INSAID Hiring Exercise

Important: Kindly go through the instructions mentioned below.

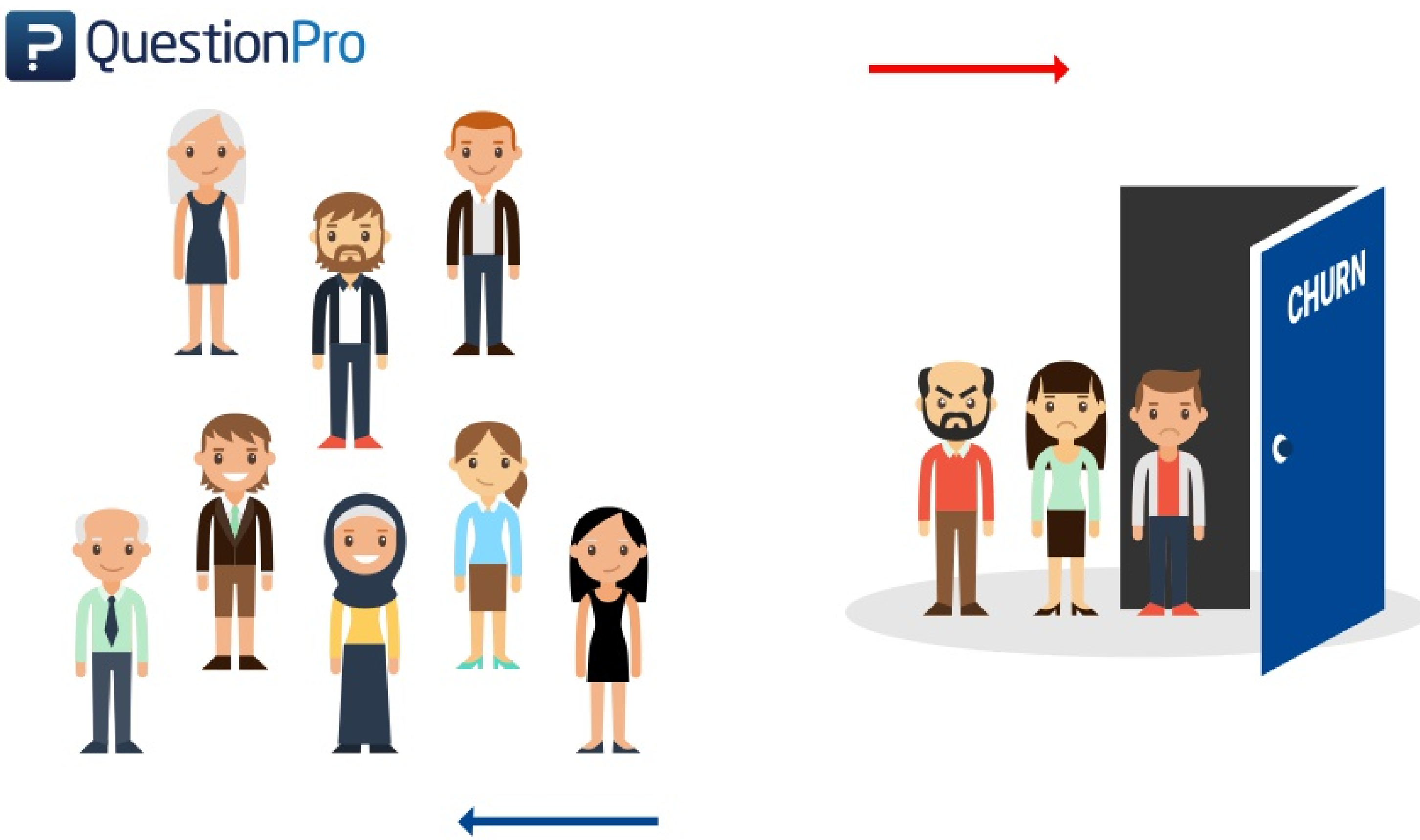
- The Sheet is structured in **4 steps**:

    1. Understanding data and manipulation
    2. Data visualization
    3. Implementing Machine Learning models(Note: It should be more than 1 algorithm)
    4. Model Evaluation and concluding with the best of the model.

- Try to break the codes in the **simplest form** and use number of code block with **proper comments** to them
- We are providing **h** different dataset to choose from(Note: You need to select any one of the dataset from this sample sheet only)
- The **interview calls** will be made solely based on how good you apply the **concepts**.
- Good Luck! Happy Coding!

In [2]:
```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

PREDICTING CUSTOMER CHURN



BUSINESS PROBLEM

Customer churn, also known as customer attrition, occurs when customers stop doing business with a company. The companies are interested in identifying segments of these customers because the price for acquiring a new customer is usually higher than retaining the old one. For example, if Netflix knew a segment of customers who were at risk of churning they could proactively engage them with special offers instead of simply losing them.

OBJECTIVE

- To develop a model for predicting customer churn at a fictitious wireless telecom company .
- Use insights from the model to develop an incentive plan for enticing would-be churners to remain with company.

CONSTRAINTS

- The only constraint is interpretability of the model.
- How to further utilise it to take business decison to avoid the customer churn

Importing importand libraries data

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

```

We will use pandas to import csv file and create the DataFrame frm it

In [2]:
```
data  = pd.read_csv('Churn.csv')#importing the data using pandas
```

Understanding the data

In [3]:
```
data.head()
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	Devic
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	

5 rows × 21 columns

In [4]:
```
data.tail()
```

Out[4]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	D
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes	...	
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No	...	
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes	...	
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	Fiber optic	No	...	
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	Yes	...	

5 rows × 21 columns

In [5]:
```
print(data.columns)
print('******************************************************')
print('shape of the data is:')
data.shape
```

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

Out[5]:
```
(7043, 21)
```

So we have 7043 data points and 21 columns out of which 1 column in our class to be predicted i.e. Churn

In [6]:

```
data.info()# to understand the datatypes
```

```
<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
```

we have 18 categorical features and 3 numeric features in the dataset

In [7]:
```
data.isnull().sum()#finding the number of missing values in data
```

Out[7]:
```
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 [8]:
```
data.nunique()
```

Out[8]:
```
customerID          7043
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                73
PhoneService           2
MultipleLines          3
InternetService        3
OnlineSecurity         3
OnlineBackup           3
DeviceProtection       3
TechSupport            3
StreamingTV            3
StreamingMovies        3
Contract               3
PaperlessBilling       2
PaymentMethod          4
MonthlyCharges      1585
TotalCharges        6531
Churn                  2
dtype: int64
```

There are no missing values in the dataset,it seems that the data has been preprocessed prior to it has been made availabe for modelling

Data Manipulation

EXPLORATORY DATA ANALYSIS

We have 2 types of features in the dataset: categorical (two or more values and without any order) and numerical. Most of the feature names are self-explanatory, except for:

- **Partner**: whether the customer has a partner or not (Yes, No),
- **Dependents**: whether the customer has dependents or not (Yes, No),
- **OnlineBackup**: whether the customer has online backup or not (Yes, No, No internet service),

- **tenure**: number of months the customer has stayed with the company,
- **MonthlyCharges**: the amount charged to the customer monthly,
- **TotalCharges**: the total amount charged to the customer.

In [9]:
```
data['TotalCharges']=pd.to_numeric(data['TotalCharges'],errors="coerce")
data.dtypes
```

Out[9]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges        float64
Churn                object
dtype: object
```

We need to convert TotalCharges column to float datatype

In [10]:
```
#separating class label and categorical and numerical features

#churn = data['Churn']#target variable
#data.drop('Churn',axis=1)

categorical_features = ["gender","SeniorCitizen","Partner","Dependents","PhoneService","MultipleLines","Inte
                        "OnlineBackup","DeviceProtection","TechSupport","StreamingTV","StreamingMovies","Con
                        "PaperlessBilling","PaymentMethod"]#categorical features

numerical_features = ["tenure", "MonthlyCharges", "TotalCharges"]#all the numerical features

```

In [11]:
```
data[numerical_features].describe()#for understanding how the numerical features in data are distributed
```

Out[11]:

	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7032.000000
mean	32.371149	64.761692	2283.300441
std	24.559481	30.090047	2266.771362
min	0.000000	18.250000	18.800000
25%	9.000000	35.500000	401.450000
50%	29.000000	70.350000	1397.475000
75%	55.000000	89.850000	3794.737500
max	72.000000	118.750000	8684.800000

- As we can see, the average time that a customer sticks with the telco is slightly more than 2 years.
- Average the Monthly Charges are $64.8 & the Average Total Charges are $2283.3.

As we can see that the tenure featre has random disreet values which will not help us much in interpreting the results,so

In [12]:

```
def employee_tenure(data):
    if data['tenure'] <=12:
        return 'within_12'
    elif (data['tenure']>12) & (data['tenure']<=24):#encdoing for duration of months
        return '12_to_24'
    elif (data['tenure']>24) & (data['tenure']<=36):
        return '24_to_36'
    elif (data['tenure']>36) & (data['tenure']<=48):
        return '36_to_48'
    elif (data['tenure']>48) & (data['tenure']<=60):
        return '48_to_60'
    elif (data['tenure']>60) & (data['tenure']<=72):
        return '60_to_72'

data['tenure_groups'] = data.apply(lambda data:employee_tenure(data),axis=1)
categorical_features.append('tenure_groups')

data = data.drop(['customerID'],axis=1)
```

In [13]:

