Predicting_Customer_Churn_in_Telecom_Operators

March 30, 2020

1 Predicting Customer Churn in Telecommunication Operators

Customer turnover refers to a decision made by the customer on the term of business relationship. Customer loyalty and customer turnover always add up to 100%. If a company has a 60% loyalty rate, then customer loss taxes are 40%. According to the 80/20 customer profitability rule, 20% of customers are generating 80% of revenue. Therefore, it is very important to predict the users who are likely to abandon the business relationship and the factors that affect how the customer's decisions. In this project, I predicted Customer Churn at a Telecommunications Operator using python and frameworks (Pandas, Numpy, scipy and Scikit-Learn).

[8]:
```
# Importing libraries and frameworks
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

import scipy.stats

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

from sklearn.feature_selection import f_classif,chi2
from sklearn.feature_selection import SelectKBest

import random

import folium
import os
from IPython.display import display
from IPython.display import Image

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import confusion_matrix, classification_report,␣
↪accuracy_score
```

```
from sklearn.externals import joblib

import warnings
warnings.filterwarnings("ignore")
```

1.1 Importing dataset

[2]:
```
# Importing train dataset
df_train = pd.read_csv("data/projeto4_telecom_treino.csv")
df_test = pd.read_csv("data/projeto4_telecom_teste.csv")
```

1.2 Exploratory Analysis

[82]:
```
# Checking dataset features
print(df_train.shape[1])
df_train.head()
```

```
21
```

[82]:
```
   id state  account_length      area_code international_plan voice_mail_plan  \
0   1    KS             128  area_code_415                 no             yes
1   2    OH             107  area_code_415                 no             yes
2   3    NJ             137  area_code_415                 no              no
3   4    OH              84  area_code_408                yes              no
4   5    OK              75  area_code_415                yes              no

   number_vmail_messages  total_day_minutes  total_day_calls  \
0                     25              265.1              110
1                     26              161.6              123
2                      0              243.4              114
3                      0              299.4               71
4                      0              166.7              113

   total_day_charge  ...  total_eve_calls  total_eve_charge  \
0             45.07  ...               99             16.78
1             27.47  ...              103             16.62
2             41.38  ...              110             10.30
3             50.90  ...               88              5.26
4             28.34  ...              122             12.61

   total_night_minutes  total_night_calls  total_night_charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
```

```
4               186.9               121               8.41

   total_intl_minutes  total_intl_calls  total_intl_charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   number_customer_service_calls  churn
0                              1     no
1                              1     no
2                              0     no
3                              2     no
4                              3     no

[5 rows x 21 columns]
```

[83]:
```
# Checking for missing values
print(pd.isna(df_train).any().any())
print(pd.isna(df_test).any().any())
print(pd.isnull(df_train).any().any())
print(pd.isnull(df_test).any().any())
```

```
False
False
False
False
```

[84]:
```
# datasets size
print(df_train.shape)
print(df_test.shape)
```

```
(3333, 21)
(1667, 21)
```

[207]:
```
df_train.columns
```

[207]:
```
Index(['id', 'state', 'account_length', 'area_code', 'international_plan',
       'voice_mail_plan', 'number_vmail_messages', 'total_day_minutes',
       'total_day_calls', 'total_day_charge', 'total_eve_minutes',
       'total_eve_calls', 'total_eve_charge', 'total_night_minutes',
       'total_night_calls', 'total_night_charge', 'total_intl_minutes',
       'total_intl_calls', 'total_intl_charge',
       'number_customer_service_calls', 'churn'],
      dtype='object')
```

