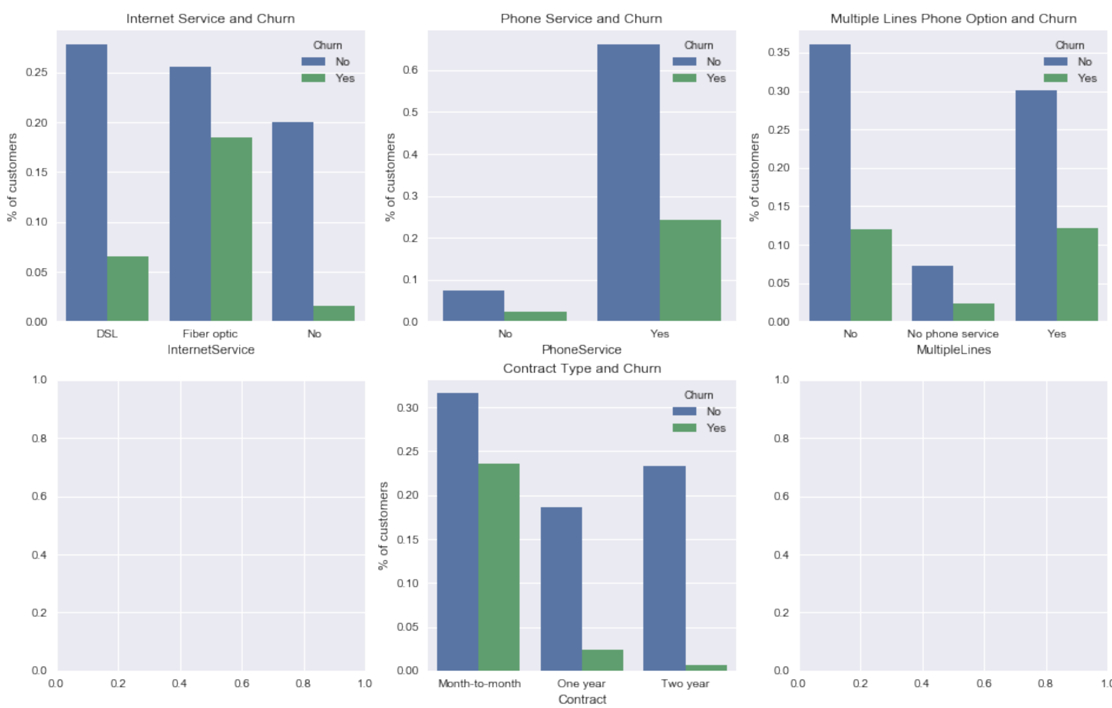
Let's compute some last computations before extracting the Dummy Variables from the dataset and proceeding to the Regression Part.

```
In [21]: for col in tcc.columns:
             print("{0}: {1}".format(col, tcc.loc[:, col].unique()))
```

```
customerID: ['7590-VHVEG' '5575-GNVDE' '3668-QPYBK' ... '4801-JZAZL' '8361-LTMKD'
 '3186-AJIEK']
gender: ['Female' 'Male']
SeniorCitizen: [0 1]
Partner: ['Yes' 'No']
Dependents: ['No' 'Yes']
tenure: [ 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 39]
PhoneService: ['No' 'Yes']
MultipleLines: ['No phone service' 'No' 'Yes']
InternetService: ['DSL' 'Fiber optic' 'No']
OnlineSecurity: ['No' 'Yes' 'No internet service']
OnlineBackup: ['Yes' 'No' 'No internet service']
DeviceProtection: ['No' 'Yes' 'No internet service']
TechSupport: ['No' 'Yes' 'No internet service']
StreamingTV: ['No' 'Yes' 'No internet service']
StreamingMovies: ['No' 'Yes' 'No internet service']
Contract: ['Month-to-month' 'One year' 'Two year']
PaperlessBilling: ['Yes' 'No']
PaymentMethod: ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
MonthlyCharges: [29.85 56.95 53.85 ... 63.1  44.2  78.7 ]
TotalCharges: [  29.85 1889.5   108.15 ...  346.45  306.6  6844.5 ]
Churn: ['No' 'Yes']
```

```
In [22]: fig, axis = plt.subplots(nrows = 2, ncols = 3, figsize = (16, 10))

         gb = tcc.groupby("InternetService")["Churn"].value_counts()/len(tcc)
         gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
         sns.barplot(x = "InternetService", y = "% of customers", data = gb, hue = "Churn", ax =
```

```
gb = tcc.groupby("PhoneService")["Churn"].value_counts()/len(tcc)
gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
sns.barplot(x = "PhoneService", y = "% of customers", data = gb, hue = "Churn", ax = ax

gb = tcc.groupby("MultipleLines")["Churn"].value_counts()/len(tcc)
gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
sns.barplot(x = "MultipleLines", y = "% of customers", data = gb, hue = "Churn", ax = a

gb = tcc.groupby("Contract")["Churn"].value_counts()/len(tcc)
gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
sns.barplot(x = "Contract", y = "% of customers", data = gb, hue = "Churn", ax = axis[1
```

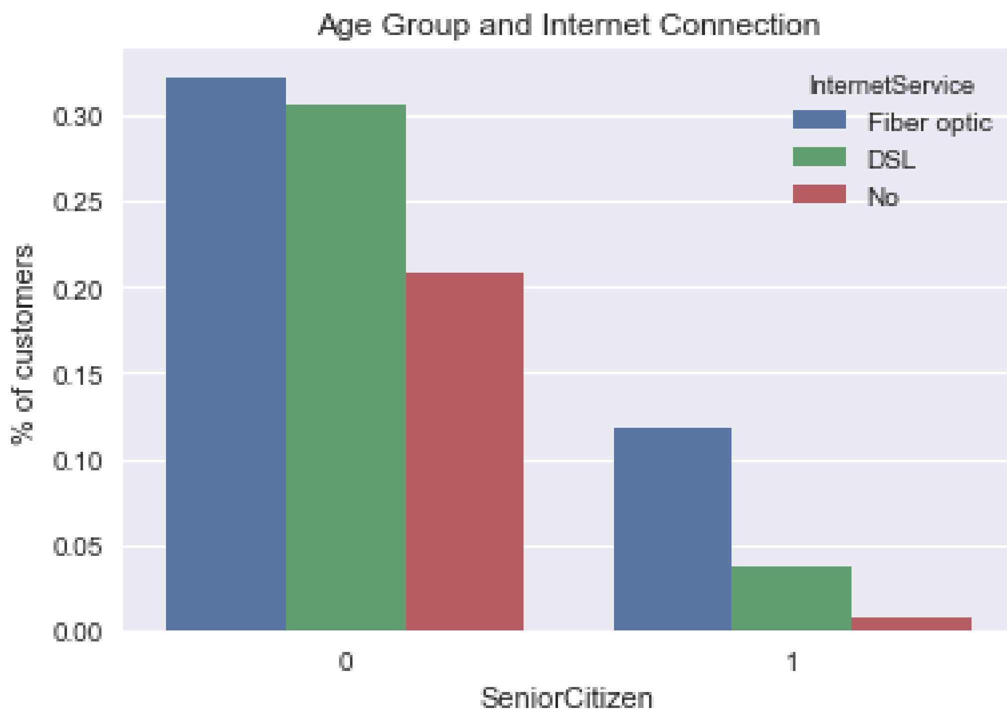


It is noticeable that the customers with Fiber optic tend to churn a lot more when compared to DSL and No Internet. Maybe the Internet connection offered is low-quality? (Other option: Elder Customers don't need an internet connection. Spoiler: No. See following graph that proves that elderly are proportionally more connected than youngsters and are only a reduced percentage of the population).

MultipleLines do not seem to affect the churn rate.

Shorter-term contract renewals are highly correlated with the churn rate. But most likely it's an omitted variable bias issue: the more I trust a provider, the more I reason in long-terms with it.

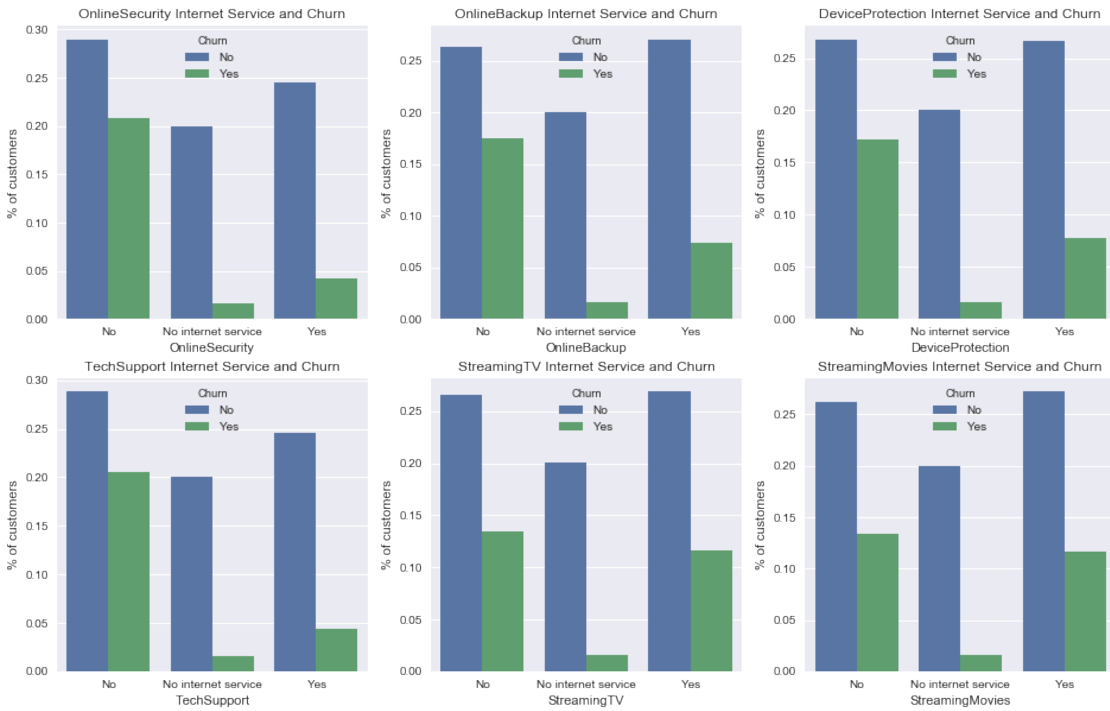
```
In [23]: gb = tcc.groupby("SeniorCitizen")["InternetService"].value_counts()/len(tcc)
         gb = gb.to_frame().rename({"InternetService": "% of customers"}, axis = 1).reset_index(
         sns.barplot(x = "SeniorCitizen", y = "% of customers", data = gb, hue = "InternetServic
```