```
data.head()
```

Out[13]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	...	Te
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	...	
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	...	
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	...	
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	...	
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No	...	

5 rows × 21 columns

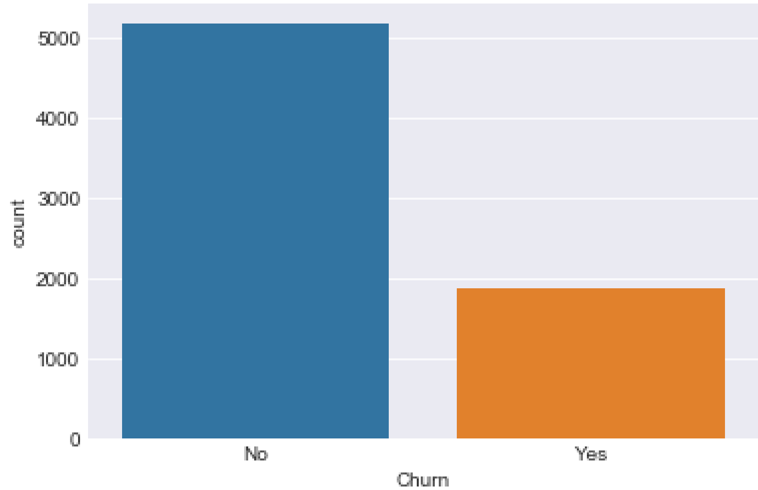
[3] Data Visualization

In [14]:
```
import itertools
from PIL import Image
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
import io
import plotly.offline as py#visualization
py.init_notebook_mode(connected=True)#visualization
import plotly.graph_objs as go#visualization
import plotly.tools as tls#visualization
import plotly.figure_factory as ff#visualization
import seaborn as sns
```

UNIVARIATE ANALYSIS

Target Variable

In [15]:
```
sns.set_style('darkgrid')
ax = sns.countplot(x="Churn", data=data)
```



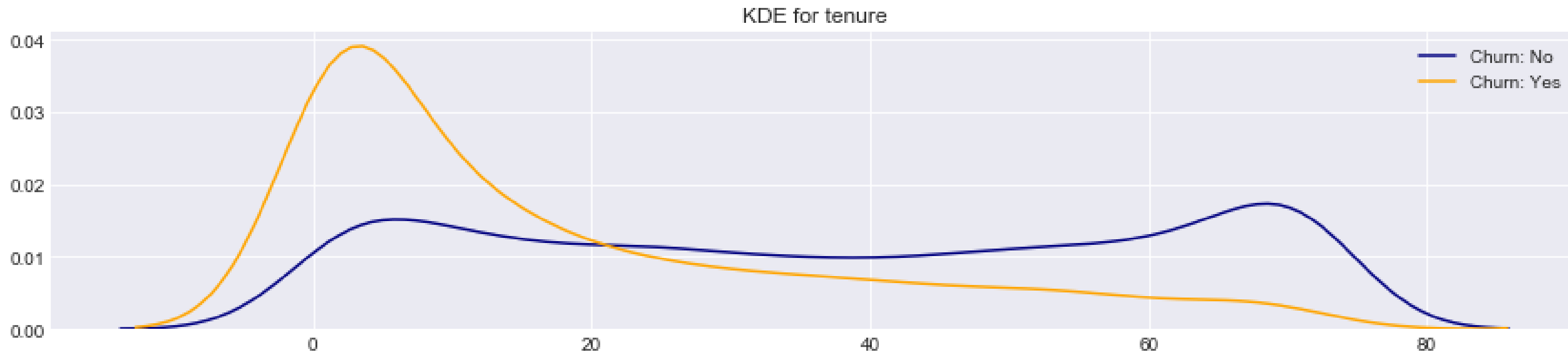
- Churn: No 73.46%

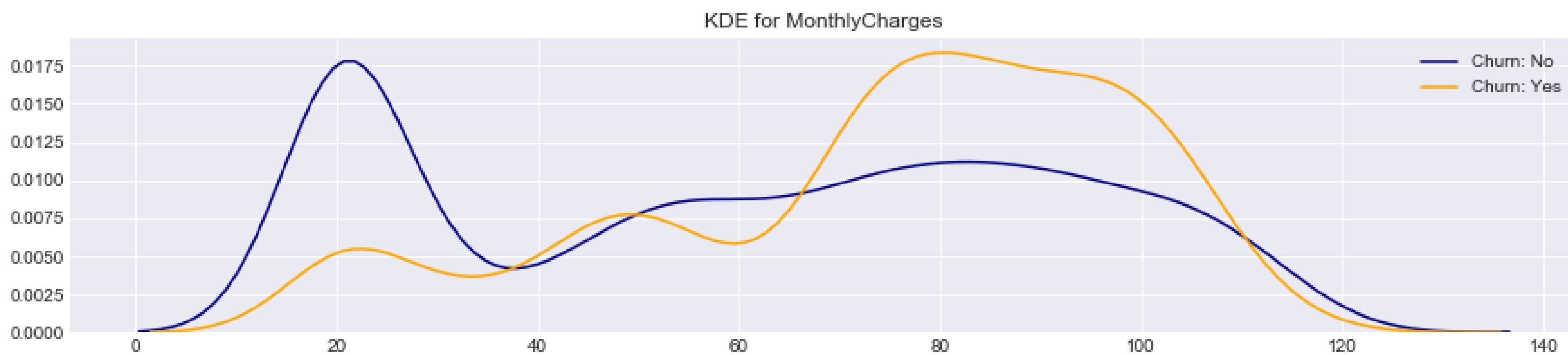
- Churn: Yes 26.547%

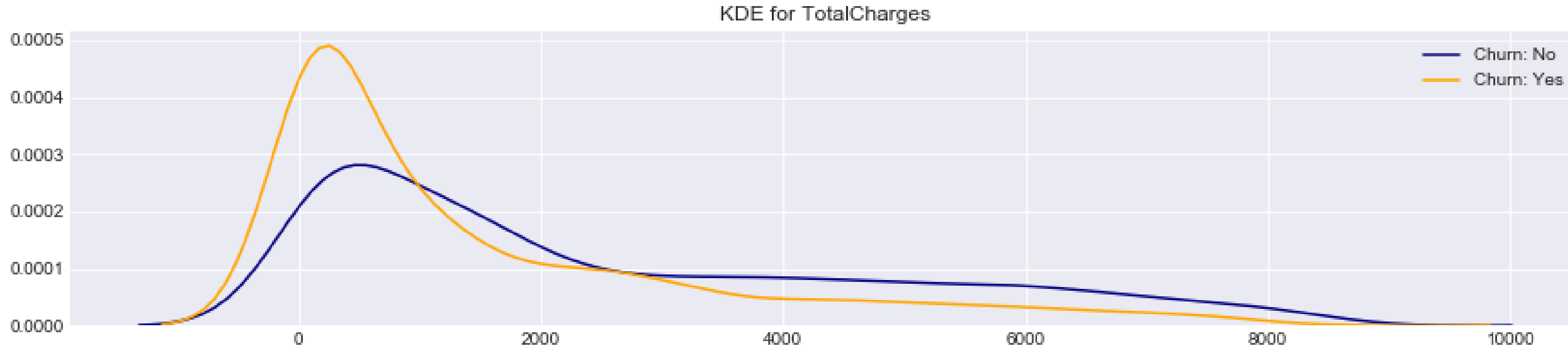
1. NUMERICAL FEATURES

There are only three numerical columns: tenure, monthly charges and total charges. The probability density distribution can be estimate using the seaborn kdeplot function.

In [16]:
```
def kdeplot(feature):
    plt.figure(figsize=(15,3))
    plt.title("KDE for {}".format(feature))
    ax0 = sns.kdeplot(data[data['Churn'] == 'No'][feature].dropna(), color= 'navy', label= 'Churn: No')
    ax1 = sns.kdeplot(data[data['Churn'] == 'Yes'][feature].dropna(), color= 'orange', label= 'Churn: Yes')
kdeplot('tenure')
kdeplot('MonthlyCharges')
kdeplot('TotalCharges')
```



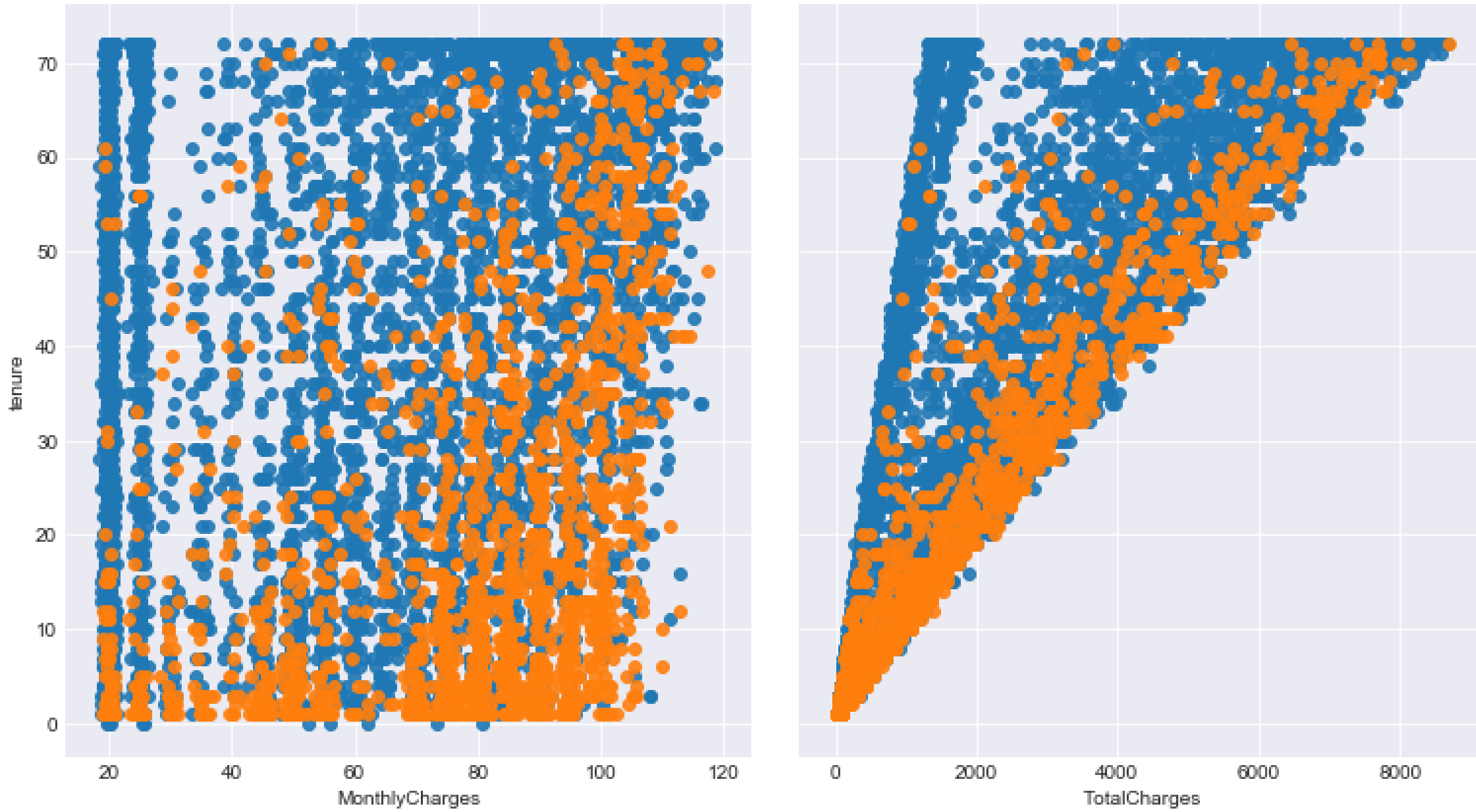




From the plots above we can conclude that:

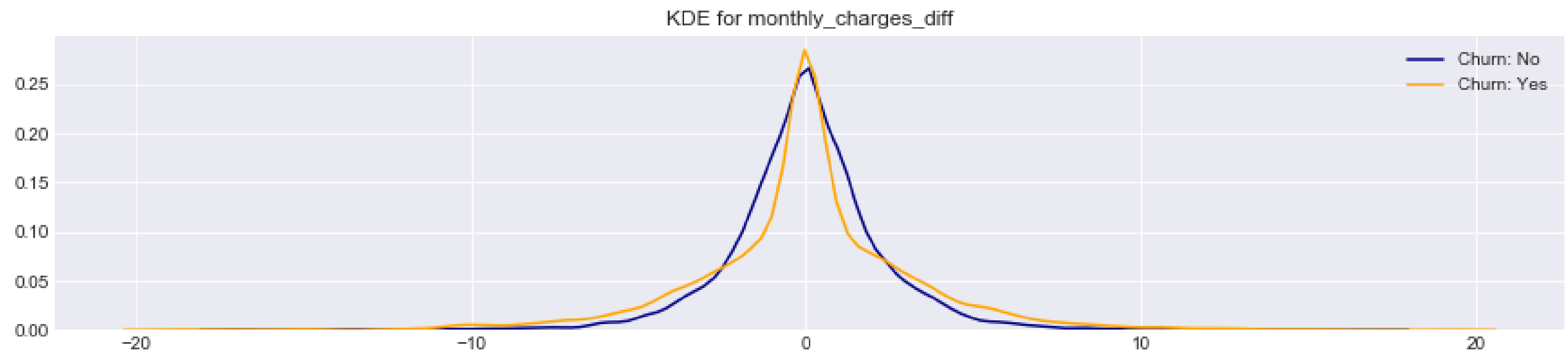
- Recent clients are more likely to churn
- Clients with higher MonthlyCharges are also more likely to churn
- Tenure and MonthlyCharges are probably important features

In [17]:
```
g = sns.PairGrid(data, y_vars=["tenure"], x_vars=["MonthlyCharges", "TotalCharges"],size = 6, hue="Churn", a
#plt.figure(figsize=(15,10))
ax = g.map(plt.scatter, alpha=0.9)
```



Another feature we can consider is the difference between the MonthlyCharges and the TotalCharges divided by the tenure:

In [18]:
```
data['total_charges_to_tenure_ratio'] = data['TotalCharges'] / data['tenure']
data['monthly_charges_diff'] = data['MonthlyCharges'] - data['total_charges_to_tenure_ratio']
kdeplot('monthly_charges_diff')

```



Not a promising feature at first glance, but it might be usefull when combined with categorical features.

2.Categorical Features

This dataset has 16 categorical features:

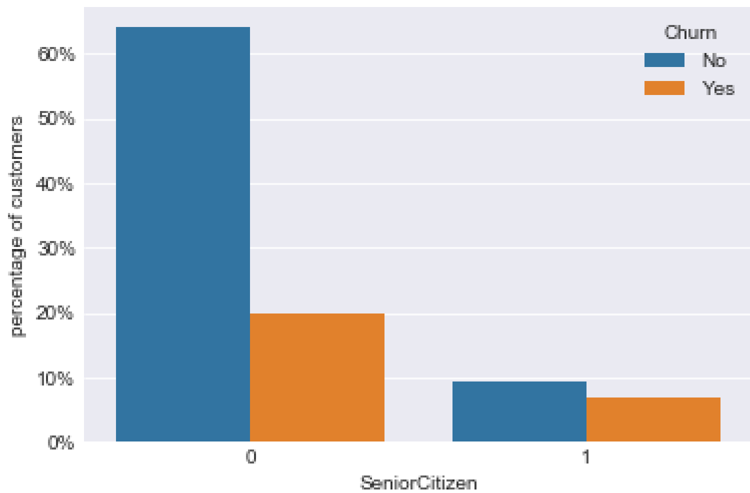
- Six binary features (Yes/No)
- Nine features with three unique values each (categories)
- One feature with four unique values

2.1 Gender and Age

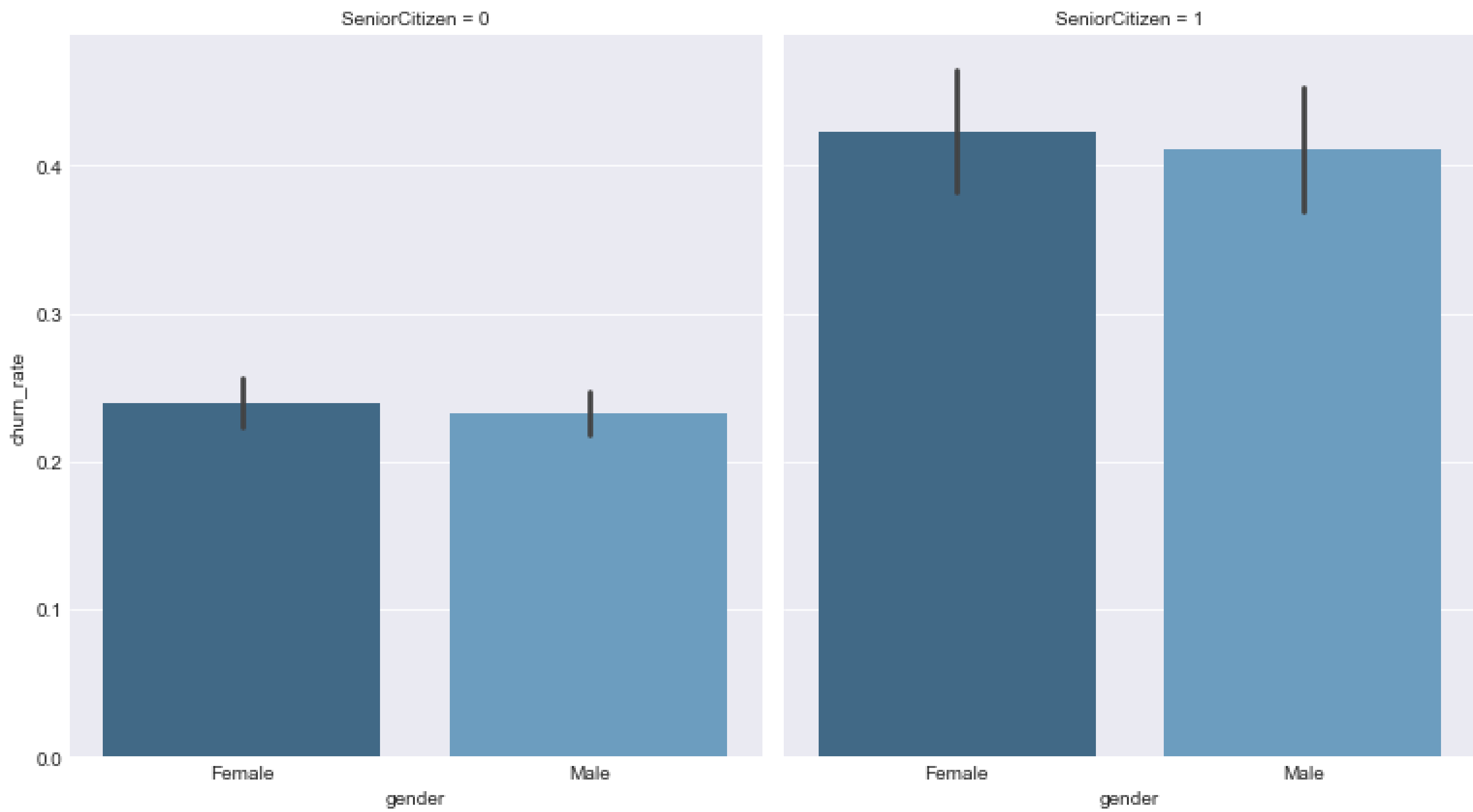
In [19]:
```
data.groupby('SeniorCitizen')['Churn'].value_counts()
```

Out[19]:
```
SeniorCitizen  Churn
0              No       4508
               Yes      1393
1              No        666
               Yes       476
Name: Churn, dtype: int64
```

In [20]:
```
def barplot_percentages(feature, orient='v', axis_name = "percentage of customers"):
    ratios = pd.DataFrame()
    g = data.groupby(feature)["Churn"].value_counts().to_frame()
    g = g.rename({"Churn": axis_name}, axis=1).reset_index()
    g[axis_name] = g[axis_name]/len(data)
    if orient == 'v':
        ax = sns.barplot(x=feature, y= axis_name, hue='Churn', data=g, orient=orient)
        ax.set_yticklabels(['{:,.0%}'.format(y) for y in ax.get_yticks()])
    else:
        ax = sns.barplot(x= axis_name, y=feature, hue='Churn', data=g, orient=orient)
        ax.set_xticklabels(['{:,.0%}'.format(x) for x in ax.get_xticks()])
    ax.plot()
barplot_percentages("SeniorCitizen")
```



In [21]:
```
data['churn_rate'] = data['Churn'].replace("No", 0).replace("Yes", 1)
g = sns.FacetGrid(data, col="SeniorCitizen", size=6, aspect=.9)
ax = g.map(sns.barplot, "gender", "churn_rate", palette = "Blues_d", order= ['Female', 'Male'])

```

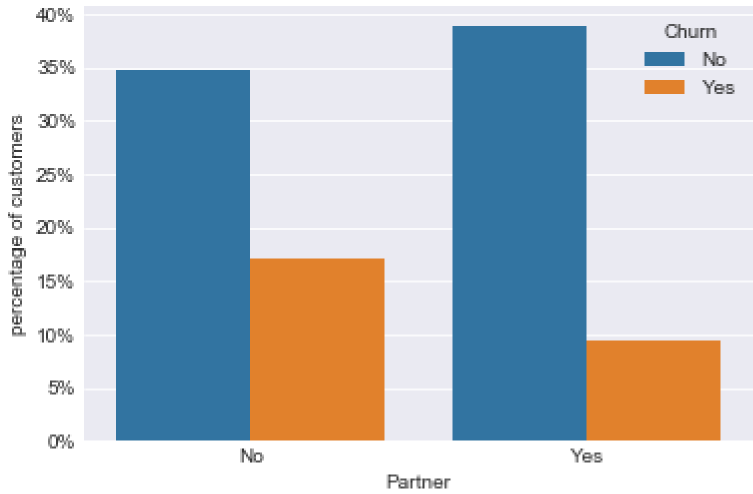


In [22]:
```
g = sns.FacetGrid(data, row='SeniorCitizen', col="gender", hue="Churn", size=4)
g.map(plt.scatter, "tenure", "MonthlyCharges", alpha=0.6)
g.add_legend();
```

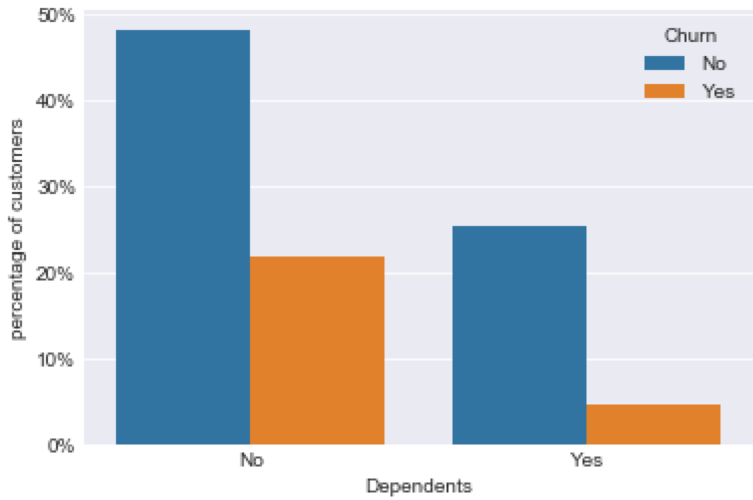
- Gender is not an indicative of churn.
- SeniorCitizens are only 16% of customers, but they have a much higher churn rate: 42% against 23% for non-senior customers.
- There are no special relations between this categorical values and the main numerical features.

2.2 Partner and Dependents

In [23]:
```
barplot_percentages("Partner")
```



In [24]:
```
barplot_percentages("Dependents")
```



- Customers that doesn't have partners are more likely to churn

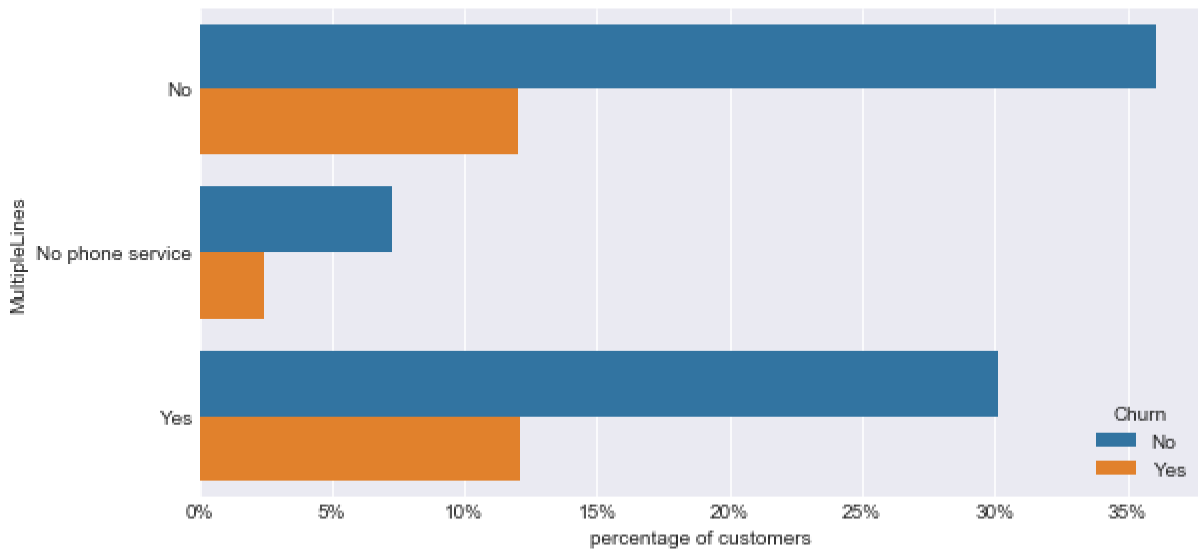
- Customers without dependents are also more likely to churn

2.3 Phone and Internet Services

Now let's look at the services that customers are using. There are only two main services: phone and internet but the former has many additionals like online backup and security.

here are only two features here: if the client has phone and if he has more than one line. Both can be summed up in one chart:

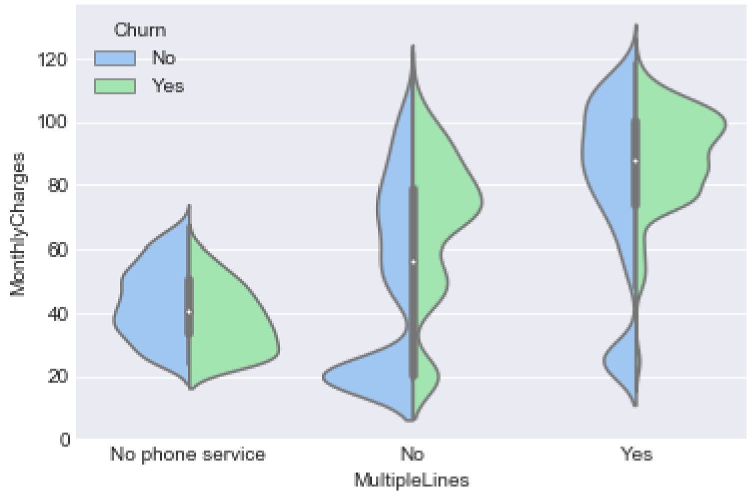
In [25]:
```
plt.figure(figsize=(9, 4.5))
barplot_percentages("MultipleLines", orient='h')
```



- Few customers doesn't have phone service
- Customers with multiple lines are more likely to churn

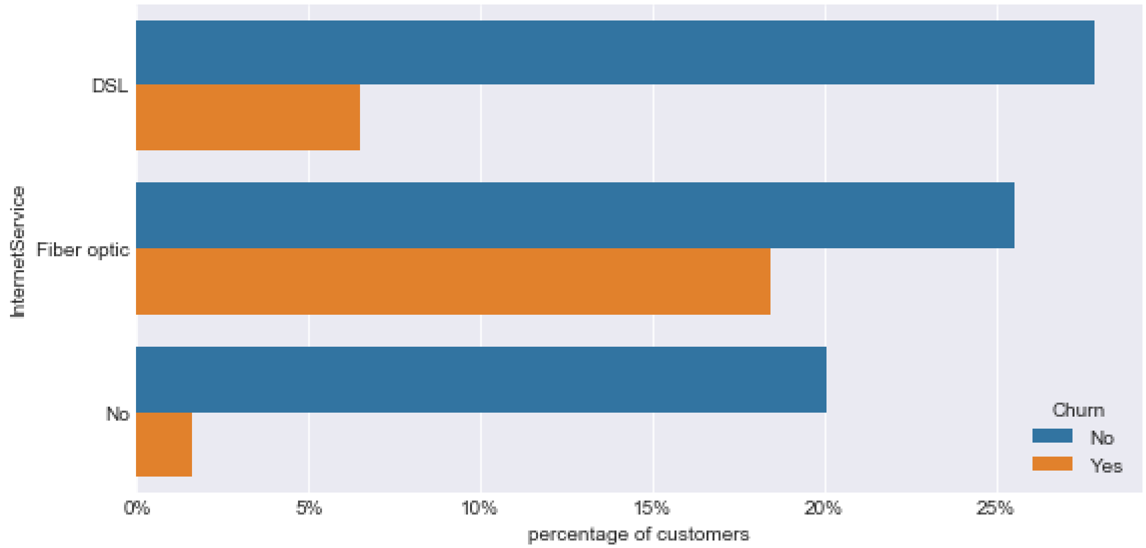
Let's see how multiple lines affects the monthly charges:

In [26]:
```
ax = sns.violinplot(x="MultipleLines", y="MonthlyCharges", hue="Churn", kind="violin",
                 split=True, palette="pastel", data=data, height=6, aspect=1.4)
```



Internet Services

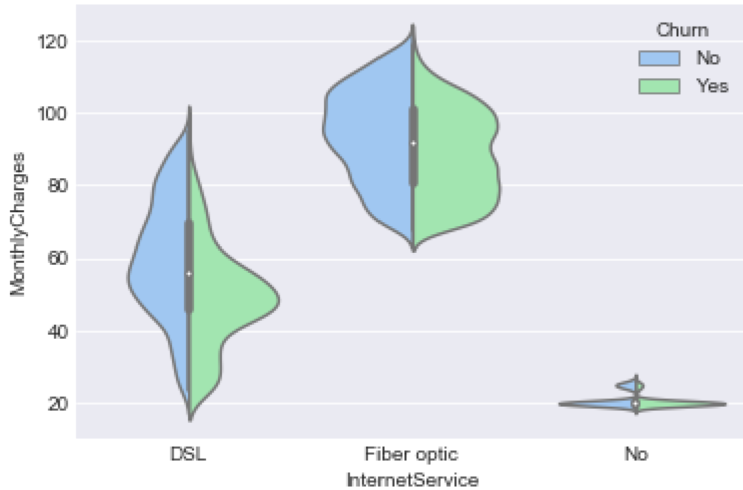
In [27]:
```
plt.figure(figsize=(9, 4.5))
barplot_percentages("InternetService", orient="h")
```



- Clients without internet have a very low churn rate
- Customers with fiber are more probable to churn than those with DSL connection

Comparing the Internet service with monthly charges:

In [28]:
```
ax = sns.violinplot(x="InternetService", y="MonthlyCharges", hue="Churn", kind="violin",
                    split=True, palette="pastel", data=data, height=5, aspect=1.4);
```



- It's interesting how customers with DSL (slower connection) and higher charges are less probable to churn

2.4 Additional Services

There are six additional services for customers with internet:

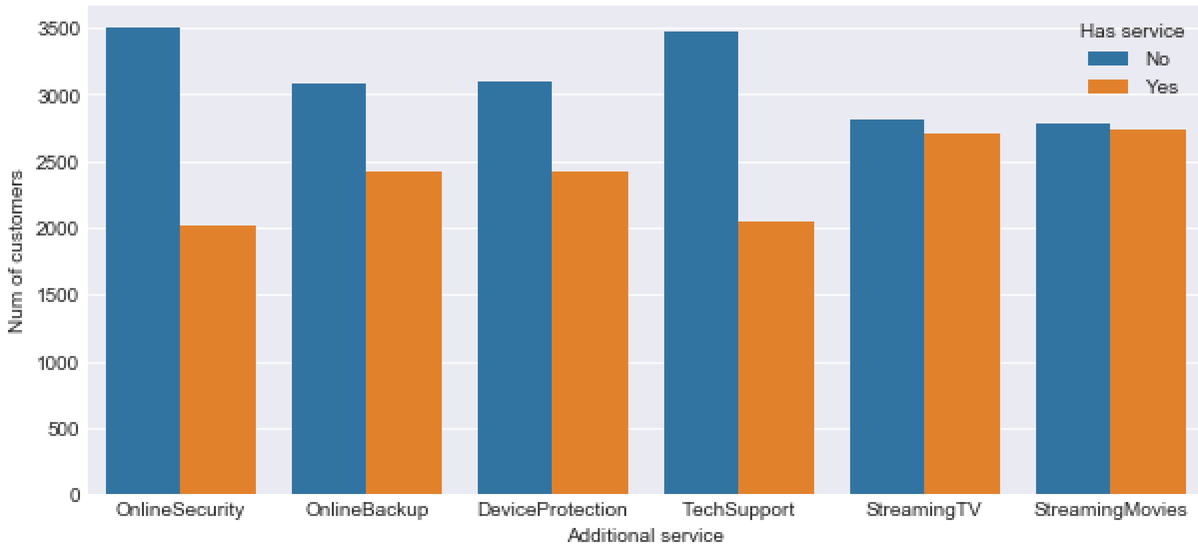
In [29]:

```
cols = ["OnlineSecurity", "OnlineBackup", "DeviceProtection", "TechSupport", "StreamingTV", "StreamingMovies
df1 = pd.melt(data[data["InternetService"] != "No"][cols]).rename({'value': 'Has service'}, axis=1)
df1.head(10)
```

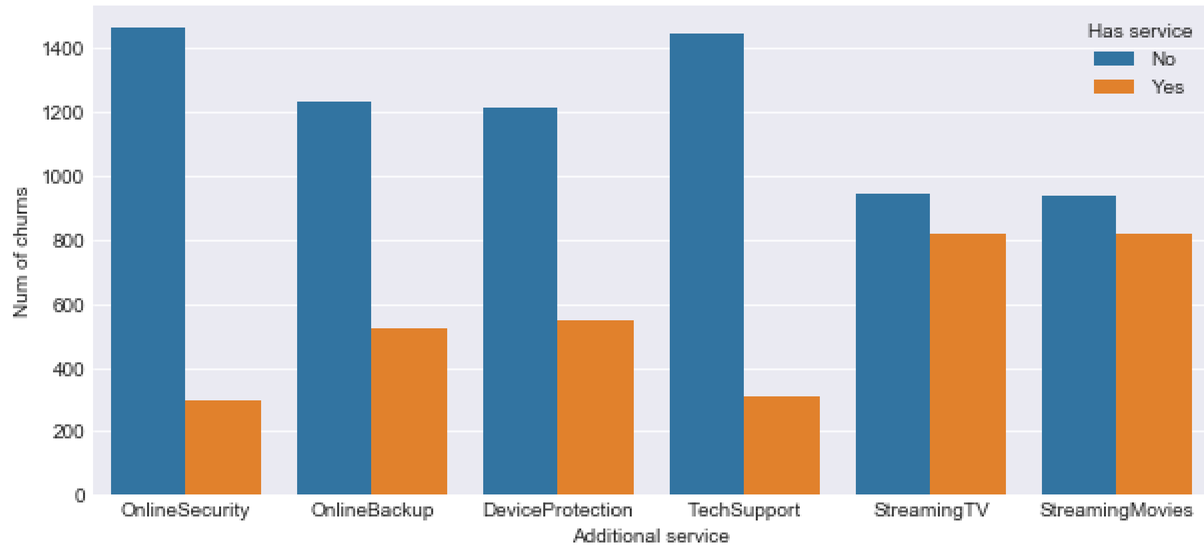
Out[29]:

	variable	Has service
0	OnlineSecurity	No
1	OnlineSecurity	Yes
2	OnlineSecurity	Yes
3	OnlineSecurity	Yes
4	OnlineSecurity	No
5	OnlineSecurity	No
6	OnlineSecurity	No
7	OnlineSecurity	Yes
8	OnlineSecurity	No
9	OnlineSecurity	Yes

In [30]:
```
plt.figure(figsize=(10, 4.5))
ax = sns.countplot(data=df1, x='variable', hue='Has service')
ax.set(xlabel='Additional service', ylabel='Num of customers')
plt.show()
```



In [31]:
```
plt.figure(figsize=(10, 4.5))
df1 = data[(data.InternetService != "No") & (data.Churn == "Yes")]
df1 = pd.melt(df1[cols]).rename({'value': 'Has service'}, axis=1)
ax = sns.countplot(data=df1, x='variable', hue='Has service', hue_order=['No', 'Yes'])
ax.set(xlabel='Additional service', ylabel='Num of churns')
plt.show()

```

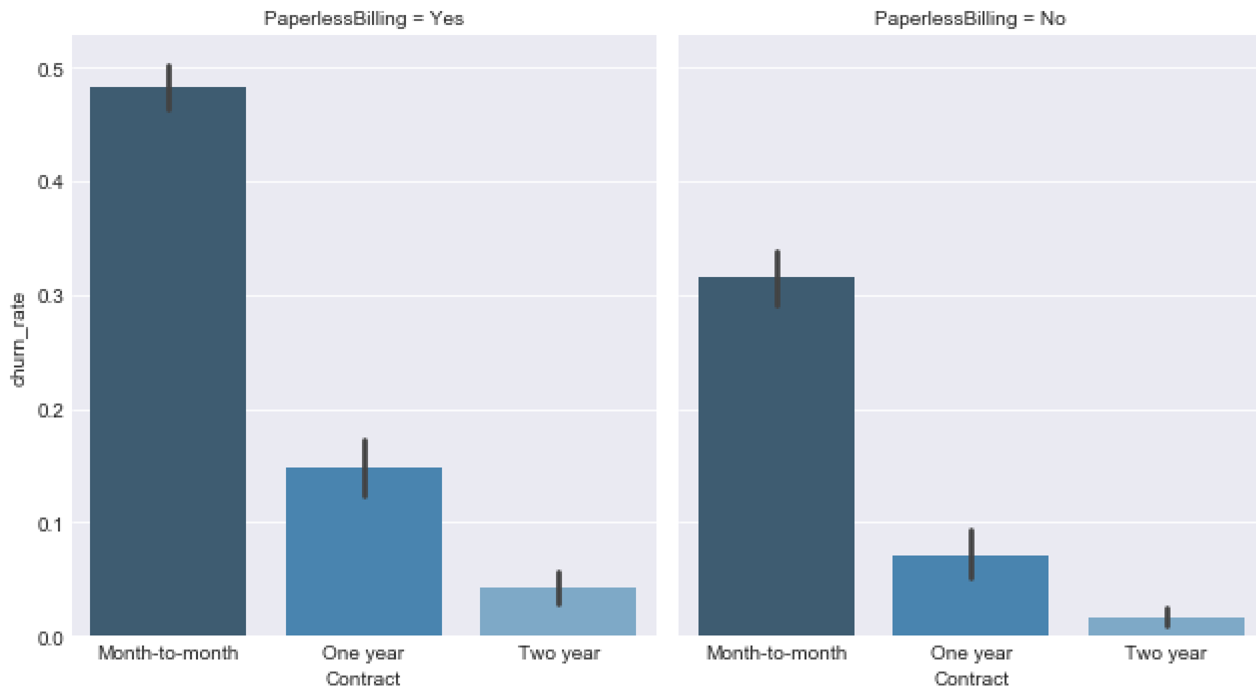


The first plot shows the total number of customers for each additional service, while the second shows the number of clients that churn. We can see that:

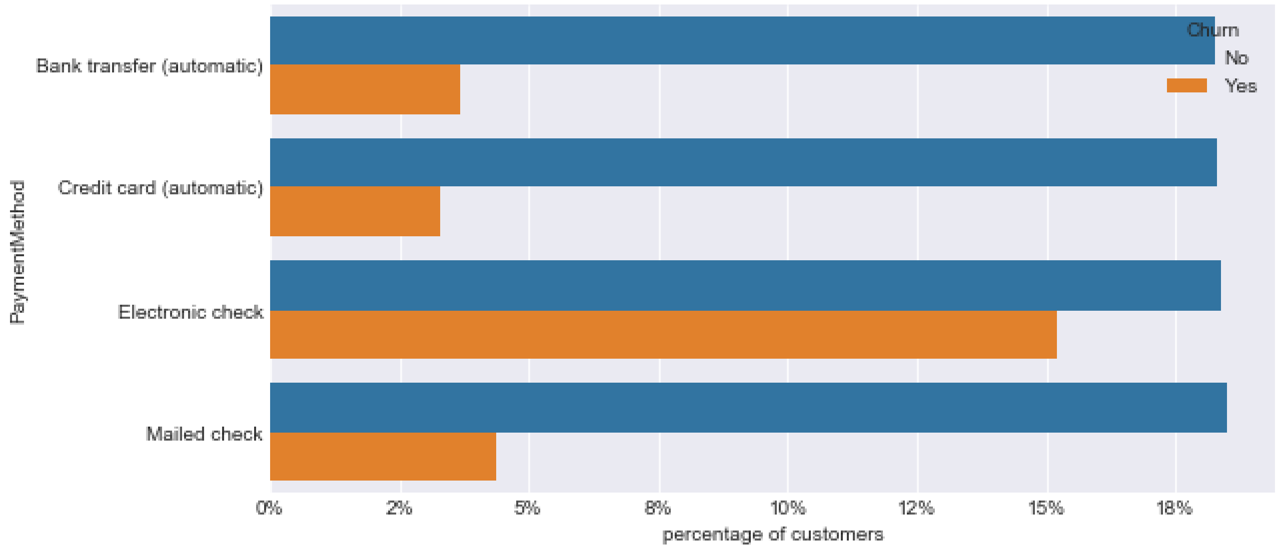
- Customers with the first 4 additionals (security to tech support) are more unlikely to churn
- Streaming service is not predictive for churn

2.5 Contract and Payment

In [32]:
```
g = sns.FacetGrid(data, col="PaperlessBilling", size=5, aspect=.9)
ax = g.map(sns.barplot, "Contract", "churn_rate", palette = "Blues_d", order= ['Month-to-month', 'One year',
```



In [33]:
```
plt.figure(figsize=(9, 4.5))
barplot_percentages("PaymentMethod", orient='h')
```

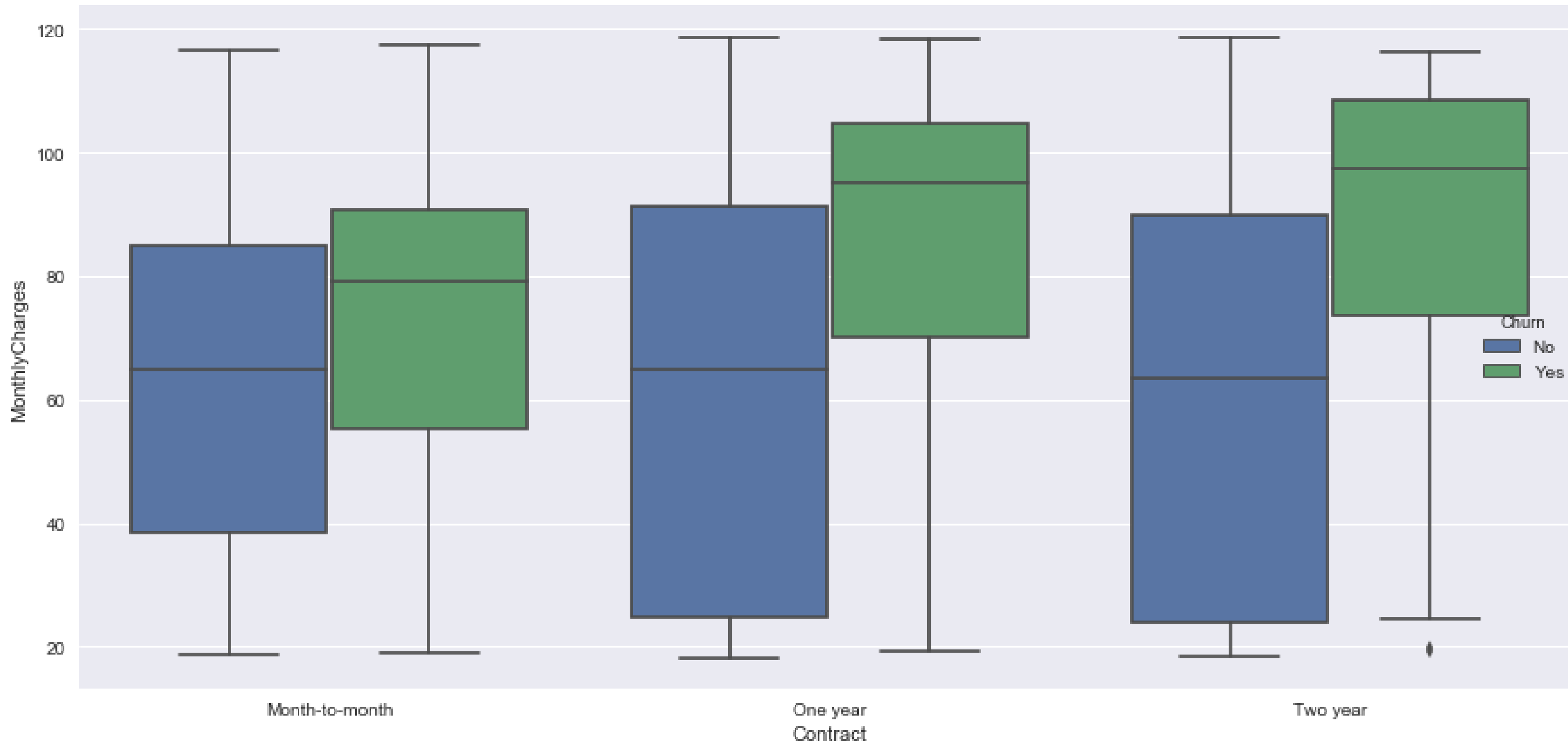


A few observations:

- Customers with paper billing are more probable to churn
- The preferred payment method is Electronic check with around 35% of customers. This method also has a very high churn rate
- Short term contracts have higher churn rates

One and two year contracts probably have contractual fines and therefore customers have to wait untill the end of contract to churn. A time-series dataset would be better to understand this kind of behaviour. Now let's have a look at the relation with numerical features:

In [34]:
```
sns.set(rc={'figure.figsize':(15,7)})
ax = sns.boxplot(x="Contract", y="MonthlyCharges", hue="Churn", data=data)
```



- Longer contracts are more affected by higher monthly charges (for churn rate).
- Mailed checks have lower charges
- There is a huge gap between customers that churn and those that dont with respect to Mailed Check

[3.2] Label Encoding the variables

In [35]:
```
#transforming the data
from sklearn.preprocessing import LabelEncoder
data = data.apply(LabelEncoder().fit_transform)
data.head(3)
```

Out[35]:

eniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	...	Contract	Paperle
0	1	0	1	0	1	0	0	2	...	0	
0	0	0	34	1	0	0	2	0	...	1	
0	0	0	2	1	0	0	2	2	...	0	

olumns

where 'Churn' == 0 means No and 'Churn' == 1 mean Yes

After encoding the variables we need to analyze the correlation between the variable,so we plot the correlation matrix

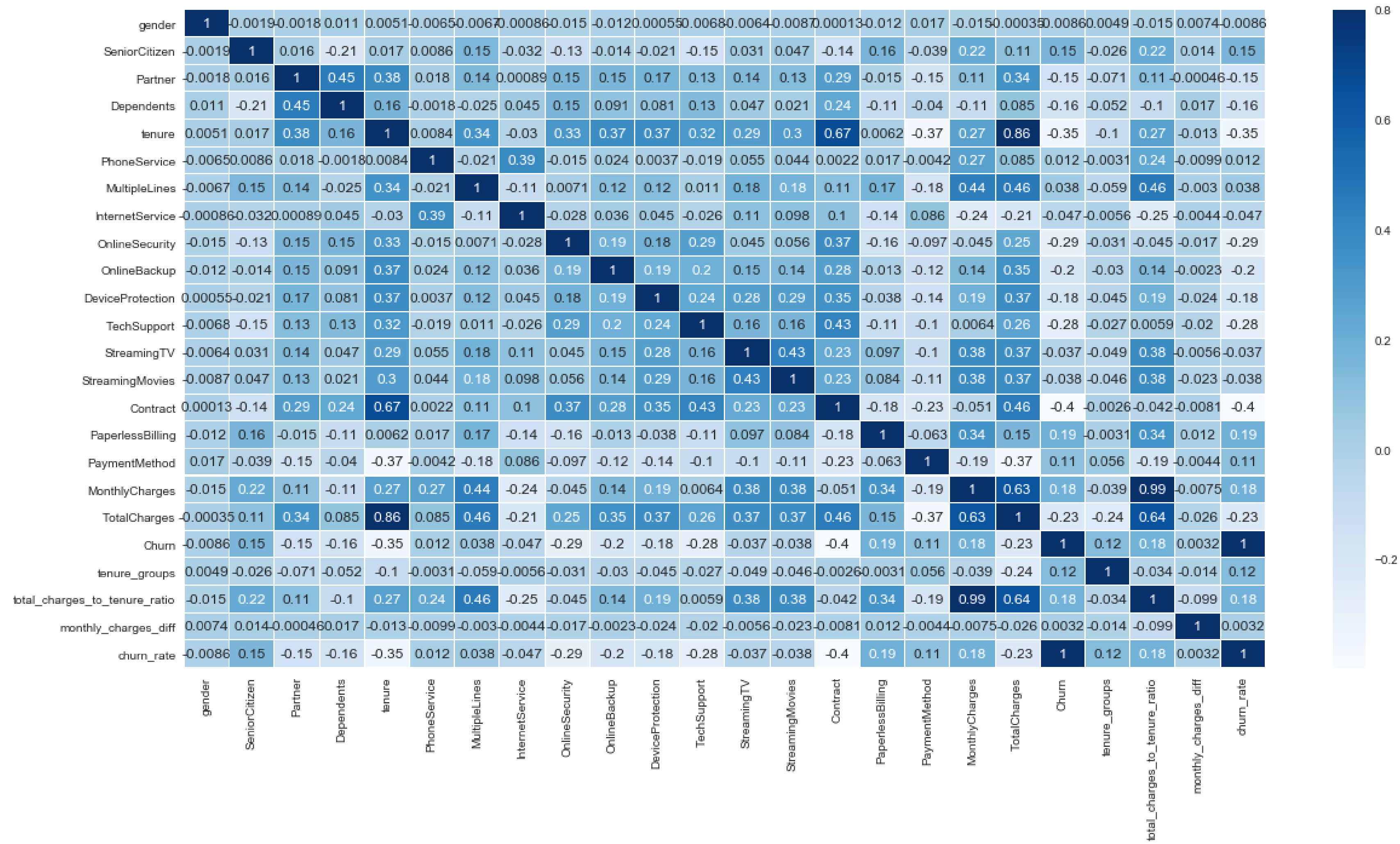
[3.3] Correlation Matrix

In [36]:

```python
# Correlation Plot
matrix = data.corr()
#Set uo the matplolib figure
f, ax = plt.subplots(figsize=(20, 10))
#Draw the heatmap using seaborn
colormap = plt.cm.Blues
sns.heatmap(matrix, linewidths=0.1, cmap = colormap, linecolor = 'White', vmax=0.8, annot=True)
```

Out[36]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2169a340630>
```



Variables: **TotalCharges**, **MonthlyCharges** & **Tenure** are the variables which seem highly correlated which seems obvious. **TotalCharges** is nothing but MonthlyCharges times **Tenure**. To avoid multicollinearity, we get rid of the TotalCharges feature in our analysis.

In [37]:
```
data = data.drop('TotalCharges',axis=1)
```

[3.5] Advanced Data Visualization and Feature Selection

We will implement T-SNE for advanced data visualization and to see how data is distributed and we will also implement Principal Component Analysis for feature selecttion and understanding variance in the daa

In [43]:
```
labels = data['Churn']
cols = ['Churn','tenure']
data = data.drop(cols,axis=1)#dropping the columns
```

Standardizing the data

In [44]:
```
from sklearn.preprocessing import StandardScaler
standardized_data = StandardScaler().fit_transform(data)#fittting the data
print(standardized_data.shape)#shape of standardized data
```

```
(7043, 20)
```

PRINCIPAL COMPONENT ANALYSIS

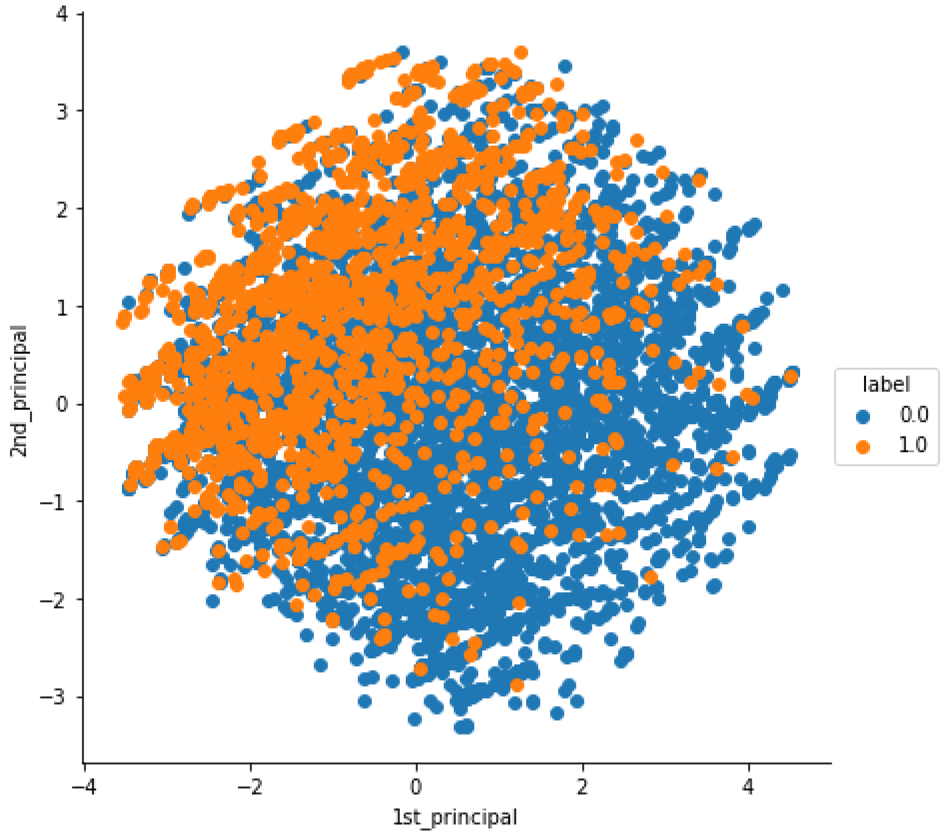
In [167]:

```
# initializing the pca
from sklearn import decomposition
pca = decomposition.PCA()

# configuring the parameters
# the number of components = 2
pca.n_components = 2
pca_data = pca.fit_transform(standardized_data)

# pca_reduced will contain the 2-d projects of simple data
print("shape of pca_reduced.shape = ", pca_data.shape)


```

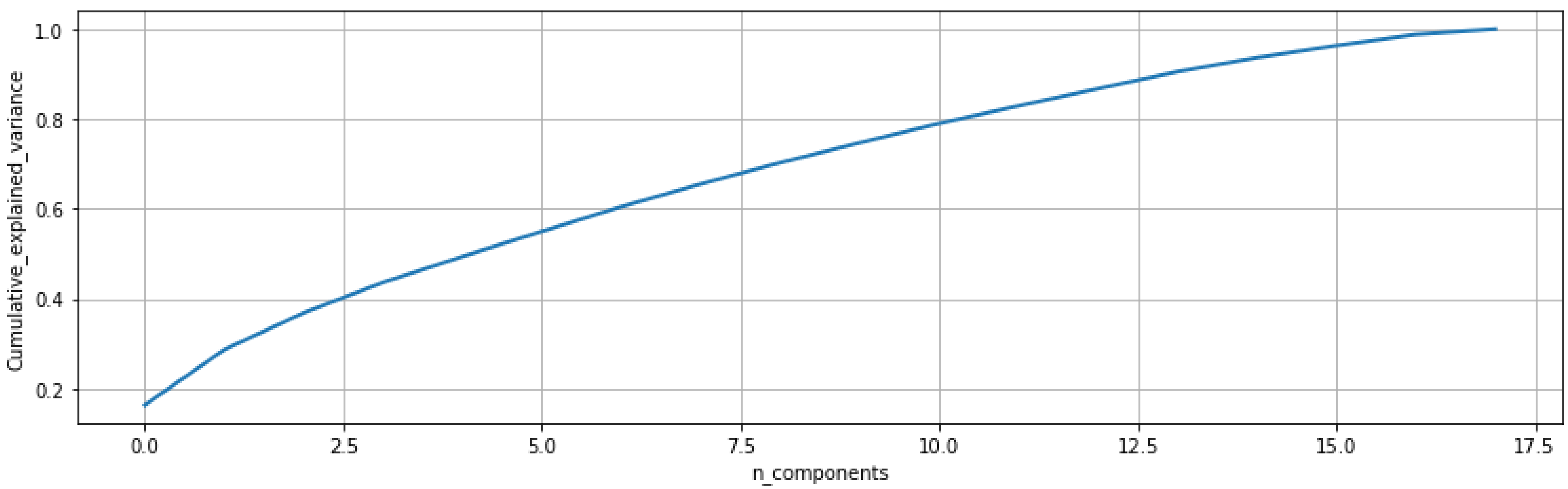
```
shape of pca_reduced.shape =  (7043, 2)
```

In [168]:

```
# attaching the label for each 2-d data point
pca_data = np.vstack((pca_data.T, labels)).T

# creating a new data fram which help us in ploting the result data
pca_df = pd.DataFrame(data=pca_data, columns=("1st_principal", "2nd_principal", "label"))
sns.FacetGrid(pca_df, hue="label", size=6).map(plt.scatter, '1st_principal', '2nd_principal').add_legend()
plt.show()
```



In [175]:
```
# PCA for dimensionality redcution
pca.n_components = 18
pca_data = pca.fit_transform(standardized_data)

percentage_var_explained = pca.explained_variance_ / np.sum(pca.explained_variance_);

cum_var_explained = np.cumsum(percentage_var_explained)

# Plot the PCA spectrum
plt.figure(1, figsize=(14, 4))

plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()


# If we take 200-dimensions, approx. 90% of variance is expalined.
```



which shows we are able to explain 80% variance in data with 10 features only,but as features are less so dropping any one of them might prove costly to us as it may hamper the interpretability of the model ,so we must fit all the features in our model for better understanding