[85]:

```python
# Compute numerical data summary statistics
df_train_num = df_train[['account_length', 'number_vmail_messages',␣
↪'total_day_minutes',
                        'total_day_calls', 'total_day_charge',␣
↪'total_eve_minutes',
                        'total_eve_calls', 'total_eve_charge',␣
↪'total_night_minutes',
                        'total_night_calls', 'total_night_charge',␣
↪'total_intl_minutes',
                        'total_intl_calls', 'total_intl_charge',␣
↪'number_customer_service_calls']].copy()





df_describe = pd.concat([df_train_num.describe().T,
              df_train_num.mad().rename('mad'),
              df_train_num.skew().rename('skew'),
              df_train_num.kurt().rename('kurt'),
              df_train_num.median().rename('median')
              ], axis=1).T

display(df_describe)
```

```
        account_length  number_vmail_messages  total_day_minutes  \
count      3333.000000            3333.000000        3333.000000
mean        101.064806               8.099010         179.775098
std          39.822106              13.688365          54.467389
min           1.000000               0.000000           0.000000
25%          74.000000               0.000000         143.700000
50%         101.000000               0.000000         179.400000
75%         127.000000              20.000000         216.400000
max         243.000000              51.000000         350.800000
mad          31.821440              11.719778          43.523455
skew          0.096606               1.264824          -0.029077
kurt         -0.107836              -0.051129          -0.019940
median      101.000000               0.000000         179.400000

        total_day_calls  total_day_charge  total_eve_minutes  total_eve_calls  \
count       3333.000000       3333.000000        3333.000000      3333.000000
mean         100.435644         30.562307         200.980348       100.114311
std           20.069084          9.259435          50.713844        19.922625
min            0.000000          0.000000           0.000000         0.000000
25%           87.000000         24.430000         166.600000        87.000000
50%          101.000000         30.500000         201.400000       100.000000
75%          114.000000         36.790000         235.300000       114.000000
```

```
max        165.000000     59.640000    363.700000    170.000000
mad         15.944943      7.398914     40.469244     15.860332
skew        -0.111787     -0.029083     -0.023877     -0.055563
kurt         0.243182     -0.019812      0.025630      0.206156
median     101.000000     30.500000    201.400000    100.000000

        total_eve_charge  total_night_minutes  total_night_calls  \
count        3333.000000          3333.000000        3333.000000
mean           17.083540           200.872037         100.107711
std             4.310668            50.573847          19.568609
min             0.000000            23.200000          33.000000
25%            14.160000           167.000000          87.000000
50%            17.120000           201.200000         100.000000
75%            20.000000           235.300000         113.000000
max            30.910000           395.000000         175.000000
mad             3.439937            40.410387          15.690341
skew           -0.023858             0.008921           0.032500
kurt            0.025487             0.085816          -0.072020
median         17.120000           201.200000         100.000000

        total_night_charge  total_intl_minutes  total_intl_calls  \
count          3333.000000         3333.000000       3333.000000
mean              9.039325           10.237294          4.479448
std               2.275873            2.791840          2.461214
min               1.040000            0.000000          0.000000
25%               7.520000            8.500000          3.000000
50%               9.050000           10.300000          4.000000
75%              10.590000           12.100000          6.000000
max              17.770000           20.000000         20.000000
mad               1.818555            2.184712          1.881093
skew              0.008886           -0.245136          1.321478
kurt              0.085663            0.609185          3.083589
median            9.050000           10.300000          4.000000

        total_intl_charge  number_customer_service_calls
count         3333.000000                    3333.000000
mean             2.764581                       1.562856
std              0.753773                       1.315491
min              0.000000                       0.000000
25%              2.300000                       1.000000
50%              2.780000                       1.000000
75%              3.270000                       2.000000
max              5.400000                       9.000000
mad              0.589880                       1.052532
skew            -0.245287                       1.091359
kurt             0.609610                       1.730914
median           2.780000                       1.000000
```

[86]:
```
# Compute categorical data summary statistics
df_train_cat = df_train[['state', 'area_code', 'international_plan',␣
 ↪'voice_mail_plan', 'churn']].copy()
df_train_cat.describe()
```

[86]:
```
       state      area_code international_plan voice_mail_plan churn
count   3333           3333               3333            3333  3333
unique    51              3                  2               2     2
top       WV  area_code_415                 no              no    no
freq     106           1655               3010            2411  2850
```