Now let's see how the "Additional Internet Services" that follow the variable pattern: ["No", "Yes", "No internet service"] affect the churn rate.

```
In [24]: fig, axis = plt.subplots(nrows = 2, ncols = 3, figsize = (16, 10))

         gb = tcc.groupby("OnlineSecurity")["Churn"].value_counts()/len(tcc)
         gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
         sns.barplot(x = "OnlineSecurity", y = "% of customers", data = gb, hue = "Churn", ax =

         gb = tcc.groupby("OnlineBackup")["Churn"].value_counts()/len(tcc)
         gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
         sns.barplot(x = "OnlineBackup", y = "% of customers", data = gb, hue = "Churn", ax = ax

         gb = tcc.groupby("DeviceProtection")["Churn"].value_counts()/len(tcc)
         gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
         sns.barplot(x = "DeviceProtection", y = "% of customers", data = gb, hue = "Churn", ax

         gb = tcc.groupby("TechSupport")["Churn"].value_counts()/len(tcc)
         gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
         sns.barplot(x = "TechSupport", y = "% of customers", data = gb, hue = "Churn", ax = axi

         gb = tcc.groupby("StreamingTV")["Churn"].value_counts()/len(tcc)
         gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
         sns.barplot(x = "StreamingTV", y = "% of customers", data = gb, hue = "Churn", ax = axi
```

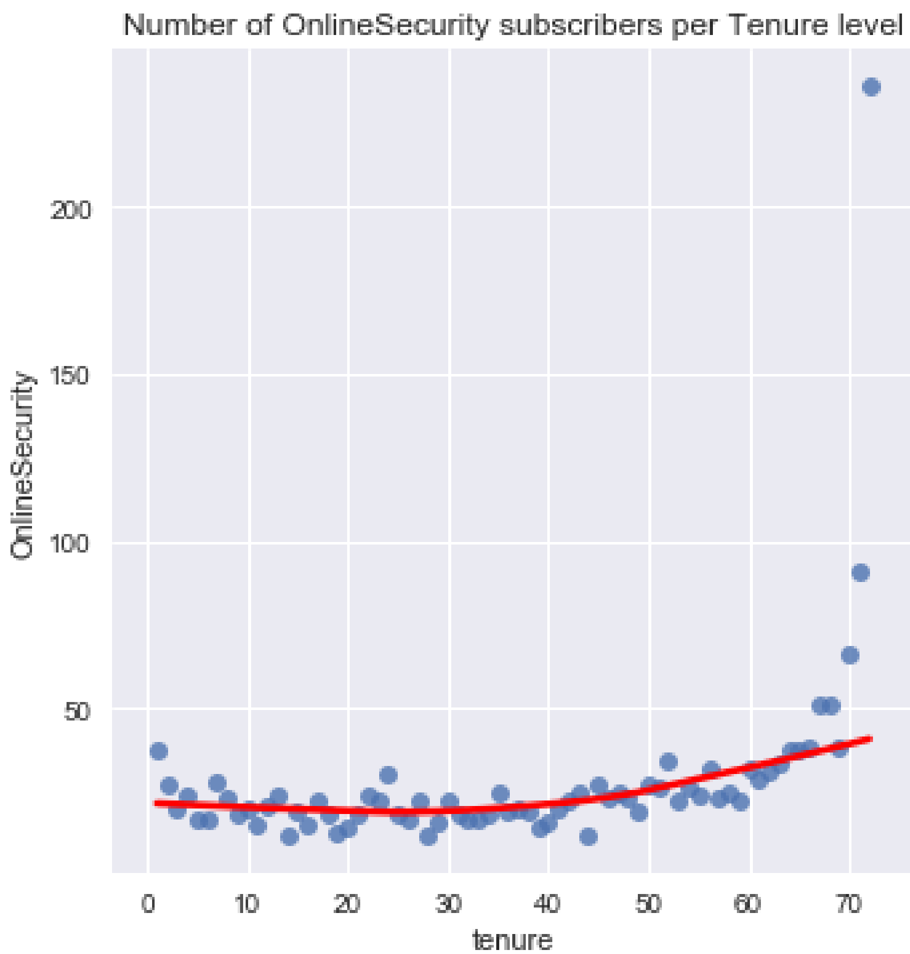
```
gb = tcc.groupby("StreamingMovies")["Churn"].value_counts()/len(tcc)
gb = gb.to_frame().rename({"Churn": "% of customers"}, axis = 1).reset_index()
sns.barplot(x = "StreamingMovies", y = "% of customers", data = gb, hue = "Churn", ax =
```



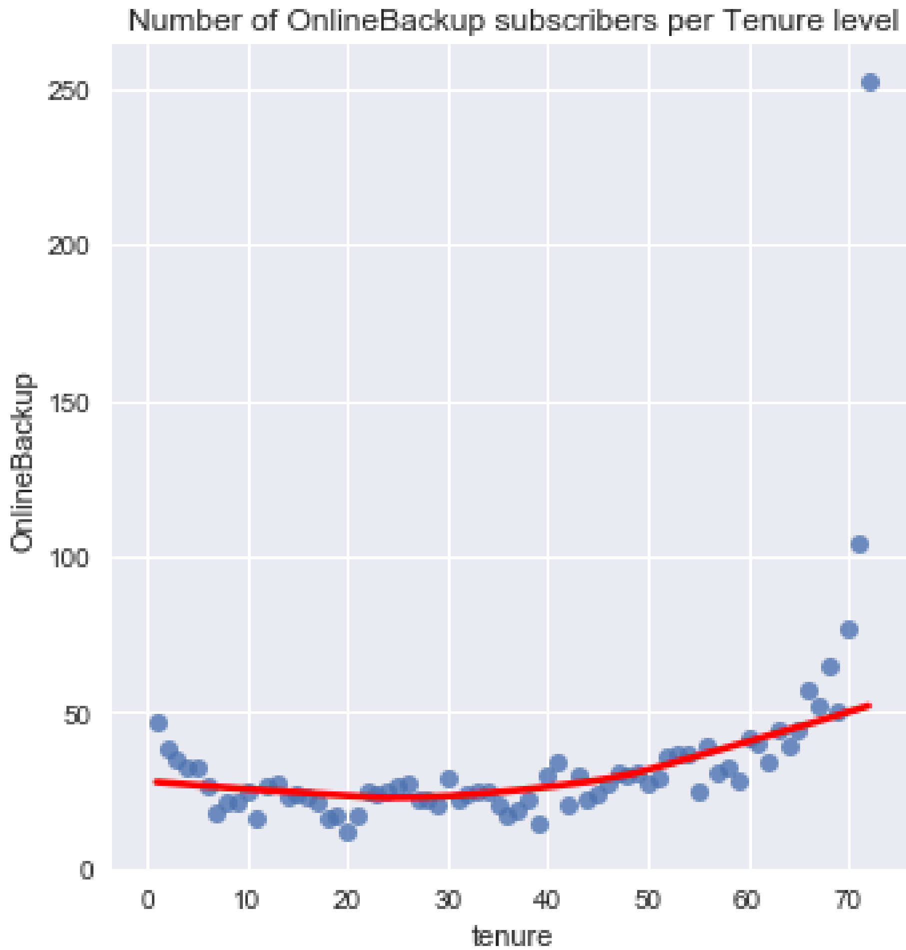
- OnlineSecurity, OnlineBackup, TechSupport seem to have a significant impact on lowering the churn. If the company wants to lower the churn rate, It may be a good idea to include these services as standard in the following order: OnlineSecurity, TechSupport, OnlineBackUp, DeviceProtection (although removing the internet connection service altogether may be potentially be more beneficial, at least the Fiber one; see graphs above for details). Although unlikely, it is also possible that these services get cumulated with tenure, and thus their effect on the churn only reflects the negative impact of tenure on the churn rate; in the next cells we will try to figure out whether this is true or not.
- StreamingTV and StreamingMovies do not seem to have a large enough effect on customer Churn Rate.

To assess whether additional services are accumulated through tenure (e.g. fidalty programs), let's run a lmplot for each additional Internet service.