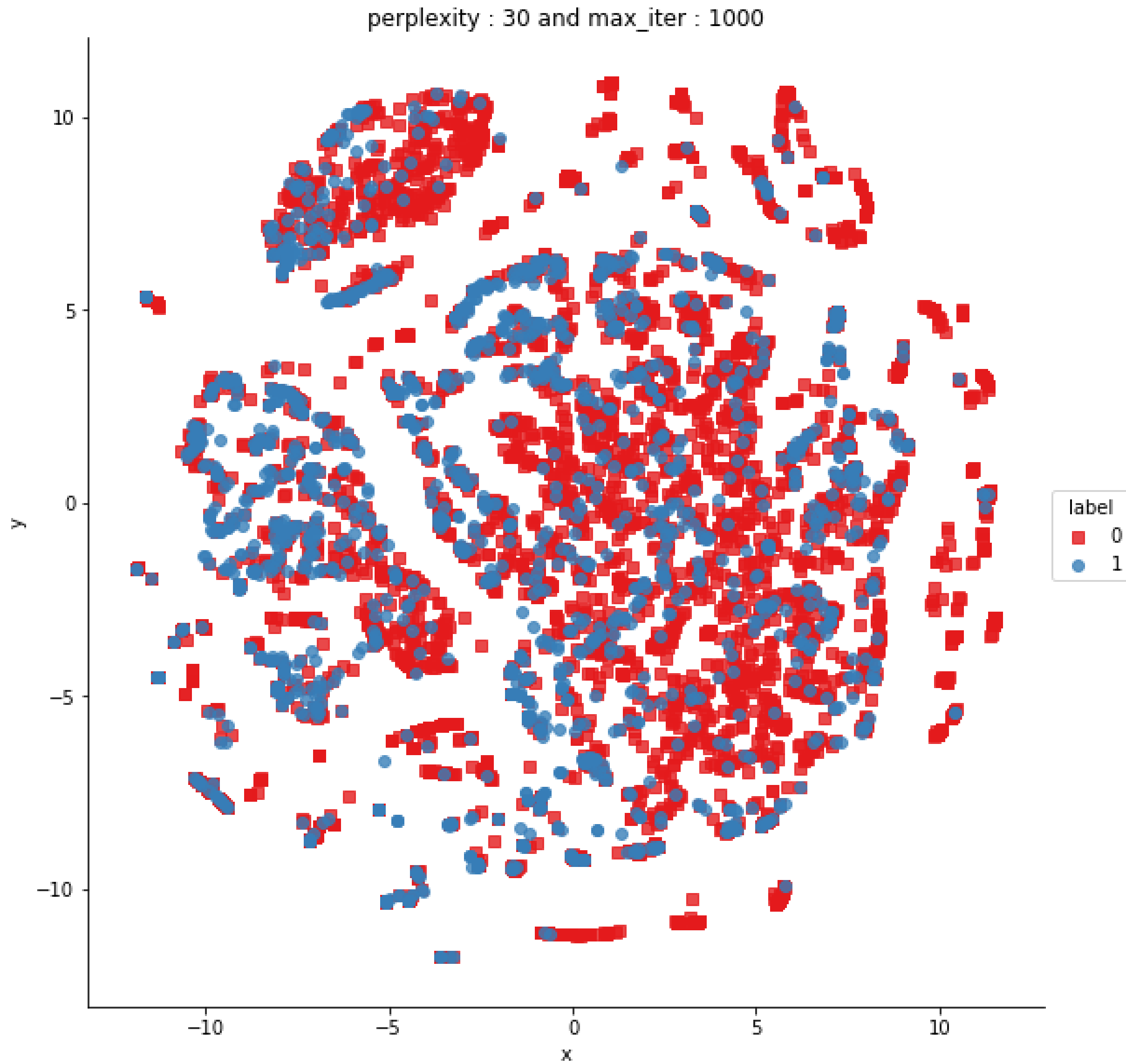
T-SNE using Scikit learn

In [172]:
```
from sklearn.manifold import TSNE
tsne2d = TSNE(
    n_components=2,
    init='random', # pca
    random_state=101,
    method='barnes_hut',
    n_iter=1000,
    verbose=2,
    angle=0.5
).fit_transform(standardized_data)
```

```
[t-SNE] Computing pairwise distances...
[t-SNE] Computing 91 nearest neighbors...
[t-SNE] Computed conditional probabilities for sample 1000 / 7043
[t-SNE] Computed conditional probabilities for sample 2000 / 7043
[t-SNE] Computed conditional probabilities for sample 3000 / 7043
[t-SNE] Computed conditional probabilities for sample 4000 / 7043
[t-SNE] Computed conditional probabilities for sample 5000 / 7043
[t-SNE] Computed conditional probabilities for sample 6000 / 7043
[t-SNE] Computed conditional probabilities for sample 7000 / 7043
[t-SNE] Computed conditional probabilities for sample 7043 / 7043
[t-SNE] Mean sigma: 0.087599
[t-SNE] Iteration 25: error = 1.7987947, gradient norm = 0.0062273
[t-SNE] Iteration 50: error = 1.7761875, gradient norm = 0.0079367
[t-SNE] Iteration 75: error = 1.6314279, gradient norm = 0.0025842
[t-SNE] Iteration 100: error = 1.5931680, gradient norm = 0.0022373
[t-SNE] KL divergence after 100 iterations with early exaggeration: 1.593168
[t-SNE] Iteration 125: error = 1.5200347, gradient norm = 0.0017202
[t-SNE] Iteration 150: error = 1.4946132, gradient norm = 0.0016028
[t-SNE] Iteration 175: error = 1.4879482, gradient norm = 0.0015681
[t-SNE] Iteration 200: error = 1.4861797, gradient norm = 0.0015647
[t-SNE] Iteration 225: error = 1.4856383, gradient norm = 0.0015594
[t-SNE] Iteration 250: error = 1.4854335, gradient norm = 0.0015632
[t-SNE] Iteration 275: error = 1.4854701, gradient norm = 0.0015617
[t-SNE] Iteration 300: error = 1.4854245, gradient norm = 0.0015586
[t-SNE] Iteration 325: error = 1.4854424, gradient norm = 0.0015585
[t-SNE] Iteration 350: error = 1.4854158, gradient norm = 0.0015587
[t-SNE] Iteration 375: error = 1.4854429, gradient norm = 0.0015584
[t-SNE] Iteration 400: error = 1.4854143, gradient norm = 0.0015587
[t-SNE] Iteration 400: error difference 0.000000. Finished.
[t-SNE] Error after 400 iterations: 1.593168
```

In [174]:

```
df = pd.DataFrame({'x':tsne2d[:,0], 'y':tsne2d[:,1] ,'label':labels})

# draw the plot in appropriate place in the grid
sns.lmplot(data=df, x='x', y='y', hue='label', fit_reg=False, size=8,palette="Set1",markers=['s','o'])
plt.title("perplexity : {} and max_iter : {}".format(30, 1000))
plt.show()
```



this visualization shows how data points are embedded in two dimensional spaces

Implement Machine Learning Models

After cleanining,manipulating and visualizing the data,now its time to build models.Let's get started

We are implementing 3 models.Models used are -

- Logistic Regression
- Random Forest
- Linear SVM

Our target variable is a binary variable. The customer either stays or leaves. Hence, we decided to use the Logistic Regression as our first model to check how the data fits the model. The models have been selected in no specific order.

Splitting the data

we wiil split the data into 7:3 ratio,i.e 70% of the data will be used for training the model and 30% data for testing the model

In [45]:
```
from sklearn.model_selection import train_test_split

X_train,X_test,Y_train,Y_test = train_test_split(data,labels,test_size = 0.3,random_state = 42)
print('trainig dataset after splitting is',X_train.shape)
print('Test datset after spliting is',X_test.shape)
```

```
trainig dataset after splitting is (4930, 20)
Test datset after spliting is (2113, 20)
```

In [46]:
```
data.head()
```

Out[46]:

	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	tenure_groups	total_charges_t
0	0	0	0	0	1	2	142	5	
2	0	0	0	1	0	3	498	1	
0	0	0	0	0	1	3	436	5	
2	2	0	0	1	0	0	266	2	
0	0	0	0	0	1	2	729	5	

Model 1: LOGISTIC REGRESSION

L2 Regularization and Grid Search Cross validation

In [47]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import StratifiedKFold

# we will tune the hyperparameter lambda for avoiding overfittting and underfitting of data
# we will use stratified Kfold for cross validation of data

param = {'C': [10**i for i in range(-4,5)]}
skf= StratifiedKFold(n_splits=5)#number of splits are set to 5
model_lr = GridSearchCV(LogisticRegression(penalty='l2'),param_grid = param,cv = skf,scoring = 'roc_auc',n_j
#using GridSearchCv
model_lr.fit(X_train,Y_train)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits

[Parallel(n_jobs=-1)]: Done  38 out of  45 | elapsed:    3.2s remaining:    0.5s
[Parallel(n_jobs=-1)]: Done  45 out of  45 | elapsed:    3.3s finished
```

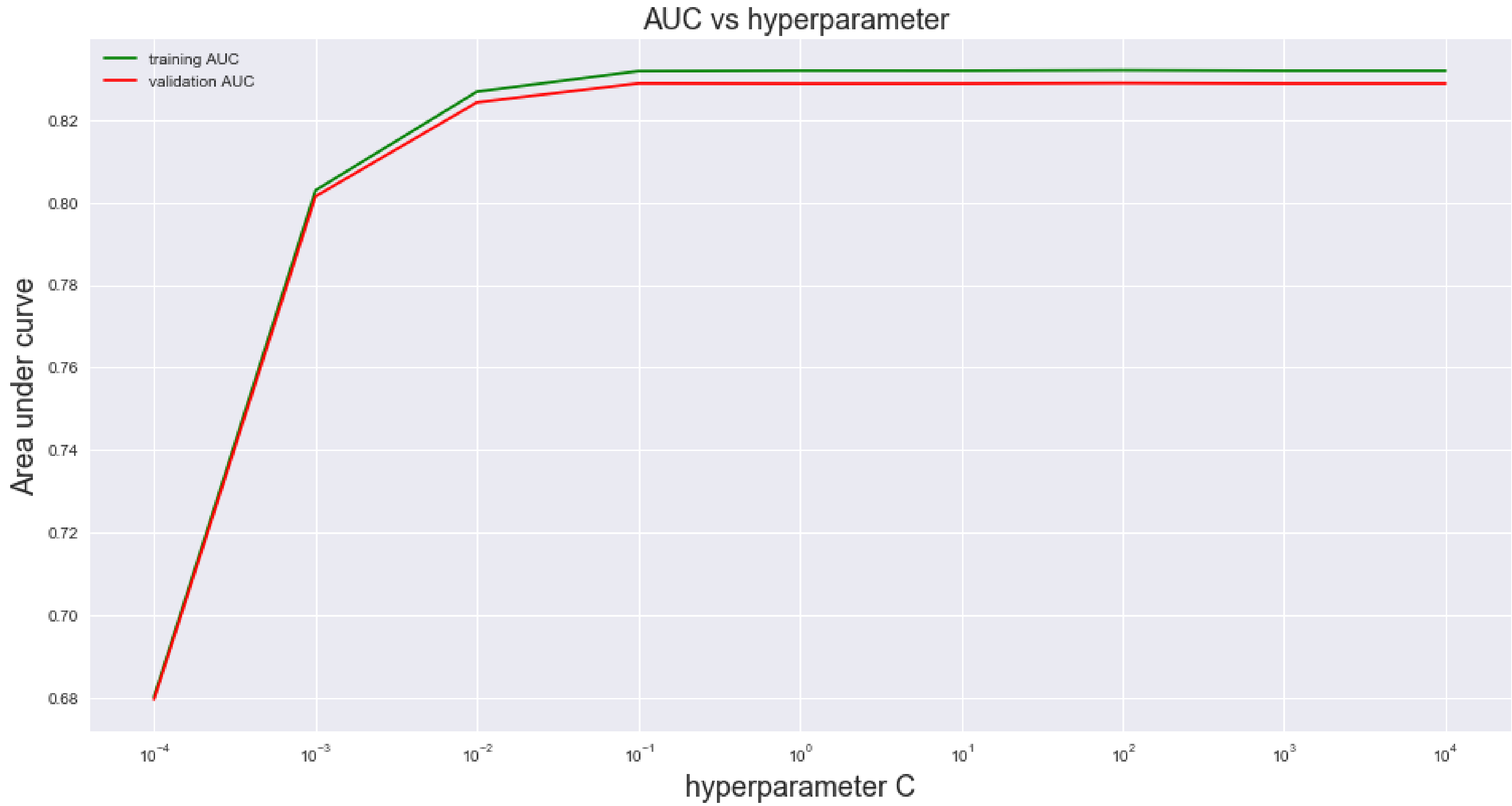
Out[47]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None, shuffle=False),
       error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params={}, iid=True, n_jobs=-1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='roc_auc', verbose=1)
```

Plottting Hyperparameter vs metric for tuning

In [48]:

```
t_auc = model_lr.cv_results_['mean_train_score']#mean training score computed for every fold
cv_auc = model_lr.cv_results_['mean_test_score']#mean cross validation score computed for every fold
val = [10**i for i in range(-4,5)]
sns.set_style('darkgrid')
plt.figure(figsize=(16,8))
plt.plot(val,t_auc,'g',label = 'training AUC')#t_auc refers to the auc on training data
plt.plot(val,cv_auc,'r',label='validation AUC')# c_auc refers to the auc on cross validation data
#plotting the graph between AUC and hyperparameter for tuning
plt.xscale('log')#taking log scale for x axis for better analysing the results
plt.xlabel('hyperparameter C',fontsize=18)
plt.ylabel('Area under curve',fontsize=18)
    #plt.xticks([])
    #plt.yticks([])
plt.legend(loc = 'best')
plt.title('AUC vs hyperparameter ',fontsize=18)

#******************************
print("************************")
best_C_lr = model_lr.best_params_
print('Best Hyperparameter value we get after tuning the model is :',best_C_lr)
```

```
************************
Best Hyperparameter value we get after tuning the model is : {'C': 100}
```



Feature Importances

- Feature Importances will tell us about most important features in helping for model interpretability

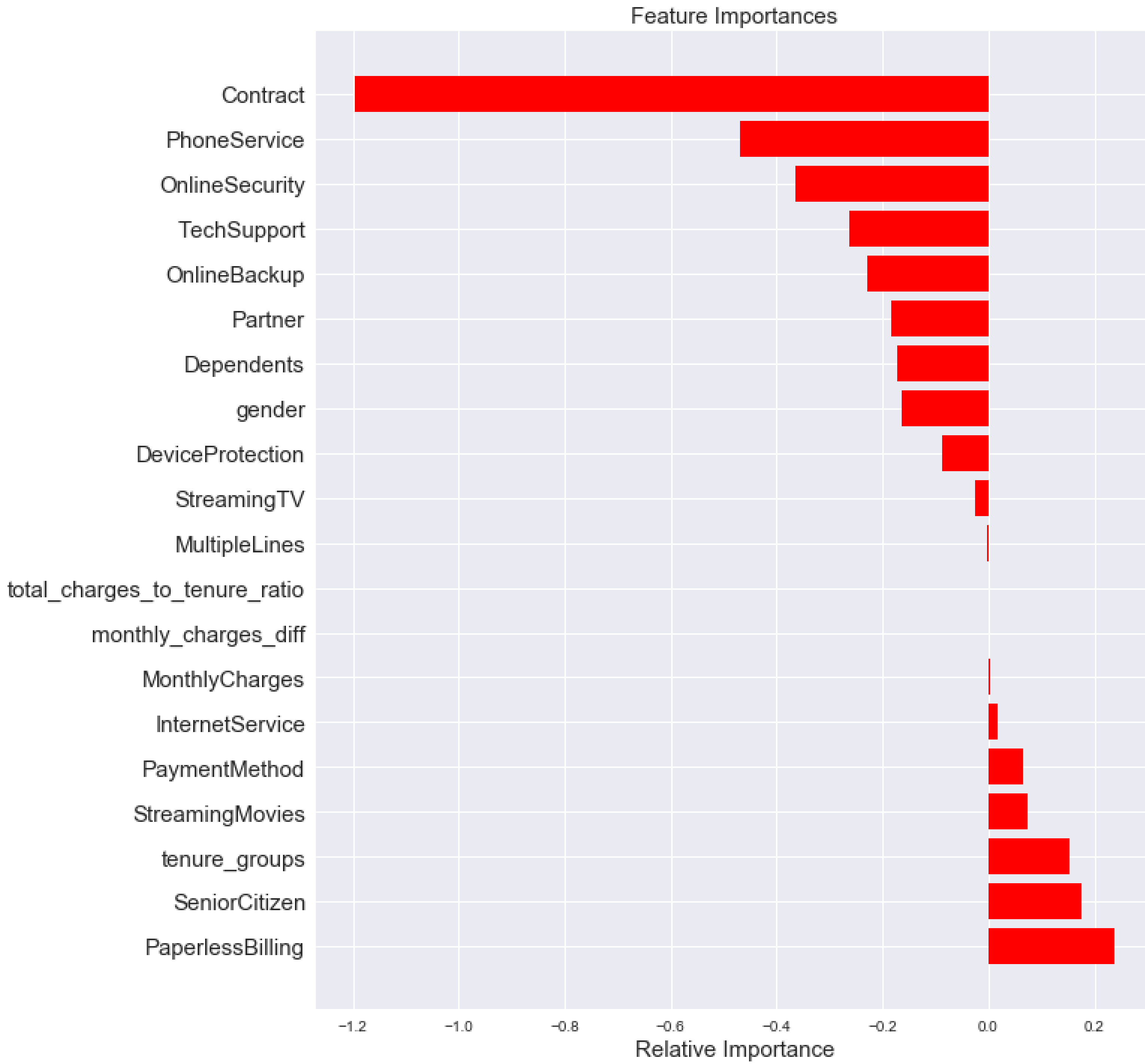
In [49]:
```
clf_optimal = LogisticRegression(C =best_C_lr['C'],penalty='l2',verbose=1)#fitting the best hyperparameter f
clf_optimal.fit(X_train,Y_train)
#print(clf_optimal.coef_)
w = clf_optimal.coef_[0]#finding the coefficients of all features
print(clf_optimal.classes_)
print(w)