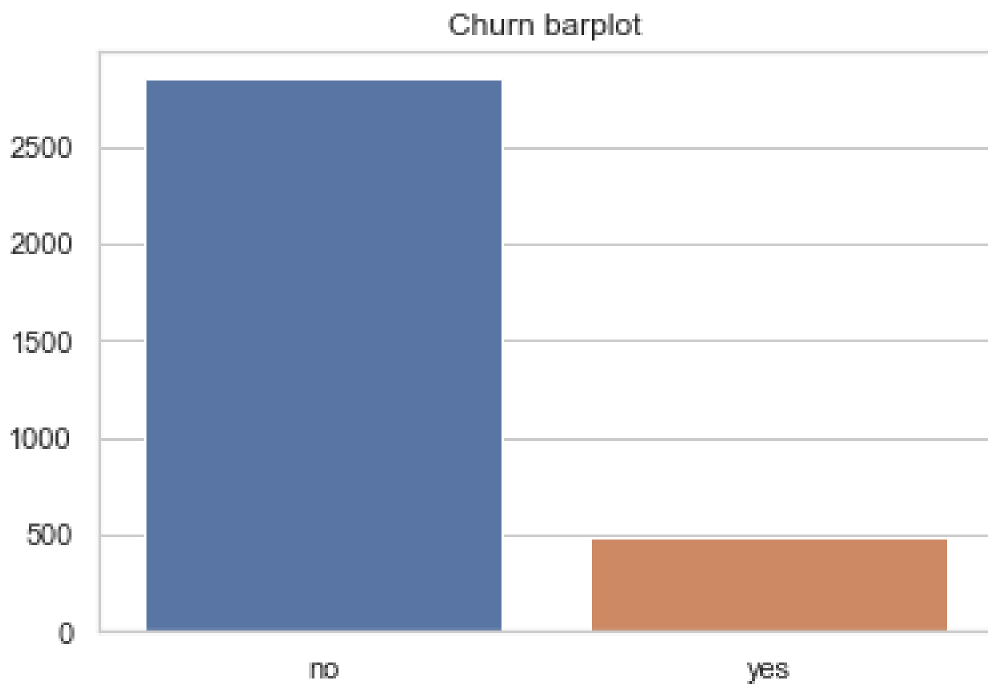
1.2.1 Univariate analysis

Checking churn variable distribution and proportion

[214]:
```
# churn values and proportion
df = pd.DataFrame(pd.Categorical(df_train.churn).describe())
display(df)

# churn variable barplot
sns.set(style="whitegrid")
sns.barplot(x=['no','yes'], y=df_train.churn.value_counts().values).
 ↪set_title('Churn barplot')
```

```
            counts     freqs
categories
no            2850  0.855086
yes            483  0.144914
```

[214]:
```
Text(0.5, 1.0, 'Churn barplot')
```

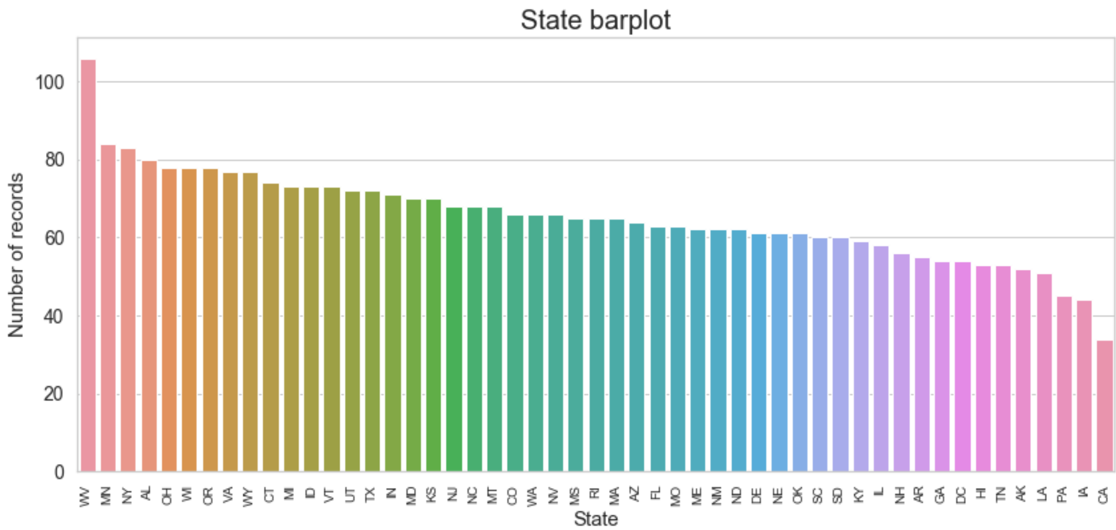


As noticed on table and graph above, churn feature is unbalanced. About 14% of customers stopped using the telecom service and 85% still using it.