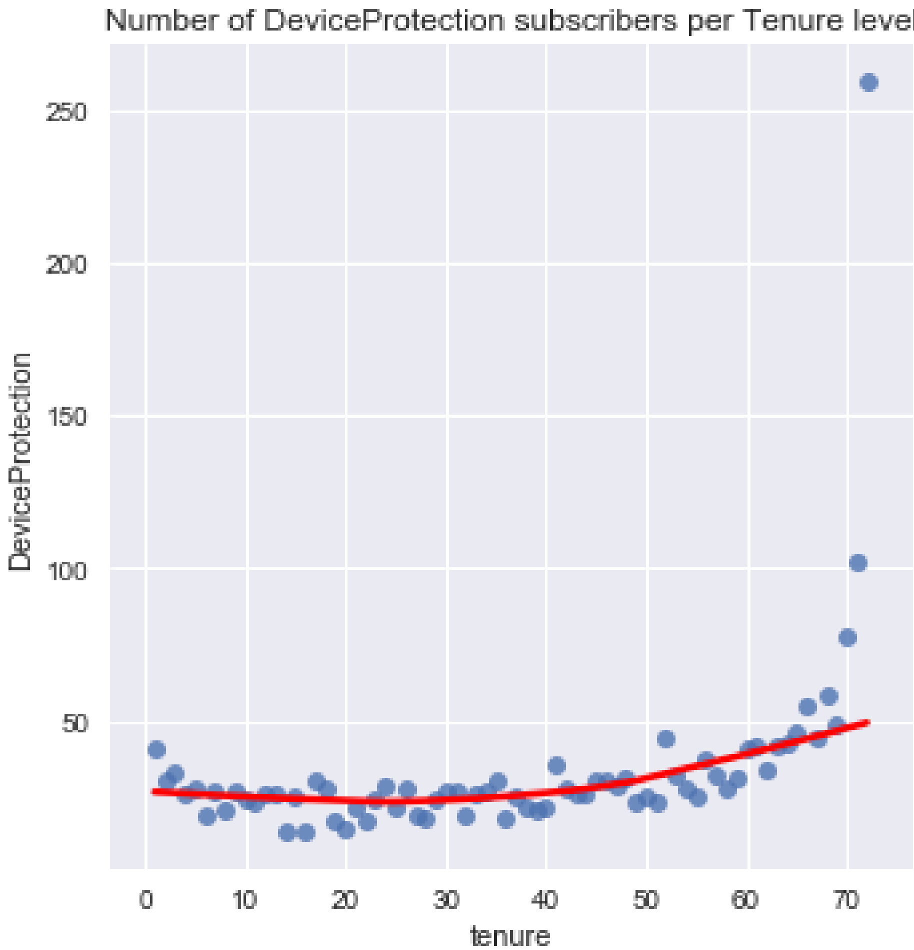
```
In [25]: gb = tcc[(tcc.OnlineSecurity != "No internet service")].replace(["Yes", "No"], [1, 0]).
         sns.lmplot("tenure", "OnlineSecurity", data = gb, line_kws={'color': 'red'}, lowess = T
         ax = plt.gca()
         ax.set_title("Number of OnlineSecurity subscribers per Tenure level");
```




```
In [26]: gb = tcc[(tcc.OnlineSecurity != "No internet service")].replace(["Yes", "No"], [1, 0]).
         sns.lmplot("tenure", "OnlineBackup", data = gb, line_kws={'color': 'red'}, lowess = Tru
         ax = plt.gca()
         ax.set_title("Number of OnlineBackup subscribers per Tenure level");
```

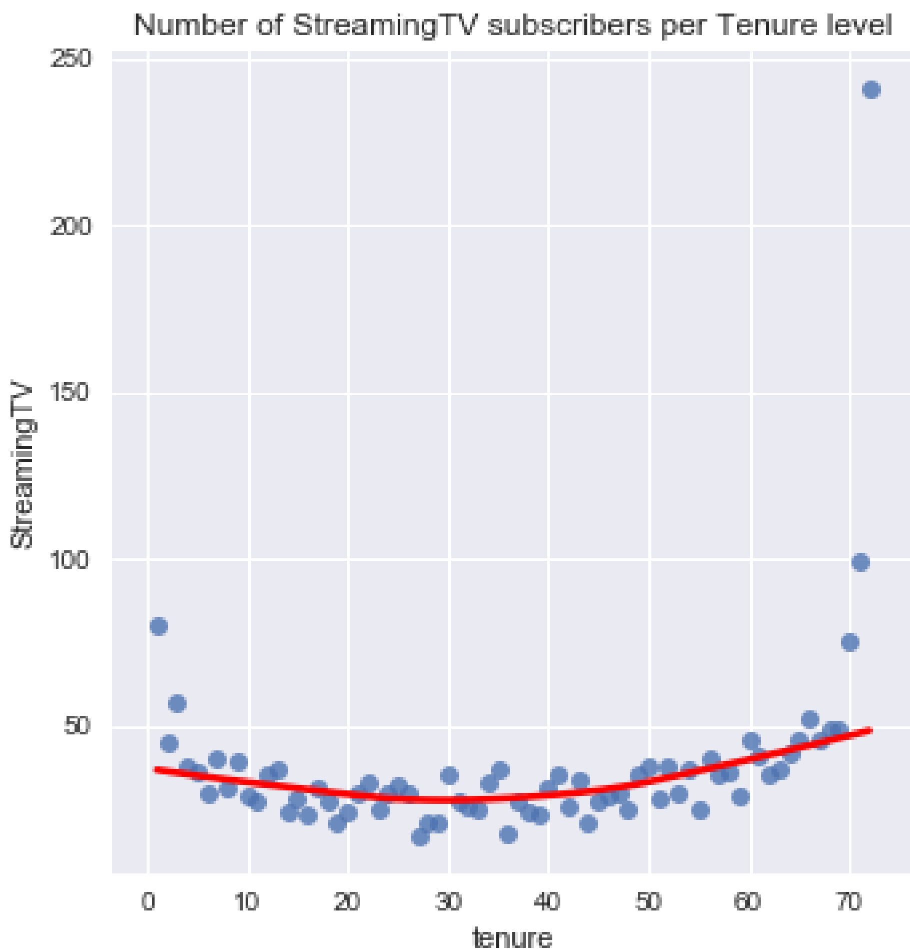



```
In [27]: gb = tcc[(tcc.OnlineSecurity != "No internet service")].replace(["Yes", "No"], [1, 0]).
         sns.lmplot("tenure", "DeviceProtection", data = gb, line_kws={'color': 'red'}, lowess =
         ax = plt.gca()
         ax.set_title("Number of DeviceProtection subscribers per Tenure level");
```

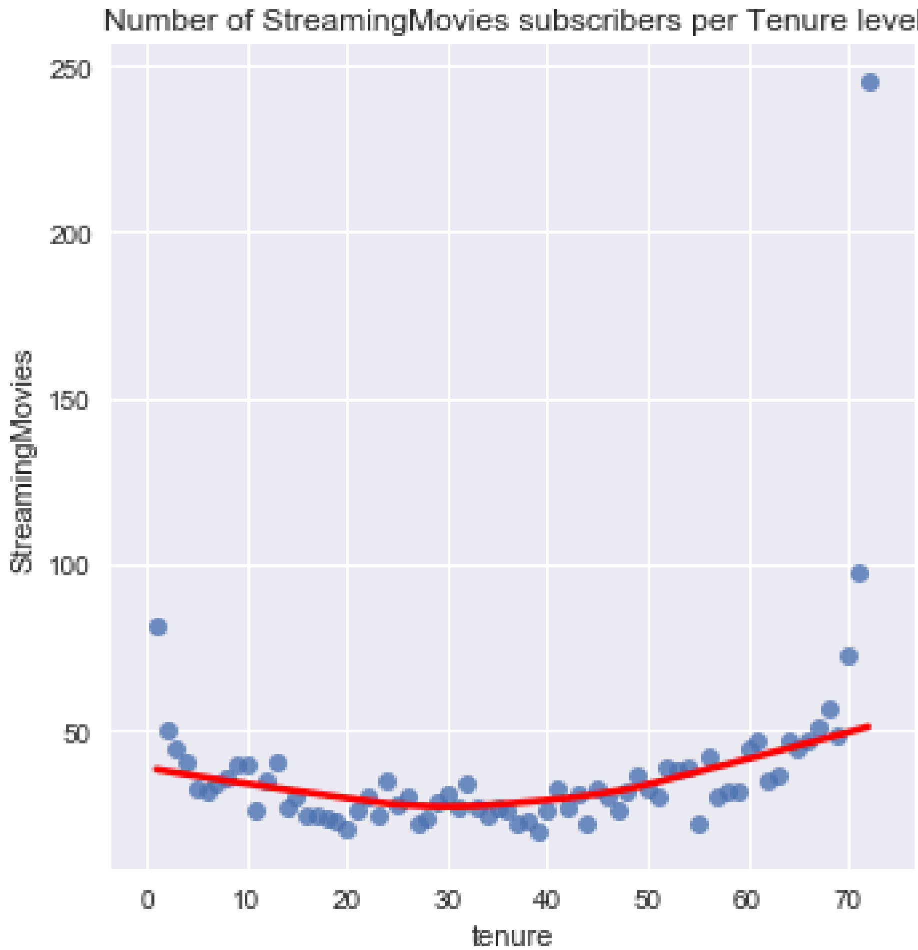



```
In [28]: gb = tcc[(tcc.OnlineSecurity != "No internet service")].replace(["Yes", "No"], [1, 0]).
         sns.lmplot("tenure", "TechSupport", data = gb, line_kws={'color': 'red'}, lowess = True
         ax = plt.gca()
         ax.set_title("Number of TechSupport subscribers per Tenure level");
```


```
In [29]: gb = tcc[(tcc.OnlineSecurity != "No internet service")].replace(["Yes", "No"], [1, 0]).
         sns.lmplot("tenure", "StreamingTV", data = gb, line_kws={'color': 'red'}, lowess = True
         ax = plt.gca()
         ax.set_title("Number of StreamingTV subscribers per Tenure level");
```