```

```
[LibLinear][0 1]
[ -1.62170213e-01   1.77199661e-01  -1.82805266e-01  -1.71684779e-01
  -4.68064476e-01  -2.51287723e-03   1.79651379e-02  -3.63548461e-01
  -2.27940605e-01  -8.69597388e-02  -2.63144957e-01  -2.61707229e-02
   7.47762120e-02  -1.19702018e+00   2.37645249e-01   6.69122849e-02
   3.34727593e-03   1.52094078e-01  -5.64429051e-04  -9.47778849e-05]
```

where class 0 denotes that customer did not churn while class 1 denotes that they churned out

In [50]:

```
features = data.columns
#features = vect.get_feature_names()#getting name of the features after fitting and transforming by countvec
#negative_indices = np.argsort(w)
indices = np.argsort(w)[::-1]
pos_dict = {}
neg_dict = {}



#print('TOP 20 important features for positive class and their coefficients in this featurization are:\n')
for i in (indices):
    pos_dict[features[i]] = w[i]
pos_df = pd.DataFrame.from_dict(pos_dict,orient = 'index',columns=['Coefficients'])
#print(pos_df)
#print("*********************************************")


plt.figure(figsize=(10,12))
plt.title('Feature Importances',fontsize=15)
plt.barh(range(len(indices)), pos_df['Coefficients'], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices],fontsize=15)
plt.xlabel('Relative Importance',fontsize=15)
plt.show()
```


Feature Importances
Contract
PhoneService
OnlineSecurity
TechSupport
OnlineBackup
Partner
Dependents
gender
DeviceProtection
StreamingTV
MultipleLines
total_charges_to_tenure_ratio
monthly_charges_diff
MonthlyCharges
InternetService
PaymentMethod
StreamingMovies
tenure_groups
SeniorCitizen
PaperlessBilling
−1.2
−1.0
−0.8
−0.6
−0.4
−0.2
0.0
0.2
Relative Importance

from the above graph we can infer a lot of things regarding interpretability from the model

- **PaperlessBilling** , **tenure_groups** , **Internet_Service** , **SeniorCitizen** , **PaymentMethod** were the features will actually favoured the model towards positive class i.e these features impacted most in a cutomer's churning out

MODEL 2: Random Forest Classifier

Grid Search Cross Validation for tuning both the hyperparameters

In [51]:

```
from sklearn.ensemble import RandomForestClassifier


estimators = [10,50,100,250,450]#list of estimators that will be tuned
depths = [3,9,11,15,50]#tuning depth to avoid overfitting and underfitting

params = {'max_depth':depths,'n_estimators':estimators}#for passing as argument
skf= StratifiedKFold(n_splits=5)#number of splits are set to 5
model_rf = GridSearchCV(RandomForestClassifier(bootstrap = True,criterion = 'gini',max_features = 'auto'),pa
                        scoring = 'roc_auc',n_jobs=-1,verbose=1)
model_rf.fit(X_train,Y_train)

```

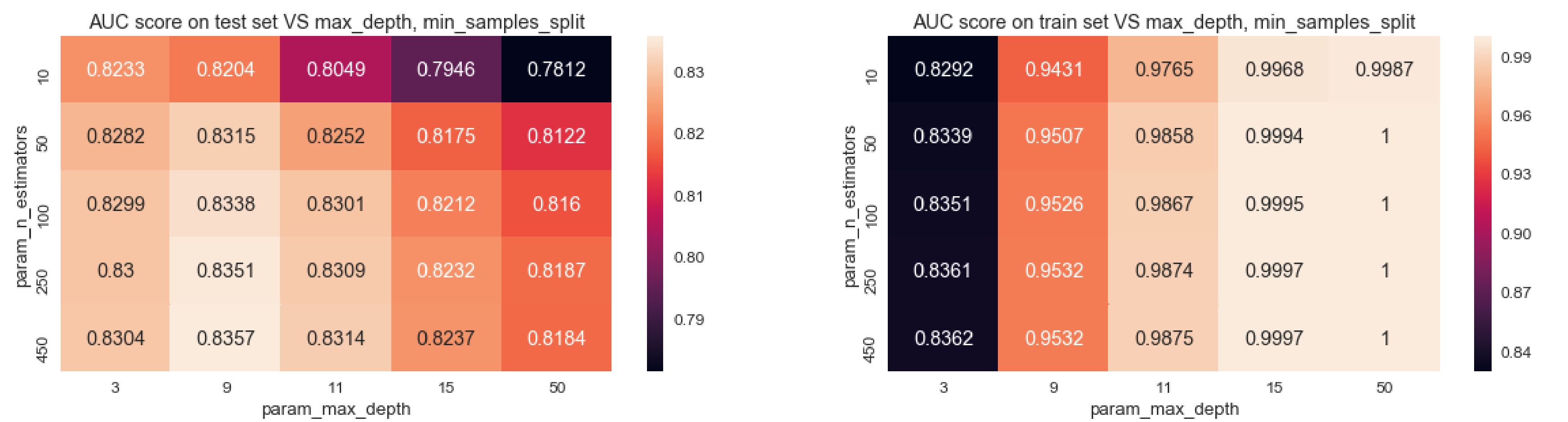
```
Fitting 5 folds for each of 25 candidates, totalling 125 fits

[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:   10.0s
[Parallel(n_jobs=-1)]: Done 125 out of 125 | elapsed:   40.8s finished
```

Out[51]:

```
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None, shuffle=False),
       error_score='raise',
       estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
            verbose=0, warm_start=False),
       fit_params={}, iid=True, n_jobs=-1,
       param_grid={'max_depth': [3, 9, 11, 15, 50], 'n_estimators': [10, 50, 100, 250, 450]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='roc_auc', verbose=1)
```

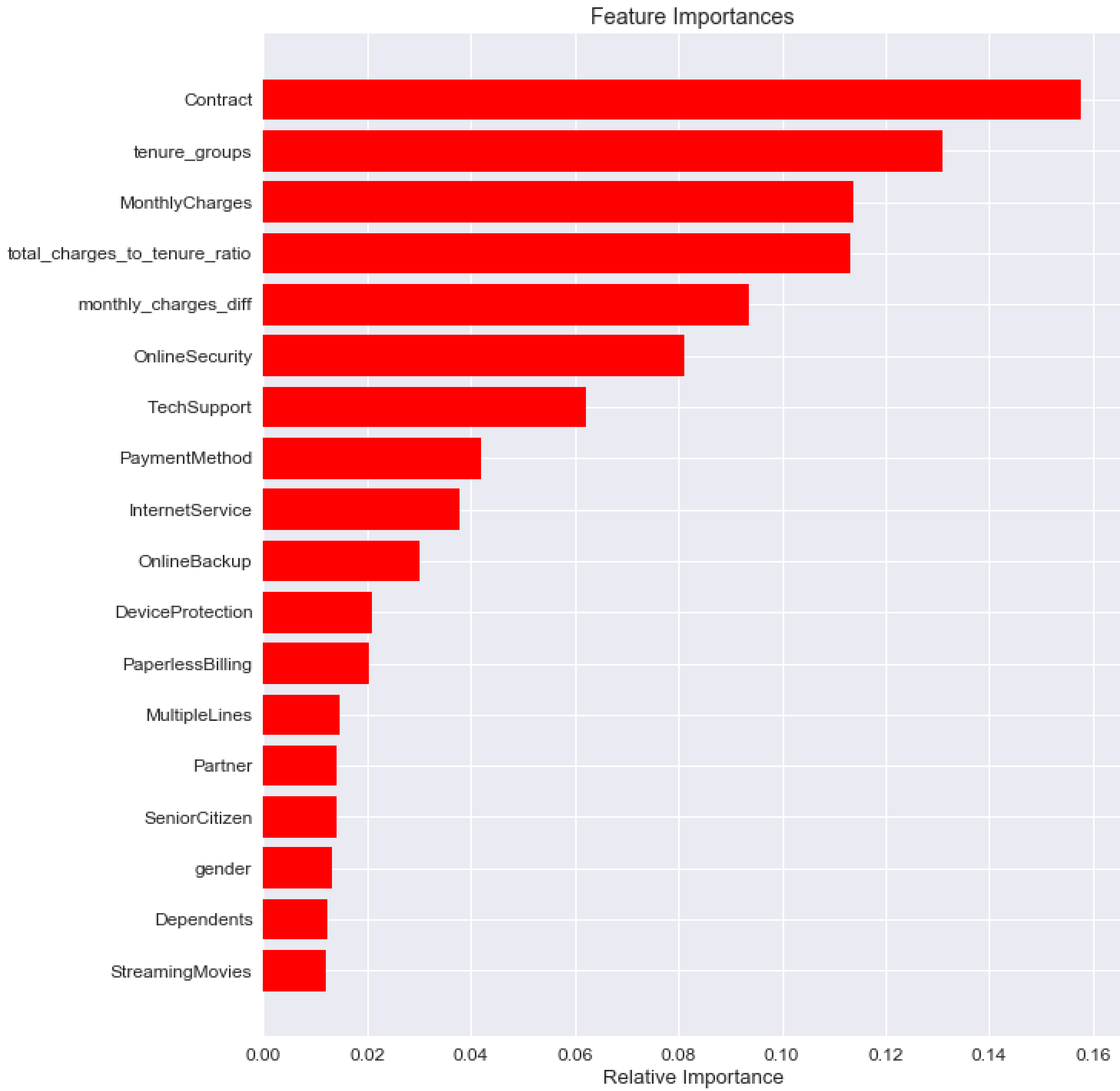
In [52]:
```python
# as we have two hyperaparameters to tune so we will plot heatmap and to show hyperparameters giving maximum
print('Best Hyperparameters are:',model_rf.best_params_)
max_depth = model_rf.best_params_['max_depth']
n_estimators = model_rf.best_params_['n_estimators']
df = pd.DataFrame(model_rf.cv_results_)#saving into the dataframe
results = df.groupby(['param_n_estimators','param_max_depth']).min().unstack()[['mean_test_score',
                                                                                'mean_train_sc
#groupby by number of estimators and maximum depth and unstacking mean train and test score

#results = results.fillna(0.1)#imputing all null values by 0.1

sns.set(font_scale = 1.2)
fig, ax = plt.subplots(figsize=(20,10))#setting the font size
plt.subplot(2,2,1)
title_test = 'AUC score on test set VS max_depth, min_samples_split'
fmt = 'png'
sns.heatmap(results.mean_test_score, annot=True, fmt='.4g');#heatmap for test score
plt.title(title_test);
#plt.savefig('{title_test}.{fmt}', format=fmt, dpi=300);
plt.subplot(2,2,2)
title_train = 'AUC score on train set VS max_depth, min_samples_split'
fmt = 'png'
sns.heatmap(results.mean_train_score, annot=True, fmt='.4g');#heatmap for train score
plt.title(title_train);
#plt.savefig('{title_train}.{fmt}', format=fmt, dpi=300);
```

```
Best Hyperparameters are: {'max_depth': 9, 'n_estimators': 450}
```



Feature Importances

In [53]:
```
optimal_clf = RandomForestClassifier(max_depth = max_depth,n_estimators = n_estimators,bootstrap = True,crit
optimal_clf.fit(X_train,Y_train)

features = data.columns
importances = optimal_clf.feature_importances_
indices = (np.argsort(importances))[-18:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```


Feature Importances
Contract
tenure_groups
MonthlyCharges
total_charges_to_tenure_ratio
monthly_charges_diff
OnlineSecurity
TechSupport
PaymentMethod
InternetService
OnlineBackup
DeviceProtection
PaperlessBilling
MultipleLines
Partner
SeniorCitizen
gender
Dependents
StreamingMovies
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
Relative Importance

Model 3: Linear SVM

SGD with hinge loss and gridsearch cv

In [68]:
```
from sklearn.linear_model import SGDClassifier
alpha = [10**i for i in range(-4,5,1)]
#tscv = TimeSeriesSplit(n_splits =  5)# for times series cross validation
params = {'alpha':alpha}

clf = SGDClassifier(penalty = 'l2',loss = 'hinge',random_state = 42)
#we will be checking for both l1 and l2 regularizations
svm = GridSearchCV(clf,param_grid = params,verbose = 1,cv = skf,scoring = 'roc_auc',return_train_score = Tru
#cv = tscv does cross validation according to time series split
svm.fit(X_train,Y_train)

```

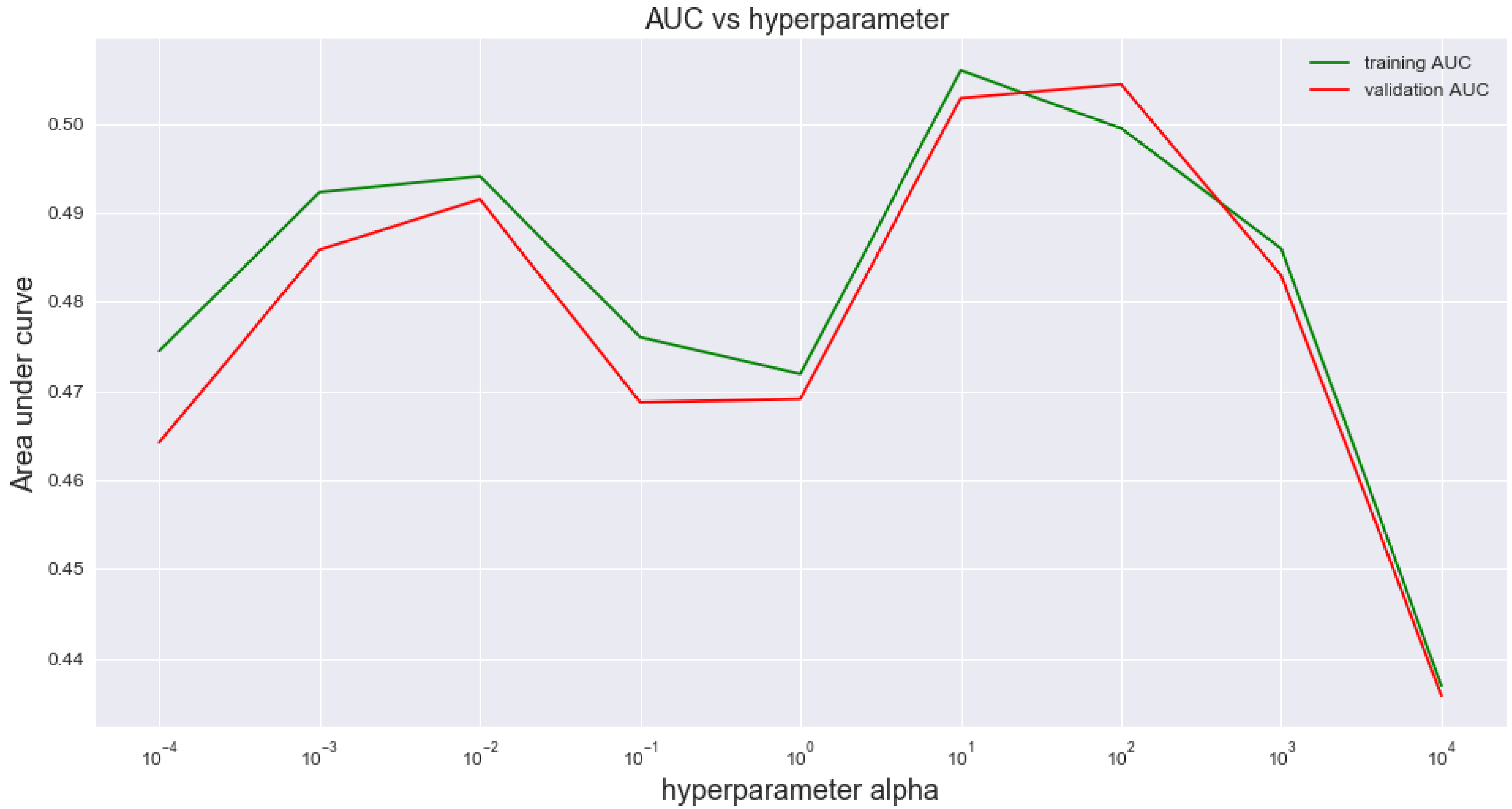
```
Fitting 5 folds for each of 9 candidates, totalling 45 fits