Categorical variables

State

[232]:
```
# State variable barplot
plt.figure(figsize=(14,6))

sns.barplot(x=df_train.state.value_counts().index,
            y=df_train.state.value_counts().values)

plt.title('State barplot', size=20)
plt.xlabel('State', size=15)
plt.ylabel('Number of records', size=15)
plt.yticks(fontsize=14)
plt.xticks(fontsize=10, rotation=90)
plt.show()
```

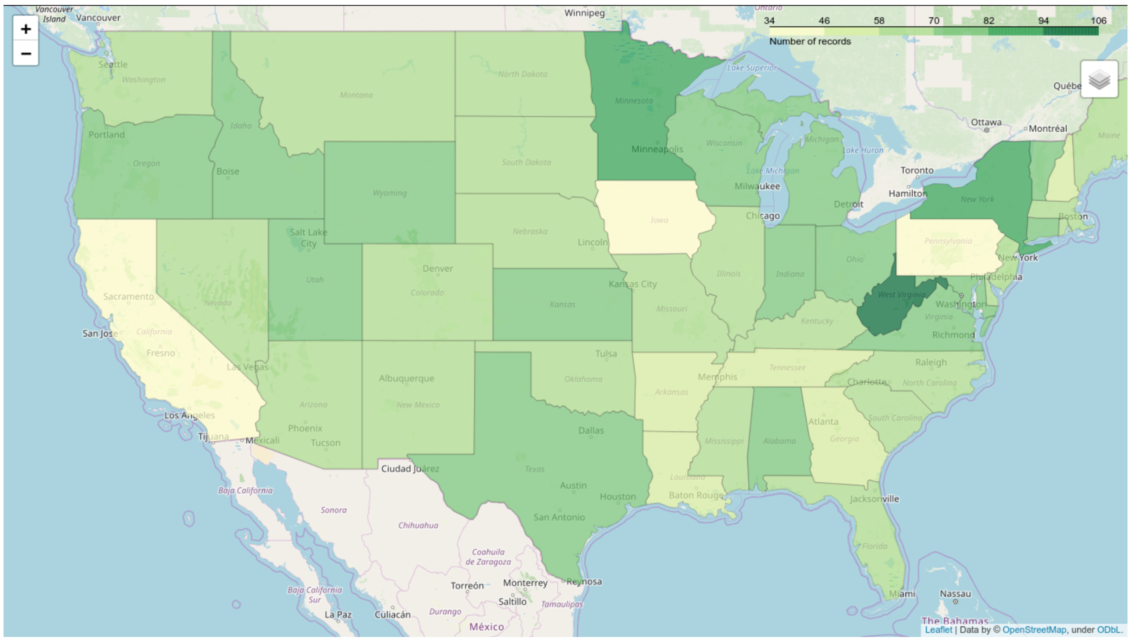


The state with the highest frequency is the West Virginia and the lowest frequency is the California. Other states with a large number of records are New York and Minnesota. ###### Number of records by State shown on the map below:

[9]:
```
# Map graph
# Load the shape of the zone (US states)
state_geo = os.path.join('', 'us-states.json')

# state data
state_data = pd.DataFrame({'state': df_train.state.value_counts().index,
                           'count': df_train.state.value_counts().values})

# Initialize the map:
m = folium.Map(location=[37, -102], zoom_start=5)

# Add the color for the chloropleth:
m.choropleth(
 geo_data=state_geo,
 name='Number of records by state',
 data=state_data,
 columns=['state', 'count'],
 key_on='feature.id',
 fill_color='YlGn',
 fill_opacity=0.7,
 line_opacity=0.2,
 legend_name='Number of records'
)
folium.LayerControl().add_to(m)

# Save to html
```

```
m.save('#registers_by_map.html')

display(m)

# Loading map image
# Image(filename='records_by_state.png')
```