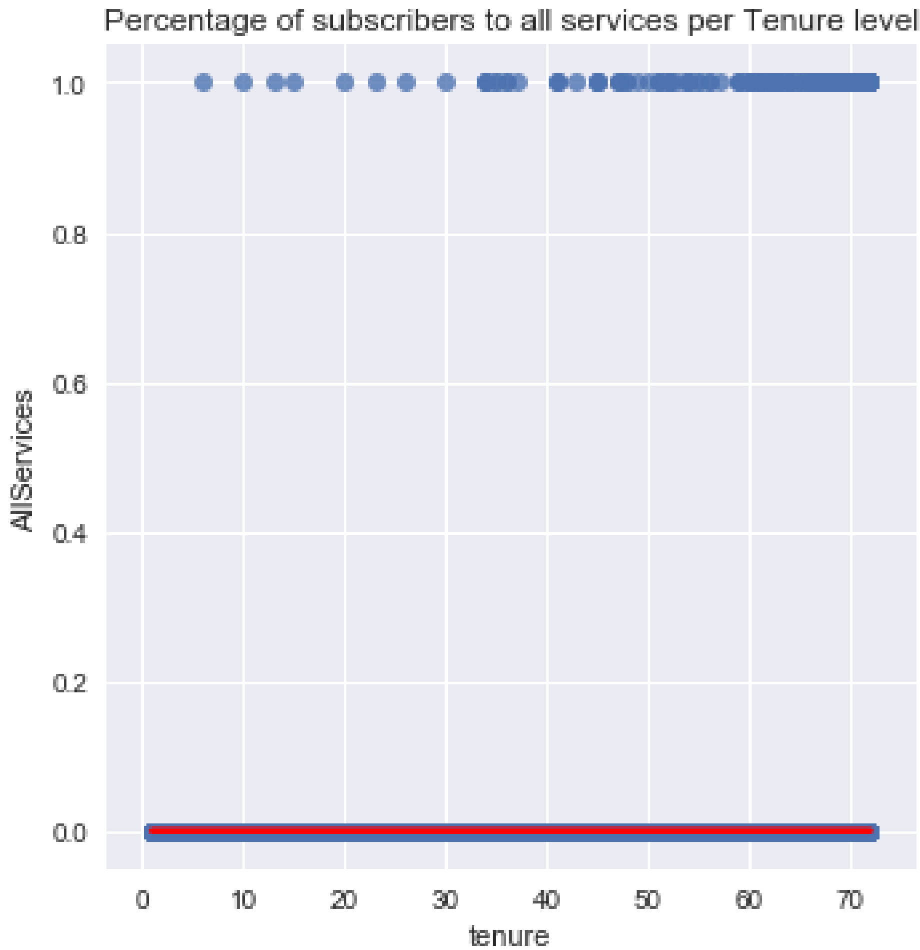

```
In [30]: gb = tcc[(tcc.OnlineSecurity != "No internet service")].replace(["Yes", "No"], [1, 0]).
         sns.lmplot("tenure", "StreamingMovies", data = gb, line_kws={'color': 'red'}, lowess =
         ax = plt.gca()
         ax.set_title("Number of StreamingMovies subscribers per Tenure level");
```



The absolute number of each Additional Service seems to move in syncro with the others as tenure increases. It does not seem that there is any significant correlation between the number of active Additional Services and tenure, although people with borderline tenures have an extremely high number of Additional Services.

It's weird that so many people with high tenures have so many additional services. Is it just that there are many people with maximum tenure although the percentage of additional services across tenure level stays the same? Hypothesis: at the beginning, the company had a launch offer all-included. Let's check the percentages of people that have these services for each tenure level.

```
In [31]: gb = tcc[(tcc.OnlineSecurity != "No internet service")].replace(["Yes", "No"], [1, 0])
         gb["AllServices"] = gb.OnlineSecurity*gb.OnlineBackup*gb.DeviceProtection*gb.TechSuppor
         sns.lmplot("tenure", "AllServices", data = gb, line_kws={'color': 'red'}, lowess = True
         ax = plt.gca()
         ax.set_title("Percentage of subscribers to all services per Tenure level");
```




```
In [32]: tvc = gb.tenure.value_counts()
         i = []
         v = []
         for tenure in tvc.index:
             i.append(tenure)
             v.append(len(gb[(gb.tenure == tenure) & (gb.AllServices == 1)])/len(gb[gb.tenure ==
```

```
In [33]: print(tvc)
         #on the left column there are the various tenure levels that basically is an index list
```

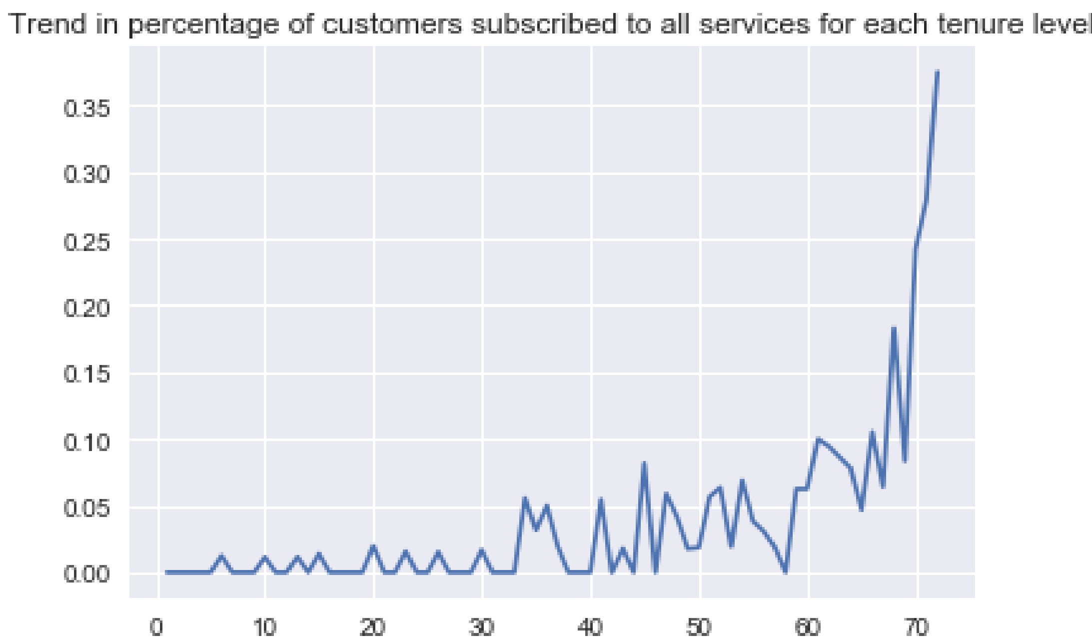
```
1     447
72    296
2     191
3     161
4     138
71    129
5     108
```

7	106
70	99
9	98
8	92
10	87
13	86
12	84
68	82
6	80
67	78
18	76
11	76
66	76
24	72
69	72
15	72
22	69
17	67
26	66
56	65
65	64
60	64
64	64
...	
43	56
31	56
46	56
41	55
25	55
50	54
19	54
34	54
27	54
57	53
51	53
62	53
21	52
55	52
58	52
40	52
53	52
42	51
20	51
37	51
47	51
33	50
28	49
45	49

```
48      48
59      48
39      44
38      43
36      40
44      39
Name: tenure, Length: 72, dtype: int64
```

```
In [34]: df = pd.DataFrame(data = v, index = i, columns = ["%AllServices"]).reset_index().sort_v
         sns.lmplot("tenure", "%AllServices", data = df, line_kws={'color': 'red'}, lowess = Tru
         ax = plt.gca()
         ax.set_title("Percentage of Customers with all Additional Services Active per Tenure le
```


```
In [35]: plt.plot(df.tenure, df["%AllServices"]);
         ax = plt.gca()
         ax.set_title("Trend in percentage of customers subscribed to all services for each tenu
```



Indeed, it seems that the people who subscribed for first have many additional services. Possible explanations: - Launch offer: all additional services forever included at a discounted price. - Selection bias: the first customers are the ones who appreciate the most the services offered by the company.

Either case, the hypothesis that additional services are accumulated through tenure can be dismissed, for two reasons: - There is a strong spike up in the percentage and number of users with all the services around tenure = 70. Nonetheless, the trend in percentage of users with all the services grows constantly, while the absolute number of the individual services stays pretty much constant across tenure levels. This means the the increase in percentage is justifiable only by a convenient launch offer all-inclusive, that rules out the large amount of active offers for customers with extremely high tenure. - if there was a cumulation of benefits, the drop on the 69th tenure value could be hardly justifiable, whereas it could be justified by a change in the offer or a decrease in interest towards the company.