[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed:    0.3s finished
```

Out[68]:
```
GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None, shuffle=False),
       error_score='raise',
       estimator=SGDClassifier(alpha=0.0001, average=False, class_weight=None, epsilon=0.1,
       eta0=0.0, fit_intercept=True, l1_ratio=0.15,
       learning_rate='optimal', loss='hinge', n_iter=5, n_jobs=1,
       penalty='l2', power_t=0.5, random_state=42, shuffle=True, verbose=0,
       warm_start=False),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'alpha': [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='roc_auc', verbose=1)
```

Plotting Hyperparameter vs AUC for tuning

In [69]:
```
t_auc = svm.cv_results_['mean_train_score']#mean training score computed for every fold
cv_auc = svm.cv_results_['mean_test_score']#mean cross validation score computed for every fold
#val = [10**i for i in range(-4,5)]
sns.set_style('darkgrid')
plt.figure(figsize=(16,8))
plt.plot(alpha,t_auc,'g',label = 'training AUC')#t_auc refers to the auc on training data
plt.plot(alpha,cv_auc,'r',label='validation AUC')# c_auc refers to the auc on cross validation data
#plotting the graph between AUC and hyperparameter for tuning
plt.xscale('log')#taking log scale for x axis for better analysing the results
plt.xlabel('hyperparameter alpha',fontsize=18)
plt.ylabel('Area under curve',fontsize=18)
    #plt.xticks([])
    #plt.yticks([])
plt.legend(loc = 'best')
plt.title('AUC vs hyperparameter ',fontsize=18)

#*******************************
print("***********************")
best_alpha_svm = svm.best_params_
print('Best Hyperparameter value we get after tuning the model is :',best_alpha_svm)
```

```
************************
Best Hyperparameter value we get after tuning the model is : {'alpha': 100}
```



Feature Importances

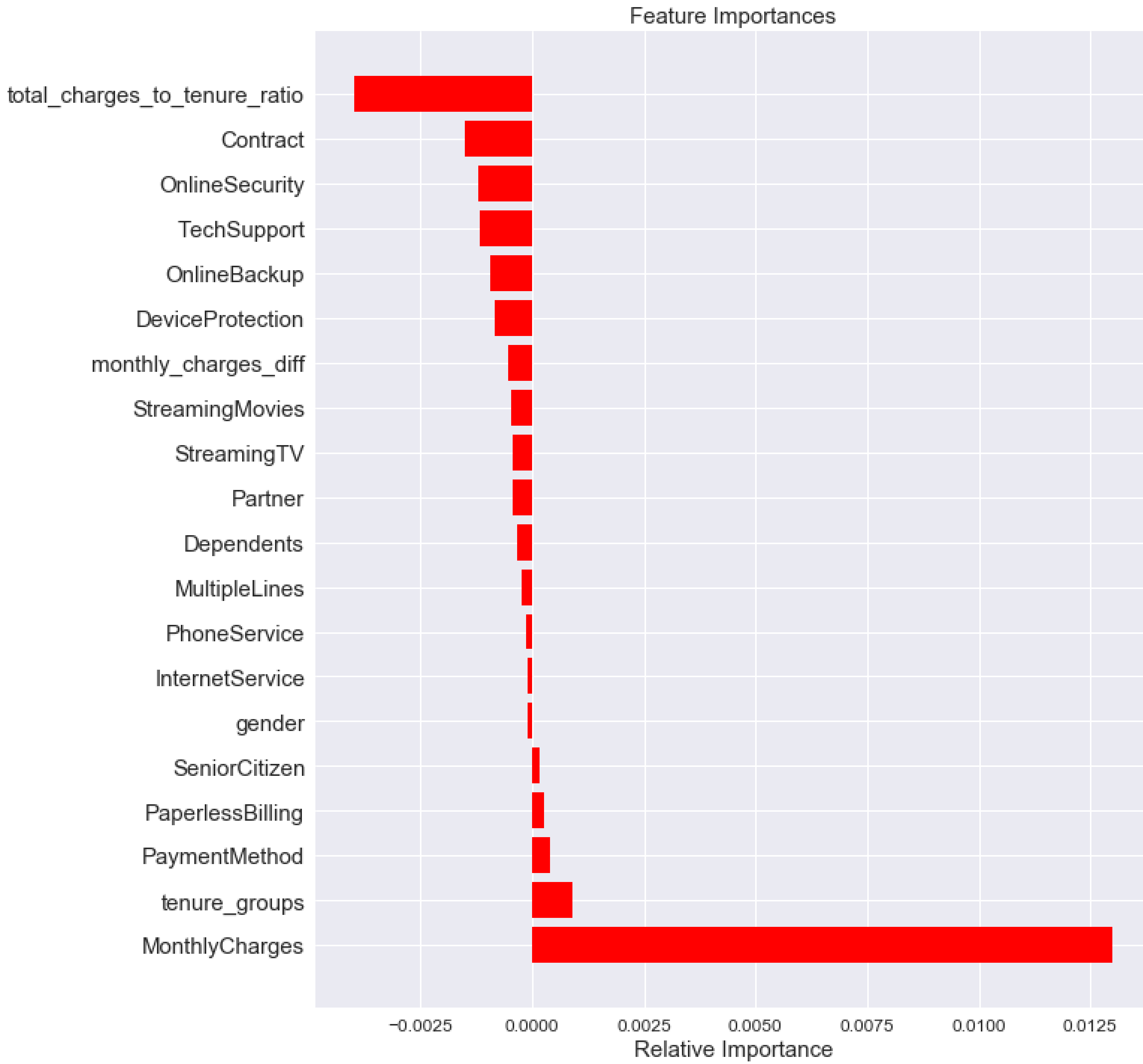
In [70]:

```
optimal_clf = SGDClassifier(alpha = best_alpha_svm['alpha'],penalty = 'l2',loss = 'hinge',random_state = 42)
#clf_optimal = LogisticRegression(C =best_C_lr['C'],penalty='l2',verbose=1)#fitting the best hyperparameter
optimal_clf.fit(X_train,Y_train)
#print(clf_optimal.coef_)
w = optimal_clf.coef_[0]#finding the coefficients of all features
print(optimal_clf.classes_)
print(w)

```

```
[0 1]
[ -8.51960447e-05   1.86214212e-04  -4.20706183e-04  -3.22933579e-04
  -1.43616190e-04  -2.34897666e-04  -1.14000422e-04  -1.20937814e-03
  -9.24579933e-04  -8.45063624e-04  -1.16880859e-03  -4.41802346e-04
  -4.61275728e-04  -1.49214787e-03   2.55182439e-04   3.97987237e-04
   1.29915854e-02   9.02672378e-04  -3.99812867e-03  -5.29026868e-04]
```

In [71]:

```
features = data.columns
#features = vect.get_feature_names()#getting name of the features after fitting and transforming by countvec
#negative_indices = np.argsort(w)
indices = np.argsort(w)[::-1]
pos_dict = {}
neg_dict = {}



#print('TOP 20 important features for positive class and their coefficients in this featurization are:\n')
for i in (indices):
    pos_dict[features[i]] = w[i]
pos_df = pd.DataFrame.from_dict(pos_dict,orient = 'index',columns=['Coefficients'])
#print(pos_df)
#print("************************************************")


plt.figure(figsize=(10,12))
plt.title('Feature Importances',fontsize=15)
plt.barh(range(len(indices)), pos_df['Coefficients'], color='r', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices],fontsize=15)
plt.xlabel('Relative Importance',fontsize=15)
plt.show()
```


Feature Importances
total_charges_to_tenure_ratio
Contract
OnlineSecurity
TechSupport
OnlineBackup
DeviceProtection
monthly_charges_diff
StreamingMovies
StreamingTV
Partner
Dependents
MultipleLines
PhoneService
InternetService
gender
SeniorCitizen
PaperlessBilling
PaymentMethod
tenure_groups
MonthlyCharges
−0.0025
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
Relative Importance

Model Evaluation

For our analysis, recall will be our target metric. We care the most about capturing as many true positives (people who are likely to churn) with our model, and we’re less concerned that we may sweep in some false negatives (people who did not churn) along with them.

We will plot ROC CURVE and Confusion Matrix for each of the classifiers

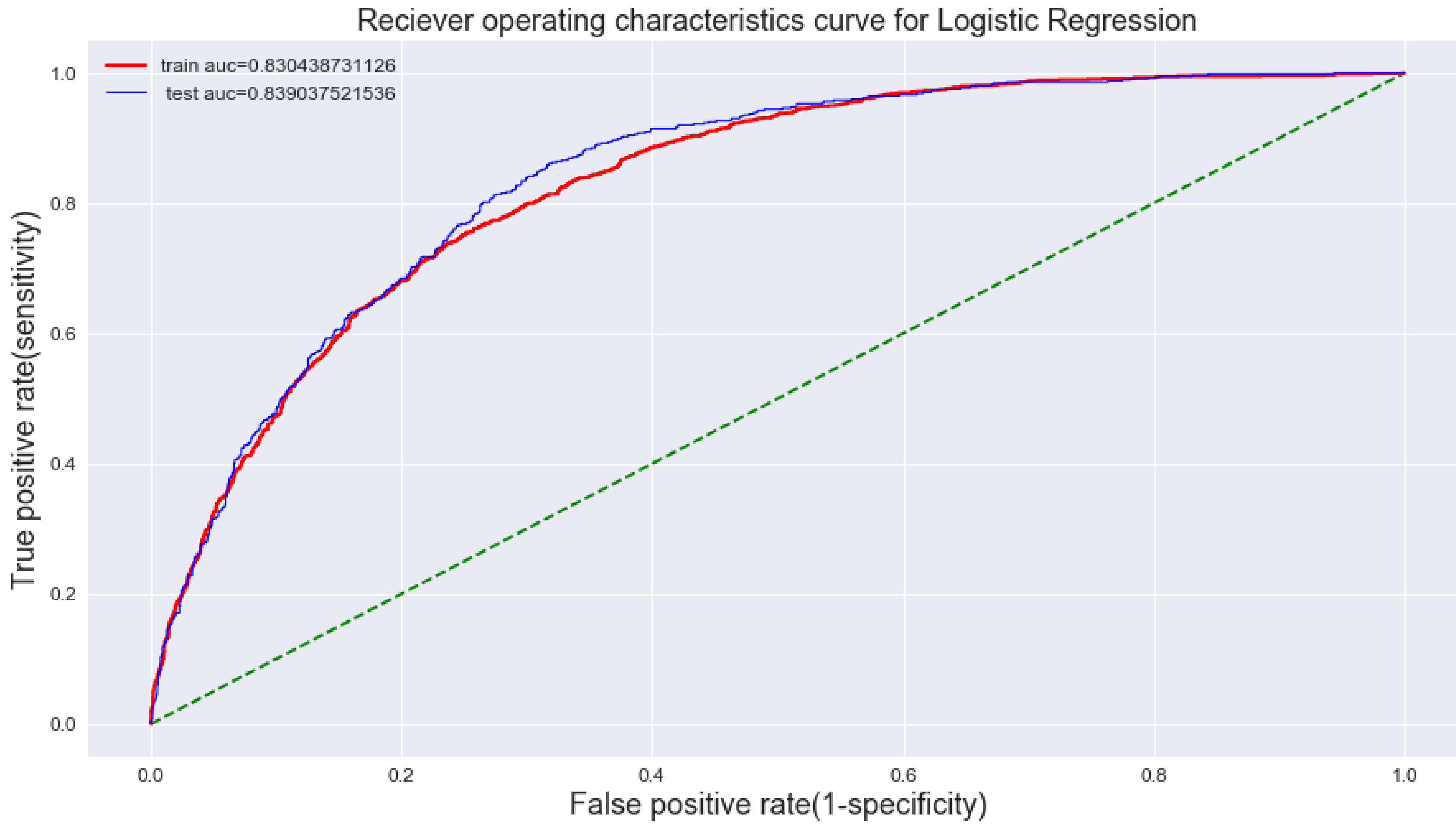
In [58]:

```
# fucntion for computing and plotting the ROC CURVE
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score


def plot_roc(train_proba,test_proba,auc_train,auc_test,t):
    print('plotting ROC on Test data')
    fpr_tr, tpr_tr, _ = roc_curve(Y_train,train_proba)
    fpr_test, tpr_test, _ = roc_curve(Y_test,test_proba)
    #calculating the fpr,tpr and thresholds for each training and test dataset
    sns.set_style('darkgrid')
    plt.figure(figsize=(15,8))
    plt.plot(np.linspace(0,1,100),np.linspace(0,1,100),"g--")#this plots the roc curve for AUC = 0.5
    plt.plot(fpr_tr,tpr_tr,'r',linewidth=2,label="train auc="+str(auc_train))
    plt.plot(fpr_test,tpr_test,'b',linewidth=1,label=" test auc="+str(auc_test))
    plt.xlabel('False positive rate(1-specificity)',fontsize=18)
    plt.ylabel('True positive rate(sensitivity)',fontsize=18)
    plt.title('Reciever operating characteristics curve for '+t,fontsize=18)
    plt.legend(loc='best')
    plt.show()

# function for confusion matrix,precision,and recall
def plot_confusion_matrix(pred_y):
    print('Confusion Matrix')
    C = confusion_matrix(Y_test, pred_y)

    A =(((C.T)/(C.sum(axis=1))).T)#for recall matrix

    B =(C/C.sum(axis=0))#for precision matrix
    plt.figure(figsize=(20,4))

    labels = [0,1]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
```

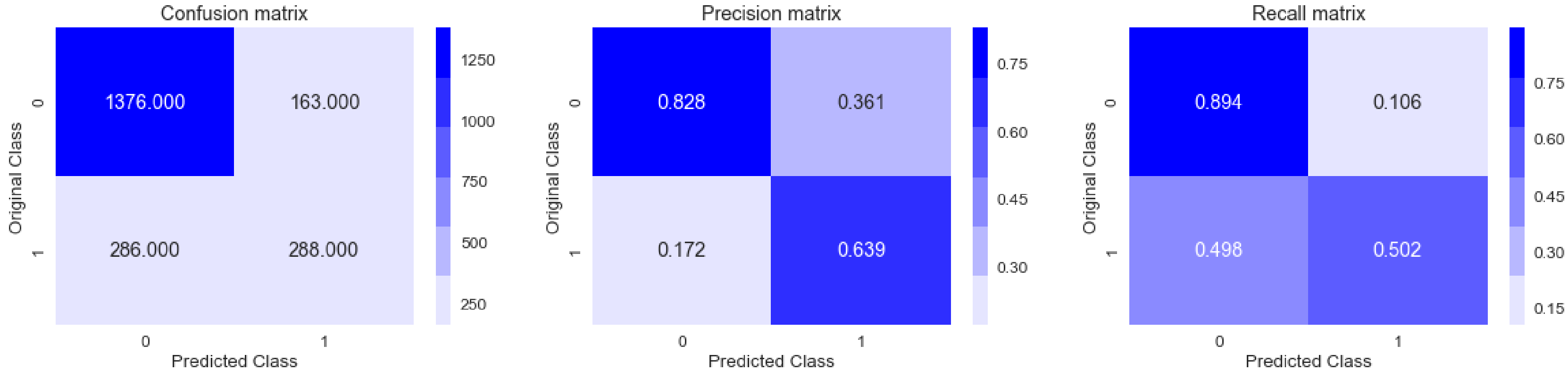
```
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()

```

In [80]:
```
#FOR LOGISTIC REGRESSION
best_lr = LogisticRegression(C= best_C_lr['C'],penalty='l2')
best_lr.fit(X_train,Y_train)
lr_train_proba = best_lr.predict_proba(X_train)[:,1]
lr_test_proba = best_lr.predict_proba(X_test)[:,1]
lr_train_auc = roc_auc_score(Y_train,lr_train_proba)
lr_test_auc = roc_auc_score(Y_test,lr_test_proba)
lr_test_pred = best_lr.predict(X_test)
#printing all the metric scores
lr_recall_score = recall_score(Y_test,lr_test_pred)
lr_precision_score = precision_score(Y_test,lr_test_pred)
lr_f1_Score = f1_score(Y_test,lr_test_pred)

print('AUC on test dataset is:',lr_test_auc)
plot_roc(lr_train_proba,lr_test_proba,lr_train_auc,lr_test_auc,'Logistic Regression')
print('**************************************************************************')
print('Matrix on test data')
plot_confusion_matrix(lr_test_pred)
```