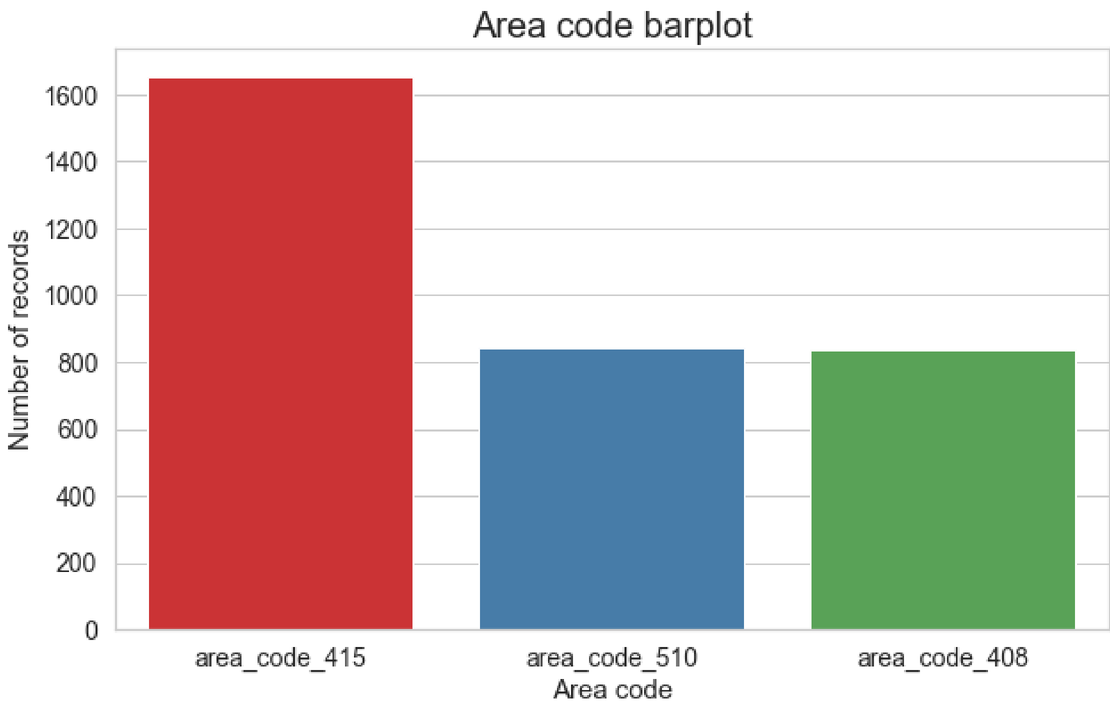
[9]:



Area code

[27]:
```
# area_code values and proportion
plt.figure(figsize=(10,6))

df = pd.DataFrame(pd.Categorical(df_train.area_code).describe())
display(df)

# area_code variable barplot
sns.set(style="whitegrid")
sns.barplot(x=df_train.area_code.value_counts().index,
            y=df_train.area_code.value_counts().values,
           palette='Set1')

plt.title('Area code barplot', size=20)
plt.xlabel('Area code', size=15)
plt.ylabel('Number of records', size=15)
plt.yticks(fontsize=14)
plt.xticks(fontsize=14)
plt.show()
```

```
                counts     freqs
categories
area_code_408      838  0.251425
area_code_415     1655  0.496550
area_code_510      840  0.252025
```