3.2.1 Encoding the dummy variables

```
In [36]: tcc = pd.get_dummies(tcc.iloc[:, 1 :])
         tcc.head()
```

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

            gender_Male  Partner_No  Partner_Yes  Dependents_No  Dependents_Yes  \
```

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

   PhoneService_No  PhoneService_Yes  MultipleLines_No  \
0                1                 0                 0
1                0                 1                 1
2                0                 1                 1
3                1                 0                 0
4                0                 1                 1

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

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

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

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

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

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

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

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

   Contract_Month-to-month  Contract_One year  Contract_Two year  \
0                        1                  0                  0
1                        0                  1                  0
2                        1                  0                  0
3                        0                  1                  0
4                        1                  0                  0

   PaperlessBilling_No  PaperlessBilling_Yes  \
0                    0                     1
1                    1                     0
2                    0                     1
3                    1                     0
4                    0                     1

   PaymentMethod_Bank transfer (automatic)  \
0                                        0
1                                        0
2                                        0
3                                        1
4                                        0

   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  Churn_No  Churn_Yes
0                           0         1          0
1                           1         1          0
2                           1         0          1
3                           0         1          0
4                           0         0          1
```

In [37]:
```python
tcc.dtypes
```

Out[37]:
```
SeniorCitizen                                int64
tenure                                       int64
MonthlyCharges                             float64
TotalCharges                               float64
gender_Female                                uint8
gender_Male                                  uint8
Partner_No                                   uint8
Partner_Yes                                  uint8
Dependents_No                                uint8
Dependents_Yes                               uint8
PhoneService_No                              uint8
PhoneService_Yes                             uint8
MultipleLines_No                             uint8
MultipleLines_No phone service               uint8
MultipleLines_Yes                            uint8
InternetService_DSL                          uint8
InternetService_Fiber optic                  uint8
InternetService_No                           uint8
OnlineSecurity_No                            uint8
OnlineSecurity_No internet service           uint8
OnlineSecurity_Yes                           uint8
OnlineBackup_No                              uint8
OnlineBackup_No internet service             uint8
OnlineBackup_Yes                             uint8
DeviceProtection_No                          uint8
DeviceProtection_No internet service         uint8
DeviceProtection_Yes                         uint8
TechSupport_No                               uint8
TechSupport_No internet service              uint8
TechSupport_Yes                              uint8
StreamingTV_No                               uint8
StreamingTV_No internet service              uint8
StreamingTV_Yes                              uint8
StreamingMovies_No                           uint8
StreamingMovies_No internet service          uint8
StreamingMovies_Yes                          uint8
Contract_Month-to-month                      uint8
Contract_One year                            uint8
```

```
Contract_Two year                              uint8
PaperlessBilling_No                            uint8
PaperlessBilling_Yes                           uint8
PaymentMethod_Bank transfer (automatic)        uint8
PaymentMethod_Credit card (automatic)          uint8
PaymentMethod_Electronic check                 uint8
PaymentMethod_Mailed check                     uint8
Churn_No                                       uint8
Churn_Yes                                      uint8
dtype: object
```

Let's have a look at the variables.

```
In [38]: for col in tcc.columns:
             print("{0}: {1}".format(col, tcc.loc[:, col].unique()))
```

```
SeniorCitizen: [0 1]
tenure: [ 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 39]
MonthlyCharges: [29.85 56.95 53.85 ... 63.1  44.2  78.7 ]
TotalCharges: [  29.85 1889.5   108.15 ...  346.45  306.6  6844.5 ]
gender_Female: [1 0]
gender_Male: [0 1]
Partner_No: [0 1]
Partner_Yes: [1 0]
Dependents_No: [1 0]
Dependents_Yes: [0 1]
PhoneService_No: [1 0]
PhoneService_Yes: [0 1]
MultipleLines_No: [0 1]
MultipleLines_No phone service: [1 0]
MultipleLines_Yes: [0 1]
InternetService_DSL: [1 0]
InternetService_Fiber optic: [0 1]
InternetService_No: [0 1]
OnlineSecurity_No: [1 0]
OnlineSecurity_No internet service: [0 1]
OnlineSecurity_Yes: [0 1]
OnlineBackup_No: [0 1]
OnlineBackup_No internet service: [0 1]
OnlineBackup_Yes: [1 0]
DeviceProtection_No: [1 0]
DeviceProtection_No internet service: [0 1]
DeviceProtection_Yes: [0 1]
TechSupport_No: [1 0]
TechSupport_No internet service: [0 1]
TechSupport_Yes: [0 1]
```

```
StreamingTV_No: [1 0]
StreamingTV_No internet service: [0 1]
StreamingTV_Yes: [0 1]
StreamingMovies_No: [1 0]
StreamingMovies_No internet service: [0 1]
StreamingMovies_Yes: [0 1]
Contract_Month-to-month: [1 0]
Contract_One year: [0 1]
Contract_Two year: [0 1]
PaperlessBilling_No: [0 1]
PaperlessBilling_Yes: [1 0]
PaymentMethod_Bank transfer (automatic): [0 1]
PaymentMethod_Credit card (automatic): [0 1]
PaymentMethod_Electronic check: [1 0]
PaymentMethod_Mailed check: [0 1]
Churn_No: [1 0]
Churn_Yes: [0 1]
```

3.3 Logistic regression

I want to build a predictive model using *Churn* as dependent variable. First let's run the regression by including all the variables.

```
In [39]: tcc.columns
```

```
Out[39]: Index(['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges',
                'gender_Female', 'gender_Male', 'Partner_No', 'Partner_Yes',
                'Dependents_No', 'Dependents_Yes', 'PhoneService_No',
                'PhoneService_Yes', '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', 'PaperlessBilling_No', 'PaperlessBilling_Yes',
                'PaymentMethod_Bank transfer (automatic)',
                'PaymentMethod_Credit card (automatic)',
                'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check',
                'Churn_No', 'Churn_Yes'],
               dtype='object')
```

Most of the variables differentiate between "No" and "No internet service". Given that the information about "Internet Service" or "No internet service" is already provided by the variable *InternetService*, we can just analyze the impact of having a service that implies having Internet Service versus not having it, without considering that a person could have for example no OnlineSecurity due to the fact that they do not have Internet Service.

TotalCharges can also be excluded from the model, since it is likely to be correlated with *MonthlyCharges* (I am going to test this hypothesis by calculating the Pearson correlation coefficient).

```
In [40]: # Pearson correlation coefficient
         print("Coefficient:",scipy.stats.pearsonr(tcc["MonthlyCharges"], tcc["TotalCharges"])[0
         print("p-value:",scipy.stats.pearsonr(tcc["MonthlyCharges"], tcc["TotalCharges"])[1])
```

```
Coefficient: 0.6510648032262024
p-value: 0.0
```

The two variables are highly correlated.

```
In [41]: tcc.head()
```

```
Out[41]:    SeniorCitizen  tenure  MonthlyCharges  TotalCharges  gender_Female  \
         0              0       1           29.85         29.85              1
         1              0      34           56.95       1889.50              0
         2              0       2           53.85        108.15              0
         3              0      45           42.30       1840.75              0
         4              0       2           70.70        151.65              1

            gender_Male  Partner_No  Partner_Yes  Dependents_No  Dependents_Yes  \
         0            0           0            1              1               0
         1            1           1            0              1               0
         2            1           1            0              1               0
         3            1           1            0              1               0
         4            0           1            0              1               0

            PhoneService_No  PhoneService_Yes  MultipleLines_No  \
         0                1                 0                 0
         1                0                 1                 1
         2                0                 1                 1
         3                1                 0                 0
         4                0                 1                 1

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

            InternetService_Fiber optic  InternetService_No  OnlineSecurity_No  \
```

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

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

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

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

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

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

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

```
   Contract_Month-to-month  Contract_One year  Contract_Two year  \
0                        1                  0                  0
1                        0                  1                  0
2                        1                  0                  0
3                        0                  1                  0
4                        1                  0                  0

   PaperlessBilling_No  PaperlessBilling_Yes  \
0                    0                     1
1                    1                     0
2                    0                     1
3                    1                     0
4                    0                     1

   PaymentMethod_Bank transfer (automatic)  \
0                                        0
1                                        0
2                                        0
3                                        1
4                                        0

   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  Churn_No  Churn_Yes
0                           0         1          0
1                           1         1          0
2                           1         0          1
3                           0         1          0
4                           0         0          1
```

Let's run a first regression including all the variables, and then progressively improve the model.

In [42]:
```
# Intercept
tcc["intercept"] = 1.0

variables = tcc.copy()[['SeniorCitizen', 'tenure', 'MonthlyCharges',
       'gender_Female', 'Partner_Yes', 'PhoneService_Yes',
        'Dependents_Yes', 'MultipleLines_Yes',
       'InternetService_DSL', 'InternetService_Fiber optic', 'OnlineSecurity_Yes',
        'OnlineBackup_Yes', 'DeviceProtection_Yes', 'TechSupport_Yes', 'StreamingTV_Yes
       'StreamingMovies_Yes', 'Contract_One year', 'Contract_Two year', 'PaperlessBilli
       'PaymentMethod_Bank transfer (automatic)', 'PaymentMethod_Credit card (automatic
```

```python
           'PaymentMethod_Electronic check', 'intercept']]

# Setting the model
logistical_regression = sm.Logit(tcc["Churn_Yes"], variables)

# Fitting the model
fitted_model = logistical_regression.fit()
fitted_model.summary2()
```

```
Optimization terminated successfully.
         Current function value: inf
         Iterations 8
```