```
AUC on test dataset is: 0.839037521536
plotting ROC on Test data
```



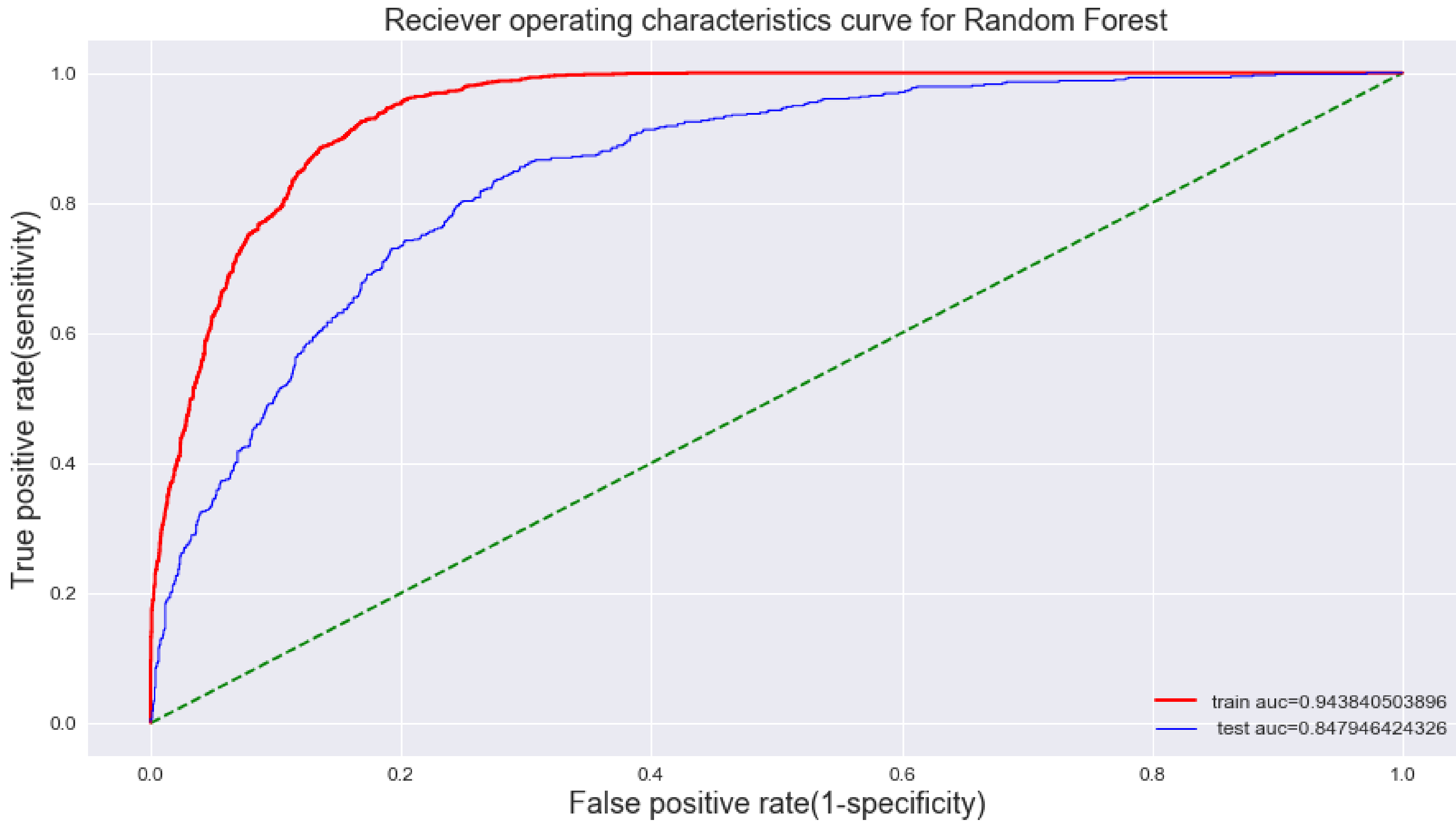

```
*************************************************************************
Matrix on test data
Confusion Matrix
```


Confusion matrix
1376.000
163.000
286.000
288.000
1250
1000
750
500
250
Precision matrix
0.828
0.361
0.172
0.639
0.75
0.60
0.45
0.30
Recall matrix
0.894
0.106
0.498
0.502
0.75
0.60
0.45
0.30
0.15
Original Class
Predicted Class
0
1

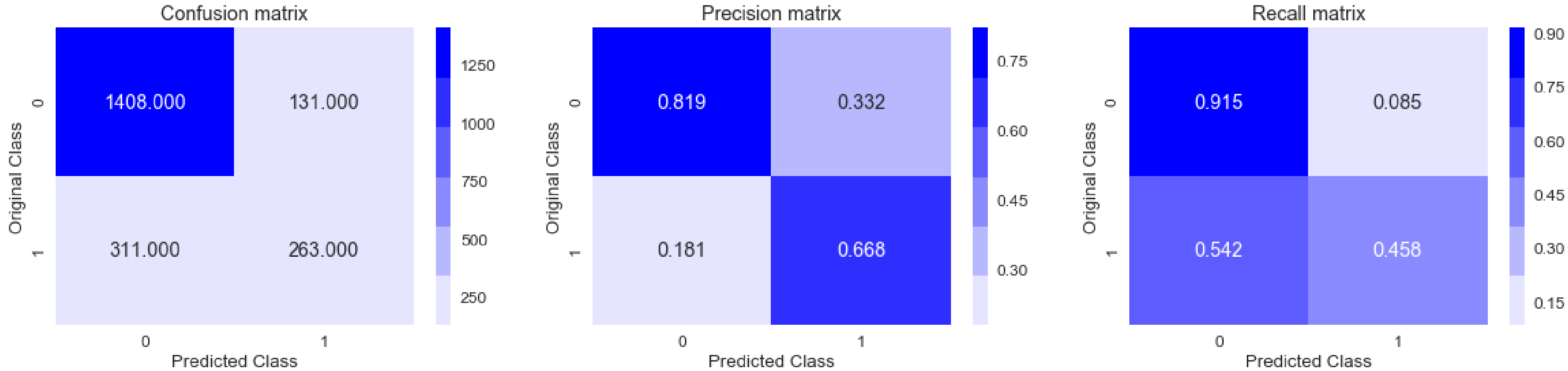
In [81]:

```python
# for Random forest
best_rf = RandomForestClassifier(max_depth =max_depth,n_estimators = n_estimators,bootstrap = True,\
                                 criterion = 'gini',max_features = 'auto')
best_rf.fit(X_train,Y_train)
rf_train_proba = best_rf.predict_proba(X_train)[:,1]
rf_test_proba = best_rf.predict_proba(X_test)[:,1]
rf_train_auc = roc_auc_score(Y_train,rf_train_proba)
rf_test_auc = roc_auc_score(Y_test,rf_test_proba)
rf_test_pred = best_rf.predict(X_test)
#printing all the metrics scores
rf_recall_score = recall_score(Y_test,rf_test_pred)
rf_precision_score = precision_score(Y_test,rf_test_pred)
rf_f1_Score = f1_score(Y_test,rf_test_pred)

print('AUC on test dataset is:',rf_test_auc)
plot_roc(rf_train_proba,rf_test_proba,rf_train_auc,rf_test_auc,'Random Forest')
print('*************************************************************************')
print('Matrix on test data')
plot_confusion_matrix(rf_test_pred)

```

```
AUC on test dataset is: 0.847946424326
plotting ROC on Test data
```



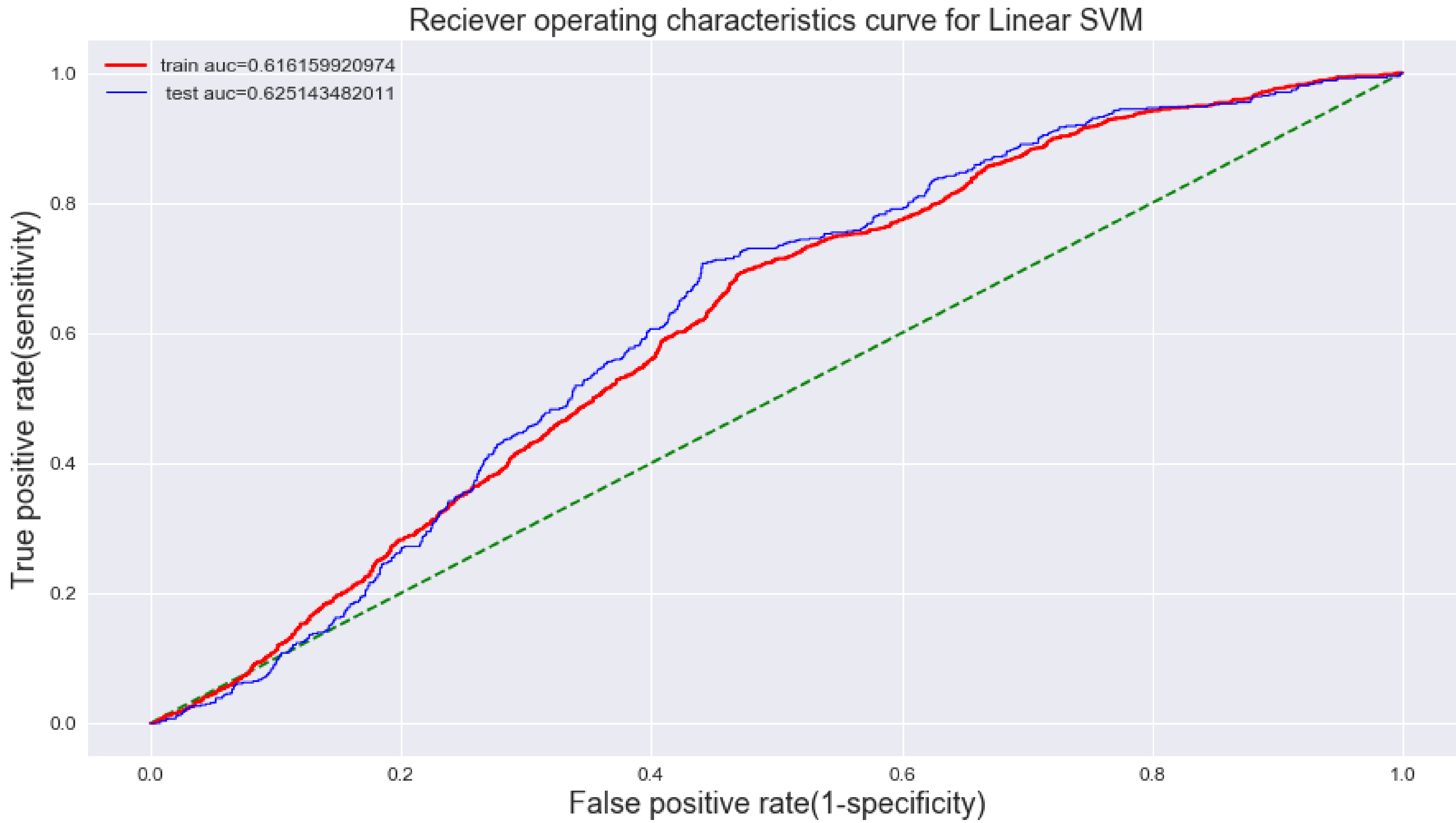

```
***************************************************************************
Matrix on test data
Confusion Matrix
```


Confusion matrix
1408.000
131.000
311.000
263.000
Original Class
Predicted Class
0
1
1250
1000
750
500
250
Precision matrix
0.819
0.332
0.181
0.668
0.75
0.60
0.45
0.30
Recall matrix
0.915
0.085
0.542
0.458
0.90
0.75
0.60
0.45
0.30
0.15

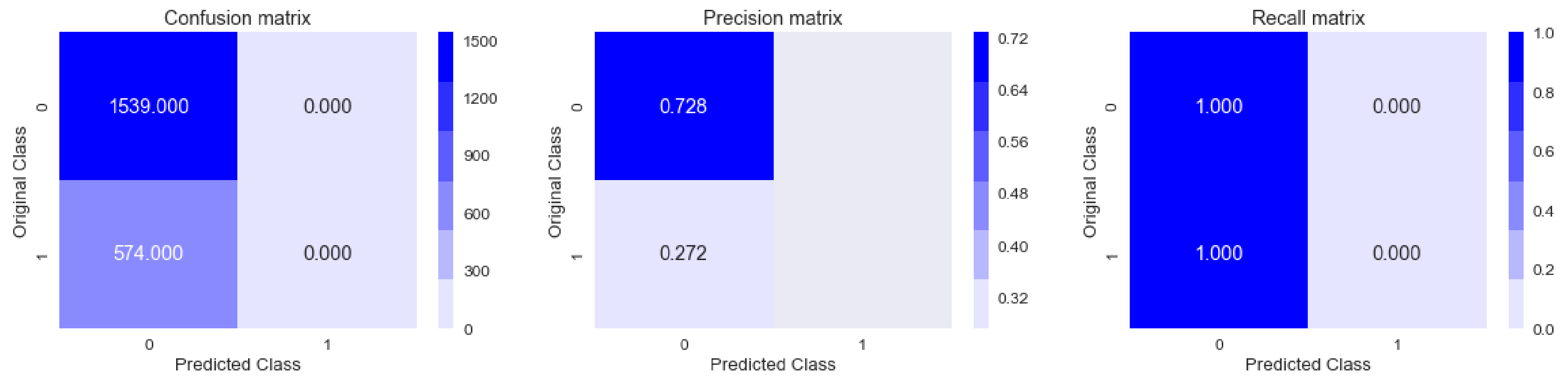
In [82]:

```
from sklearn.calibration import CalibratedClassifierCV
clf_optimal = SGDClassifier(alpha = best_alpha_svm['alpha'],penalty = 'l2',loss = 'hinge',random_state = 42)
clf_optimal.fit(X_train,Y_train)
clb = CalibratedClassifierCV(clf_optimal,cv = 5,method = 'sigmoid')
clb.fit(X_train,Y_train)
train_proba = clb.predict_proba(X_train)[:,1]
test_proba = clb.predict_proba(X_test)[:,1]
    # = clb.predict(train_set)
pred_test = clb.predict(X_test)

train_auc = roc_auc_score(Y_train,train_proba)
test_auc = roc_auc_score(Y_test,test_proba)

#printing all the metric scores

svm_recall_score = recall_score(Y_test,pred_test)
svm_precision_score = precision_score(Y_test,pred_test)
svm_f1_Score = f1_score(Y_test,pred_test)
#print('AUC on training data is',train_auc)
print('AUC on test data is',test_auc)
#print('AUC on test dataset is:',rf_test_auc)
plot_roc(train_proba,test_proba,train_auc,test_auc,'Linear SVM')
print('***************************************************************************')
print('Matrix on test data')
plot_confusion_matrix(pred_test)

```

```
AUC on test data is 0.625143482011
plotting ROC on Test data
```




```
****************************************************************************
Matrix on test data
Confusion Matrix
```



Conclusion and observations

In [84]:

```python
from prettytable import PrettyTable

#tabl
table = PrettyTable()
no = [1,2,3]
models = ['Logistic Regression using L2 regularization','Random Forest','Linear SVM suing l2 regularization'
recall_scores = [lr_recall_score,rf_recall_score,svm_recall_score]
precision_scores = [lr_precision_score,rf_precision_score,svm_precision_score]
f1_scores = [lr_f1_Score,rf_f1_Score,svm_f1_Score]
AUC = [lr_test_auc,rf_test_auc,test_auc]#their respective auc scores

table.add_column("SNo",no)
table.add_column('models',models)
table.add_column('precision score',precision_scores)
table.add_column('recall_scores',recall_scores)
table.add_column('f1_score',f1_scores)
#table.add_column('Regularization',regularization)
#table.add_column('Hyperparameter(alpha)',alphas)
table.add_column('AUC on test',AUC)

print(table)
```

```
+-----+---------------------------------------------+-----------------+----------------+-----------------+------
----------+
| SNo |                    models                   | precision score | recall_scores  |     f1_score    |  AUC
on test   |
+-----+---------------------------------------------+-----------------+----------------+-----------------+------
----------+
|  1  | Logistic Regression using L2 regularization |  0.638580931264 | 0.501742160279 | 0.561951219512 | 0.839
037521536 |
|  2  |                Random Forest                |  0.667512690355 | 0.45818815331  | 0.543388429752 | 0.847
946424326 |
|  3  |      Linear SVM suing l2 regularization     |       0.0       |      0.0       |       0.0       | 0.625
143482011 |
+-----+---------------------------------------------+-----------------+----------------+-----------------+------
----------+
```

- Logistic Regression perfomed best with best recall score ,though AUC score for random forest is better than the Logistic regression

Tenure and longer contracts: These variables have positive impacts in reducing churn. In charge with this informations, the selling and customer success departaments could push longer contract to clients. Each month that the client stays increases the chances of the client staying yet another month.

- More comments on Tenure The churn is very high after one month, and we have two main hypotheses for that:
- Our client (the telecom) does not make a good screening process to accecpt or not clients. This is a opportunitty to yet another project, risk modelling for new customers acceptance. Our onboarding process is too bad (we may take too long to install the service in the customer's house, the product may be hard to use, etc)

Monthly Charges Cheaper payments :have a good effect on churn. We could further investigate it to find out what is the effect in the life-time value when the price is decrease for a certain service plan. We could get new Monthly charges that would optimize life-time value of the client. The second usage of this insight is more direct. If a customer wants to finish his contract with the telecom, offering the customer a discount for a certain time is a good practice. The changes of churn decreases and even when the discount is over, the chances of churn are smaller because of the increase in tenure.

Phone Service and InternetService : has a bad effect on Churn, and PhoneService has a null effect . Our hypotheses are that the customers don't care much about the PhoneService and that our InternetService is bad. The telecom could survey clients about the PhoneService and InternetService to test these hypotheses. If they turn out to be true, maybe reducing the offer of PhoneService to a niche group and adjustments to the InternetService could improve our profits.

The Model Note: the model has not achieved the desired results and can not be used by the business as is. Improvements are commented in this document. In this section, we would like to expose what could be done with a good prediction model. One of the main uses of the models would be to automate customer services. For instance, since decreases in Montly charges improve churn, the clients with the highest probabilities of churn could receive automatic discounts or coupons.

What can be done

Look at their profile, identify characteristics and analyse past interactions with your product and then simply talk to them. Ask for feedback, communicate latest developments that might be from interest or educate them on new product features. Approach customers likely to churn, but make sure that you come up with relevant things that may fit their individual needs. It will create a feeling of being understood and bind them to you and your business.