Out[42]:

```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                                     Results: Logit
=====================================================================================
Model:                   Logit                       Pseudo R-squared:         inf
Dependent Variable:      Churn_Yes                   AIC:                      inf
Date:                    2021-04-18 15:13            BIC:                      inf
No. Observations:        7032                        Log-Likelihood:           -inf
Df Model:                22                          LL-Null:                  0.000
Df Residuals:            7009                        LLR p-value:              1.000
Converged:               1.0000                      Scale:                    1.000
No. Iterations:          8.0000
-------------------------------------------------------------------------------------
                                        Coef.  Std.Err.    z     P>|z|   [0.025  0.975
-------------------------------------------------------------------------------------
SeniorCitizen                          0.2181   0.0849   2.5680 0.0102  0.0516  0.384
tenure                                -0.0344   0.0024 -14.4672 0.0000 -0.0390 -0.029
MonthlyCharges                        -0.0325   0.0320  -1.0181 0.3086 -0.0952  0.030
gender_Female                          0.0206   0.0649   0.3168 0.7514 -0.1066  0.147
Partner_Yes                           -0.0010   0.0778  -0.0127 0.9899 -0.1534  0.151
PhoneService_Yes                       0.1601   0.6531   0.2451 0.8063 -1.1200  1.440
Dependents_Yes                        -0.1640   0.0897  -1.8290 0.0674 -0.3398  0.011
MultipleLines_Yes                      0.4641   0.1782   2.6039 0.0092  0.1148  0.813
InternetService_DSL                    1.6163   0.8125   1.9892 0.0467  0.0238  3.208
InternetService_Fiber optic            3.3322   1.6057   2.0753 0.0380  0.1852  6.479
OnlineSecurity_Yes                    -0.1992   0.1798  -1.1077 0.2680 -0.5515  0.153
OnlineBackup_Yes                       0.0509   0.1764   0.2884 0.7730 -0.2949  0.396
DeviceProtection_Yes                   0.1629   0.1774   0.9182 0.3585 -0.1848  0.510
TechSupport_Yes                       -0.1695   0.1817  -0.9328 0.3509 -0.5257  0.186
StreamingTV_Yes                        0.5936   0.3287   1.8061 0.0709 -0.0506  1.237
StreamingMovies_Yes                    0.6057   0.3291   1.8404 0.0657 -0.0394  1.250
Contract_One year                     -0.6625   0.1067  -6.2088 0.0000 -0.8716 -0.453
Contract_Two year                     -1.3350   0.1745  -7.6498 0.0000 -1.6771 -0.993
PaperlessBilling_Yes                   0.3360   0.0743   4.5228 0.0000  0.1904  0.481
```

```
PaymentMethod_Bank transfer (automatic)  0.0048   0.1137   0.0424 0.9662 -0.2181  0.227
PaymentMethod_Credit card (automatic)   -0.0827   0.1154  -0.7160 0.4740 -0.3089  0.143
PaymentMethod_Electronic check           0.3184   0.0956   3.3327 0.0009  0.1312  0.505
intercept                               -1.0317   0.1754  -5.8805 0.0000 -1.3755 -0.687
==========================================================================================

"""
```

To improve results' goodness *PaymentMethod* can be transformed in order to analyze the difference between automatic Payment Method and non automatic. Clients with automatic payment are less likely to churn with respect to clients with no automatic payment. I am not interested in the difference between Bank transfer and Credit card, or between Electronic check or Mailed check.

```
In [43]: # Transforming PaymentMethod
         tcc["PaymentMethod_Automatic"] = tcc["PaymentMethod_Bank transfer (automatic)"] + tcc["

In [44]: variables = tcc[['SeniorCitizen', 'tenure', 'MonthlyCharges',
                'gender_Female', 'Partner_Yes',
                 'Dependents_Yes', 'MultipleLines_Yes',
                'InternetService_DSL', 'InternetService_Fiber optic', 'OnlineSecurity_Yes',
                 'OnlineBackup_Yes', 'DeviceProtection_Yes', 'TechSupport_Yes', 'StreamingTV_Yes
                'StreamingMovies_Yes', 'Contract_One year', 'Contract_Two year', 'PaperlessBilli
                'PaymentMethod_Automatic', 'intercept']]

         # Setting the model
         logistical_regression = sm.Logit(tcc["Churn_Yes"], variables)

         # Fitting the model
         fitted_model = logistical_regression.fit()
         fitted_model.summary2()

Optimization terminated successfully.
         Current function value: inf
         Iterations 8


Out[44]: <class 'statsmodels.iolib.summary2.Summary'>
         """
                                   Results: Logit
         ===========================================================================
         Model:                   Logit                 Pseudo R-squared:    inf
         Dependent Variable:      Churn_Yes             AIC:                 inf
         Date:                    2021-04-18 15:13      BIC:                 inf
         No. Observations:        7032                  Log-Likelihood:      -inf
         Df Model:                19                    LL-Null:             0.0000
         Df Residuals:            7012                  LLR p-value:         1.0000
         Converged:               1.0000                Scale:               1.0000
         No. Iterations:          8.0000
```

```
--------------------------------------------------------------------------
                            Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
--------------------------------------------------------------------------
SeniorCitizen               0.2324   0.0847   2.7452 0.0060  0.0665  0.3984
tenure                     -0.0340   0.0024 -14.3208 0.0000 -0.0386 -0.0293
MonthlyCharges             -0.0256   0.0062  -4.1323 0.0000 -0.0377 -0.0134
gender_Female               0.0245   0.0648   0.3779 0.7055 -0.1025  0.1514
Partner_Yes                 0.0106   0.0775   0.1363 0.8916 -0.1414  0.1625
Dependents_Yes             -0.1729   0.0895  -1.9323 0.0533 -0.3483  0.0025
MultipleLines_Yes           0.4368   0.0901   4.8478 0.0000  0.2602  0.6134
InternetService_DSL         1.5185   0.1728   8.7856 0.0000  1.1797  1.8573
InternetService_Fiber optic 3.1091   0.3360   9.2538 0.0000  2.4506  3.7676
OnlineSecurity_Yes         -0.2464   0.0909  -2.7109 0.0067 -0.4245 -0.0682
OnlineBackup_Yes            0.0147   0.0819   0.1798 0.8573 -0.1458  0.1753
DeviceProtection_Yes        0.1224   0.0838   1.4603 0.1442 -0.0419  0.2868
TechSupport_Yes            -0.2221   0.0920  -2.4149 0.0157 -0.4023 -0.0418
StreamingTV_Yes             0.5393   0.0993   5.4299 0.0000  0.3447  0.7340
StreamingMovies_Yes         0.5515   0.0983   5.6088 0.0000  0.3588  0.7442
Contract_One year          -0.6807   0.1065  -6.3886 0.0000 -0.8895 -0.4718
Contract_Two year          -1.3595   0.1742  -7.8046 0.0000 -1.7009 -1.0181
PaperlessBilling_Yes        0.3526   0.0740   4.7640 0.0000  0.2075  0.4976
PaymentMethod_Automatic    -0.2634   0.0725  -3.6356 0.0003 -0.4055 -0.1214
intercept                  -0.9218   0.1699  -5.4251 0.0000 -1.2548 -0.5888
==========================================================================

"""
```

Now, remove from the model *OnlineBackup*, *DeviceProtection*, *gender* and *partner* as they are not significant.

```
In [45]: variables = tcc[['SeniorCitizen', 'tenure', 'MonthlyCharges',
                 'Dependents_Yes', 'MultipleLines_Yes',
                'InternetService_DSL', 'InternetService_Fiber optic', 'OnlineSecurity_Yes',
                 'TechSupport_Yes', 'StreamingTV_Yes',
                'StreamingMovies_Yes', 'Contract_One year', 'Contract_Two year', 'PaperlessBilli
                'PaymentMethod_Automatic', 'intercept']]

         # Setting the model
         logistical_regression = sm.Logit(tcc["Churn_Yes"], variables)

         # Fitting the model
         fitted_model = logistical_regression.fit()
         fitted_model.summary2()

Optimization terminated successfully.
         Current function value: inf
         Iterations 8
```

```
Out[45]: <class 'statsmodels.iolib.summary2.Summary'>
"""
                                    Results: Logit
==============================================================================
Model:                   Logit                  Pseudo R-squared:     inf
Dependent Variable:      Churn_Yes              AIC:                  inf
Date:                    2021-04-18 15:13       BIC:                  inf
No. Observations:        7032                   Log-Likelihood:       -inf
Df Model:                15                     LL-Null:              0.0000
Df Residuals:            7016                   LLR p-value:          1.0000
Converged:               1.0000                 Scale:                1.0000
No. Iterations:          8.0000
------------------------------------------------------------------------------
                             Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
------------------------------------------------------------------------------
SeniorCitizen                0.2369   0.0841   2.8167 0.0049  0.0721  0.4017
tenure                      -0.0334   0.0022 -14.9806 0.0000 -0.0377 -0.0290
MonthlyCharges              -0.0223   0.0054  -4.1124 0.0000 -0.0330 -0.0117
Dependents_Yes              -0.1685   0.0812  -2.0754 0.0379 -0.3276 -0.0094
MultipleLines_Yes            0.4121   0.0873   4.7226 0.0000  0.2411  0.5831
InternetService_DSL          1.4781   0.1696   8.7163 0.0000  1.1457  1.8105
InternetService_Fiber optic  2.9706   0.3111   9.5479 0.0000  2.3608  3.5804
OnlineSecurity_Yes          -0.2644   0.0895  -2.9551 0.0031 -0.4398 -0.0890
TechSupport_Yes             -0.2333   0.0911  -2.5598 0.0105 -0.4119 -0.0547
StreamingTV_Yes              0.5206   0.0966   5.3908 0.0000  0.3313  0.7098
StreamingMovies_Yes          0.5337   0.0955   5.5890 0.0000  0.3465  0.7208
Contract_One year           -0.6715   0.1063  -6.3159 0.0000 -0.8799 -0.4631
Contract_Two year           -1.3458   0.1739  -7.7372 0.0000 -1.6867 -1.0049
PaperlessBilling_Yes         0.3517   0.0739   4.7563 0.0000  0.2067  0.4966
PaymentMethod_Automatic     -0.2607   0.0724  -3.6008 0.0003 -0.4026 -0.1188
intercept                   -0.9820   0.1522  -6.4529 0.0000 -1.2803 -0.6837
==============================================================================

"""
```

To improve regression interpretability, instead of considering *tenure* as a continuous variable, let's divide it into 4 clusters.

```
In [46]: tcc["tenure"].describe()
```

```
Out[46]: count    7032.000000
         mean       32.421786
         std        24.545260
         min         1.000000
         25%         9.000000
         50%        29.000000
         75%        55.000000
         max        72.000000
         Name: tenure, dtype: float64
```

In [47]:
```
tcc["tenure_0:18"]  = 0
tcc["tenure_19:36"] = 0
tcc["tenure_37:54"] = 0
tcc["tenure_55:72"] = 0

tcc.loc[tcc.tenure <= 18, "tenure_0:18"] = 1
tcc.loc[((tcc.tenure >= 19) & (tcc.tenure <= 36)), "tenure_19:36"] = 1
tcc.loc[((tcc.tenure >= 37) & (tcc.tenure <= 54)), "tenure_37:54"] = 1
tcc.loc[tcc.tenure >= 55, "tenure_55:72"] = 1
```

In [48]:
```
tcc.head()
```

Out[48]:
```
   SeniorCitizen  tenure  MonthlyCharges  TotalCharges  gender_Female  \
0              0       1           29.85         29.85              1
1              0      34           56.95       1889.50              0
2              0       2           53.85        108.15              0
3              0      45           42.30       1840.75              0
4              0       2           70.70        151.65              1

   gender_Male  Partner_No  Partner_Yes  Dependents_No  Dependents_Yes  \
0            0           0            1              1               0
1            1           1            0              1               0
2            1           1            0              1               0
3            1           1            0              1               0
4            0           1            0              1               0

   PhoneService_No  PhoneService_Yes  MultipleLines_No  \
0                1                 0                 0
1                0                 1                 1
2                0                 1                 1
3                1                 0                 0
4                0                 1                 1

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

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

   OnlineSecurity_No internet service  OnlineSecurity_Yes  OnlineBackup_No  \
```

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

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

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

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

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

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

   Contract_Month-to-month  Contract_One year  Contract_Two year  \
0                        1                  0                  0
1                        0                  1                  0
2                        1                  0                  0
3                        0                  1                  0
4                        1                  0                  0
```

```
   PaperlessBilling_No  PaperlessBilling_Yes  \
0                    0                     1
1                    1                     0
2                    0                     1
3                    1                     0
4                    0                     1

   PaymentMethod_Bank transfer (automatic)  \
0                                        0
1                                        0
2                                        0
3                                        1
4                                        0

   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  Churn_No  Churn_Yes  intercept  \
0                           0         1          0        1.0
1                           1         1          0        1.0
2                           1         0          1        1.0
3                           0         1          0        1.0
4                           0         0          1        1.0

   PaymentMethod_Automatic  tenure_0:18  tenure_19:36  tenure_37:54  \
0                        0            1             0             0
1                        0            0             1             0
2                        0            1             0             0
3                        1            0             0             1
4                        0            1             0             0

   tenure_55:72
0             0
1             0
2             0
3             0
4             0
```

In [49]: tcc.columns

```
Out[49]: Index(['SeniorCitizen', 'tenure', 'MonthlyCharges', 'TotalCharges',
       'gender_Female', 'gender_Male', 'Partner_No', 'Partner_Yes',
       'Dependents_No', 'Dependents_Yes', 'PhoneService_No',
       'PhoneService_Yes', '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', 'PaperlessBilling_No', 'PaperlessBilling_Yes',
               'PaymentMethod_Bank transfer (automatic)',
               'PaymentMethod_Credit card (automatic)',
               'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check',
               'Churn_No', 'Churn_Yes', 'intercept', 'PaymentMethod_Automatic',
               'tenure_0:18', 'tenure_19:36', 'tenure_37:54', 'tenure_55:72'],
              dtype='object')
```

Let's run a new regression.

```
In [50]: variables = tcc[['SeniorCitizen', 'MonthlyCharges',
                'Dependents_Yes', 'MultipleLines_Yes',
               'InternetService_DSL', 'InternetService_Fiber optic', 'OnlineSecurity_Yes',
                'TechSupport_Yes', 'StreamingTV_Yes',
               'StreamingMovies_Yes', 'Contract_One year', 'Contract_Two year', 'PaperlessBilli
               'PaymentMethod_Automatic', 'tenure_19:36',
               'tenure_37:54', 'tenure_55:72','intercept']]

         # Setting the model
         logistical_regression = sm.Logit(tcc["Churn_Yes"], variables)

         # Fitting the model
         fitted_model = logistical_regression.fit()
         fitted_model.summary2()

Optimization terminated successfully.
         Current function value: inf
         Iterations 8


Out[50]: <class 'statsmodels.iolib.summary2.Summary'>
         """
                                    Results: Logit
         ============================================================================
         Model:                   Logit                 Pseudo R-squared:      inf
         Dependent Variable:      Churn_Yes             AIC:                   inf
         Date:                    2021-04-18 15:13      BIC:                   inf
         No. Observations:        7032                  Log-Likelihood:        -inf
```

```
Df Model:               17               LL-Null:              0.0000
Df Residuals:           7014             LLR p-value:          1.0000
Converged:              1.0000           Scale:                1.0000
No. Iterations:         8.0000
---------------------------------------------------------------------------
                             Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
---------------------------------------------------------------------------
SeniorCitizen                0.2163   0.0834   2.5939 0.0095  0.0529  0.3796
MonthlyCharges              -0.0241   0.0054  -4.4338 0.0000 -0.0347 -0.0134
Dependents_Yes              -0.1773   0.0810  -2.1888 0.0286 -0.3361 -0.0185
MultipleLines_Yes            0.3552   0.0870   4.0819 0.0000  0.1846  0.5257
InternetService_DSL          1.5124   0.1692   8.9363 0.0000  1.1807  1.8441
InternetService_Fiber optic  3.0432   0.3113   9.7772 0.0000  2.4331  3.6532
OnlineSecurity_Yes          -0.2995   0.0891  -3.3616 0.0008 -0.4741 -0.1249
TechSupport_Yes             -0.2273   0.0911  -2.4962 0.0126 -0.4058 -0.0488
StreamingTV_Yes              0.5093   0.0965   5.2785 0.0000  0.3202  0.6984
StreamingMovies_Yes          0.5195   0.0953   5.4515 0.0000  0.3327  0.7063
Contract_One year           -0.8226   0.1058  -7.7771 0.0000 -1.0299 -0.6153
Contract_Two year           -1.6991   0.1763  -9.6352 0.0000 -2.0447 -1.3535
PaperlessBilling_Yes         0.3442   0.0739   4.6567 0.0000  0.1993  0.4891
PaymentMethod_Automatic     -0.3071   0.0720  -4.2664 0.0000 -0.4481 -0.1660
tenure_19:36                -1.0302   0.0917 -11.2343 0.0000 -1.2099 -0.8505
tenure_37:54                -1.0475   0.1087  -9.6389 0.0000 -1.2605 -0.8345
tenure_55:72                -1.4846   0.1336 -11.1100 0.0000 -1.7465 -1.2227
intercept                   -1.0397   0.1527  -6.8065 0.0000 -1.3391 -0.7403
===========================================================================

"""
```

Let's calculate the Variance Inflation Factor to see if there is multicollinearity among variables.

In [51]:
```python
vif = pd.DataFrame()
vif["Variables"]  = variables.columns[0:-1]
vif["VIF Factor"] = [variance_inflation_factor(variables.values, i) for i in range(vari
vif
```

Out[51]:

	Variables	VIF Factor
0	SeniorCitizen	1.136310
1	MonthlyCharges	25.813526
2	Dependents_Yes	1.113071
3	MultipleLines_Yes	1.783075
4	InternetService_DSL	6.105011
5	InternetService_Fiber optic	22.929960
6	OnlineSecurity_Yes	1.612586
7	TechSupport_Yes	1.696227
8	StreamingTV_Yes	2.326602
9	StreamingMovies_Yes	2.298974
10	Contract_One year	1.592891

```
11             Contract_Two year    2.515315
12          PaperlessBilling_Yes    1.202396
13       PaymentMethod_Automatic    1.194147
14                  tenure_19:36    1.354482
15                  tenure_37:54    1.597842
16                  tenure_55:72    2.727589
```

The two *InternetService* variables have a high VIF, along with *MonthlyCharges*. A possible explanation is that customers who have the Optic Fiber connection pay a different price compared to those who have a DSL connection. For this reason, it's advisable excluding *MonthlyCharges* , and then re-run VIF analysis. I should expect a low VIF for both *InternetService* variables.

I am also going to re-insert in our regression *OnlineBackup* and *DeviceProtection*, which were removed earlier on, as they might have been affected by multicollinearity.

```
In [52]: variables = tcc[['SeniorCitizen',
                 'Dependents_Yes', 'MultipleLines_Yes',
                  'InternetService_DSL', 'InternetService_Fiber optic', 'OnlineSecurity_Yes',
                 'TechSupport_Yes', "OnlineBackup_Yes", "DeviceProtection_Yes", 'StreamingTV_Yes
                'StreamingMovies_Yes', 'Contract_One year', 'Contract_Two year', 'PaperlessBilli
                'PaymentMethod_Automatic', 'tenure_19:36',
                'tenure_37:54', 'tenure_55:72','intercept']]

         vif = pd.DataFrame()
         vif["Variables"]  = variables.columns[0:-1]
         vif["VIF Factor"] = [variance_inflation_factor(variables.values, i) for i in range(vari
         vif
```

```
Out[52]:                     Variables  VIF Factor
         0               SeniorCitizen    1.135121
         1              Dependents_Yes    1.113321
         2           MultipleLines_Yes    1.318733
         3         InternetService_DSL    3.179673
         4 InternetService_Fiber optic    3.832837
         5          OnlineSecurity_Yes    1.398430
         6             TechSupport_Yes    1.469348
         7            OnlineBackup_Yes    1.368252
         8        DeviceProtection_Yes    1.473568
         9             StreamingTV_Yes    1.619436
         10        StreamingMovies_Yes    1.625435
         11          Contract_One year    1.599506
         12          Contract_Two year    2.533654
         13       PaperlessBilling_Yes    1.203220
         14    PaymentMethod_Automatic    1.194569
         15               tenure_19:36    1.363429
         16               tenure_37:54    1.632503
         17               tenure_55:72    2.849949
```

Indeed, data proves that *MonthlyCharges* greatly depend on *InternetService*.

Now, let's just run the logistic regression as before, this time without *MonthlyCharges*.

In [53]:
```python
# Setting the model
logistical_regression = sm.Logit(tcc["Churn_Yes"], variables)

# Fitting the model
fitted_model = logistical_regression.fit()
fitted_model.summary2()
```

```
Optimization terminated successfully.
         Current function value: inf
         Iterations 8
```

Out[53]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                              Results: Logit
===========================================================================
Model:                  Logit                Pseudo R-squared:    inf
Dependent Variable:     Churn_Yes            AIC:                 inf
Date:                   2021-04-18 15:13     BIC:                 inf
No. Observations:       7032                 Log-Likelihood:      -inf
Df Model:               18                   LL-Null:             0.0000
Df Residuals:           7013                 LLR p-value:         1.0000
Converged:              1.0000               Scale:               1.0000
No. Iterations:         8.0000
---------------------------------------------------------------------------
                             Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
---------------------------------------------------------------------------
SeniorCitizen                0.2338   0.0832   2.8099 0.0050  0.0707  0.3969
Dependents_Yes              -0.1817   0.0809  -2.2450 0.0248 -0.3403 -0.0231
MultipleLines_Yes            0.1766   0.0758   2.3286 0.0199  0.0280  0.3253
InternetService_DSL          1.0621   0.1289   8.2382 0.0000  0.8094  1.3148
InternetService_Fiber optic  1.8412   0.1319  13.9622 0.0000  1.5827  2.0997
OnlineSecurity_Yes          -0.4312   0.0836  -5.1581 0.0000 -0.5951 -0.2674
TechSupport_Yes             -0.3674   0.0848  -4.3324 0.0000 -0.5336 -0.2012
OnlineBackup_Yes            -0.1853   0.0755  -2.4526 0.0142 -0.3333 -0.0372
DeviceProtection_Yes        -0.0451   0.0778  -0.5794 0.5623 -0.1977  0.1075
StreamingTV_Yes              0.2713   0.0790   3.4331 0.0006  0.1164  0.4262
StreamingMovies_Yes          0.2865   0.0787   3.6384 0.0003  0.1322  0.4409
Contract_One year           -0.8431   0.1061  -7.9492 0.0000 -1.0510 -0.6353
Contract_Two year           -1.7148   0.1770  -9.6876 0.0000 -2.0617 -1.3679
PaperlessBilling_Yes         0.3531   0.0738   4.7835 0.0000  0.2084  0.4977
PaymentMethod_Automatic     -0.3130   0.0719  -4.3524 0.0000 -0.4539 -0.1720
tenure_19:36                -1.0103   0.0920 -10.9763 0.0000 -1.1907 -0.8299
tenure_37:54                -1.0075   0.1107  -9.0988 0.0000 -1.2246 -0.7905
tenure_55:72                -1.4340   0.1375 -10.4319 0.0000 -1.7035 -1.1646
intercept                   -1.5151   0.1121 -13.5117 0.0000 -1.7348 -1.2953
===========================================================================

"""
```

OnlineBackup is now significant, whereas *DeviceProtection* stays unsignificant. So the latter can be removed from the model.

```
In [54]: variables = tcc[['SeniorCitizen',
                 'Dependents_Yes', 'MultipleLines_Yes',
                  'InternetService_DSL', 'InternetService_Fiber optic', 'OnlineSecurity_Yes',
                 'TechSupport_Yes', "OnlineBackup_Yes", 'StreamingTV_Yes',
                'StreamingMovies_Yes', 'Contract_One year', 'Contract_Two year', 'PaperlessBilli
                'PaymentMethod_Automatic', 'tenure_19:36',
                'tenure_37:54', 'tenure_55:72','intercept']]

         # Setting the model
         logistical_regression = sm.Logit(tcc["Churn_Yes"], variables)

         # Fitting the model
         fitted_model = logistical_regression.fit()
         fitted_model.summary2()
```

```
Optimization terminated successfully.
         Current function value: inf
         Iterations 8
```

```
Out[54]: <class 'statsmodels.iolib.summary2.Summary'>
         """
                                       Results: Logit
         ============================================================================
         Model:                   Logit                  Pseudo R-squared:     inf
         Dependent Variable:      Churn_Yes              AIC:                  inf
         Date:                    2021-04-18 15:13       BIC:                  inf
         No. Observations:        7032                   Log-Likelihood:       -inf
         Df Model:                17                     LL-Null:              0.0000
         Df Residuals:            7014                   LLR p-value:          1.0000
         Converged:               1.0000                 Scale:                1.0000
         No. Iterations:          8.0000
         ----------------------------------------------------------------------------
                                     Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
         ----------------------------------------------------------------------------
         SeniorCitizen               0.2334   0.0832   2.8057 0.0050  0.0704  0.3965
         Dependents_Yes             -0.1819   0.0809  -2.2476 0.0246 -0.3405 -0.0233
         MultipleLines_Yes           0.1762   0.0758   2.3234 0.0202  0.0276  0.3249
         InternetService_DSL         1.0541   0.1282   8.2235 0.0000  0.8029  1.3054
         InternetService_Fiber optic 1.8322   0.1310  13.9916 0.0000  1.5756  2.0889
         OnlineSecurity_Yes         -0.4310   0.0836  -5.1557 0.0000 -0.5948 -0.2671
         TechSupport_Yes            -0.3706   0.0846  -4.3795 0.0000 -0.5364 -0.2047
         OnlineBackup_Yes           -0.1864   0.0755  -2.4685 0.0136 -0.3344 -0.0384
         StreamingTV_Yes             0.2662   0.0785   3.3903 0.0007  0.1123  0.4200
         StreamingMovies_Yes         0.2812   0.0782   3.5963 0.0003  0.1280  0.4345
```

```
Contract_One year          -0.8483   0.1057  -8.0254 0.0000 -1.0555 -0.6412
Contract_Two year          -1.7220   0.1766  -9.7507 0.0000 -2.0681 -1.3759
PaperlessBilling_Yes        0.3538   0.0738   4.7938 0.0000  0.2091  0.4984
PaymentMethod_Automatic    -0.3145   0.0719  -4.3764 0.0000 -0.4553 -0.1736
tenure_19:36               -1.0135   0.0919 -11.0306 0.0000 -1.1935 -0.8334
tenure_37:54               -1.0141   0.1102  -9.2040 0.0000 -1.2300 -0.7981
tenure_55:72               -1.4425   0.1367 -10.5496 0.0000 -1.7105 -1.1745
intercept                  -1.5123   0.1120 -13.5003 0.0000 -1.7319 -1.2928
=============================================================================

"""
```

THIS IS THE FINAL MODEL. Let's get the marginal effect of the variables in order to be able to easily interpret them.

In [55]:
```
margeff = fitted_model.get_margeff()
margeff.summary()
```

Out[55]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
        Logit Marginal Effects
=====================================
Dep. Variable:              Churn_Yes
Method:                          dydx
At:                           overall
==================================================================================
                                dy/dx    std err          z      P>|z|      [0.025
----------------------------------------------------------------------------------
SeniorCitizen                  0.0321      0.011      2.813      0.005       0.010
Dependents_Yes                -0.0250      0.011     -2.250      0.024      -0.047
MultipleLines_Yes              0.0242      0.010      2.327      0.020       0.004
InternetService_DSL            0.1447      0.017      8.372      0.000       0.111
InternetService_Fiber optic    0.2516      0.017     14.835      0.000       0.218
OnlineSecurity_Yes            -0.0592      0.011     -5.196      0.000      -0.082
TechSupport_Yes               -0.0509      0.012     -4.406      0.000      -0.074
OnlineBackup_Yes              -0.0256      0.010     -2.474      0.013      -0.046
StreamingTV_Yes                0.0365      0.011      3.400      0.001       0.015
StreamingMovies_Yes            0.0386      0.011      3.609      0.000       0.018
Contract_One year             -0.1165      0.014     -8.141      0.000      -0.145
Contract_Two year             -0.2365      0.024     -9.809      0.000      -0.284
PaperlessBilling_Yes           0.0486      0.010      4.826      0.000       0.029
PaymentMethod_Automatic       -0.0432      0.010     -4.400      0.000      -0.062
tenure_19:36                  -0.1392      0.012    -11.459      0.000      -0.163
tenure_37:54                  -0.1392      0.015     -9.461      0.000      -0.168
tenure_55:72                  -0.1981      0.018    -10.933      0.000      -0.234
==================================================================================
"""
```

Results: - Both *InternetService* variables present a positive impact on the churn rate, with Optic Fiber's being almost twice the of DSL's. It might be a good idea to consider discontinuing at least the Optic Fiber service or improving it. - Senior customers tend to churn more easily. - Additional Internet Services (*OnlineSecurity*, *TechSupport*, *OnlineBackup*) negatively affect Churn Rate and are therefore a potential way to decrease it in a managerial setting. *DeviceProtection* on the other hand is inconsistent with plottings, and it appears that its effect is largely explained by the other variables of the model. *StreamingMovies* and *StreamingTV* are significant and positively affect the Churn Rate: the management might consider stop offering those services.

4 Concluding thoughts

Many companies are diverting resources away from the goal of capturing new customers and are instead focusing on retaining the existing ones. The commercial relationship with customers must be kept and reinforced, and, for this purpose, companies should build strong customer defection-avoiding schemes.

That is why companies must have a reliable prediction model that allows them to identify,with enough anticipation, those clients that show symptoms of propensity to switch service providers and, thus, launch efficient retention actions.

However, there may be clients that the company will decide not to retain even if their intention to change is identified in advance, since the expected return on the prolongation of their customer life does not justify the cost of the necessary commercial action. Since I did not cover this issue, I will leave it for further researches.

Note though that, as reported in Haenlein and Kaplan (2012), careless abandonment of the less profitable customers may lead to unexpected negative reactions from the valuable ones that companies aim to retain.