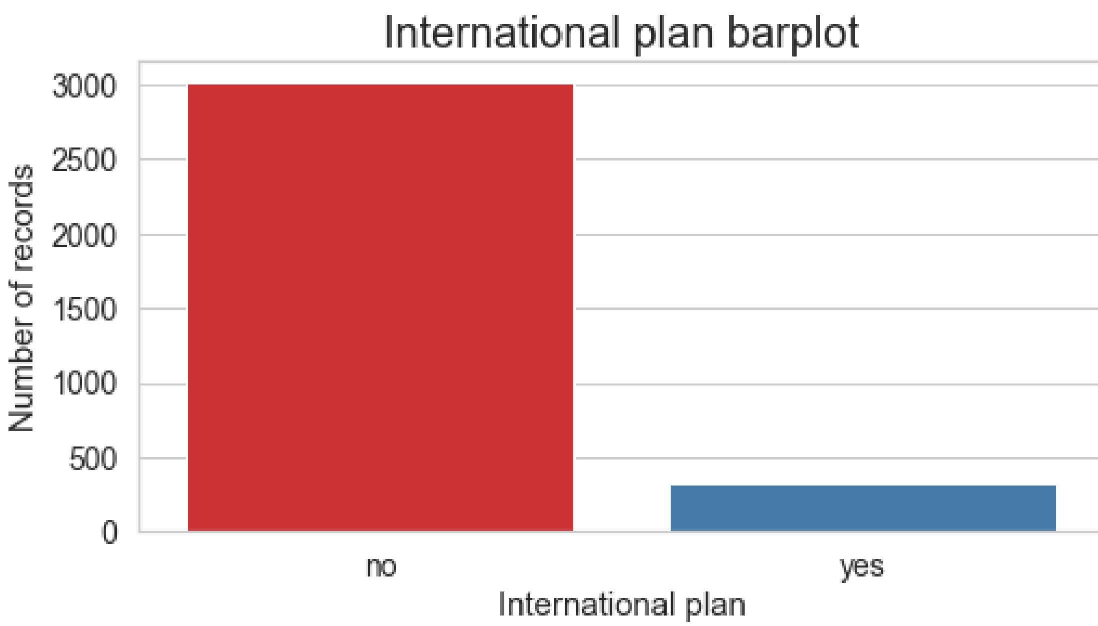


Code area 415 has the largest number of records. ##### International plan

[29]:
```
# international_plan values and proportion
plt.figure(figsize=(8,4))

df = pd.DataFrame(pd.Categorical(df_train.international_plan).describe())
display(df)

# international_plan variable barplot
sns.set(style="whitegrid")
sns.barplot(x=df_train.international_plan.value_counts().index,
            y=df_train.international_plan.value_counts().values,
           palette='Set1')

plt.title('International plan barplot', size=20)
plt.xlabel('International plan', size=15)
plt.ylabel('Number of records', size=15)
plt.yticks(fontsize=14)
plt.xticks(fontsize=14)
```

```
plt.show()
```

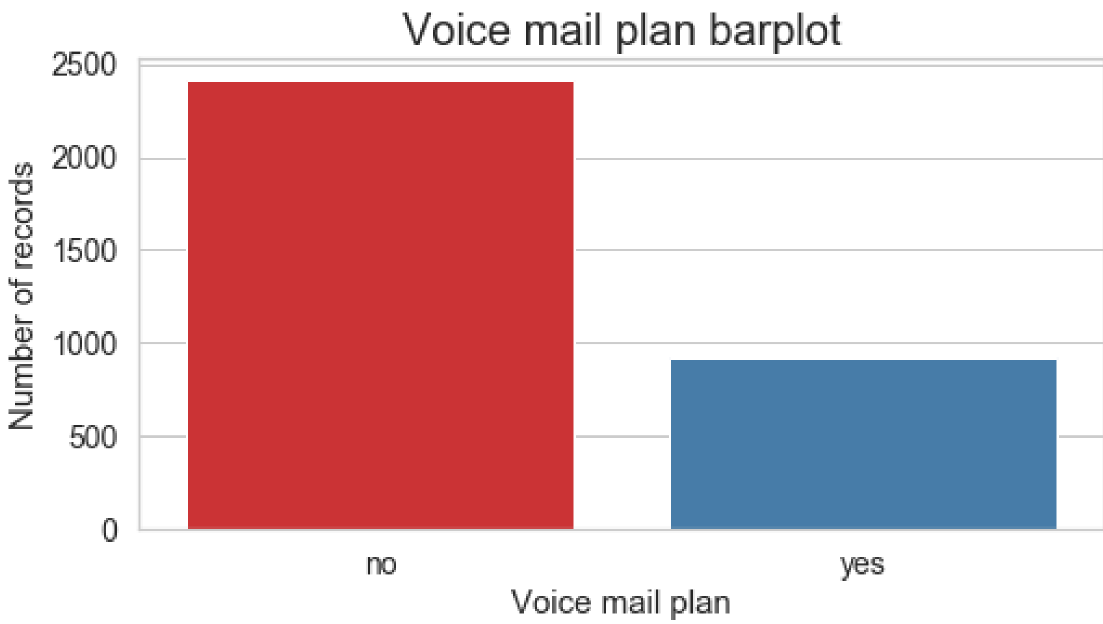
```
             counts    freqs
categories
no             3010  0.90309
yes             323  0.09691
```



Most customers do not have international plan. ##### Voice mail plan

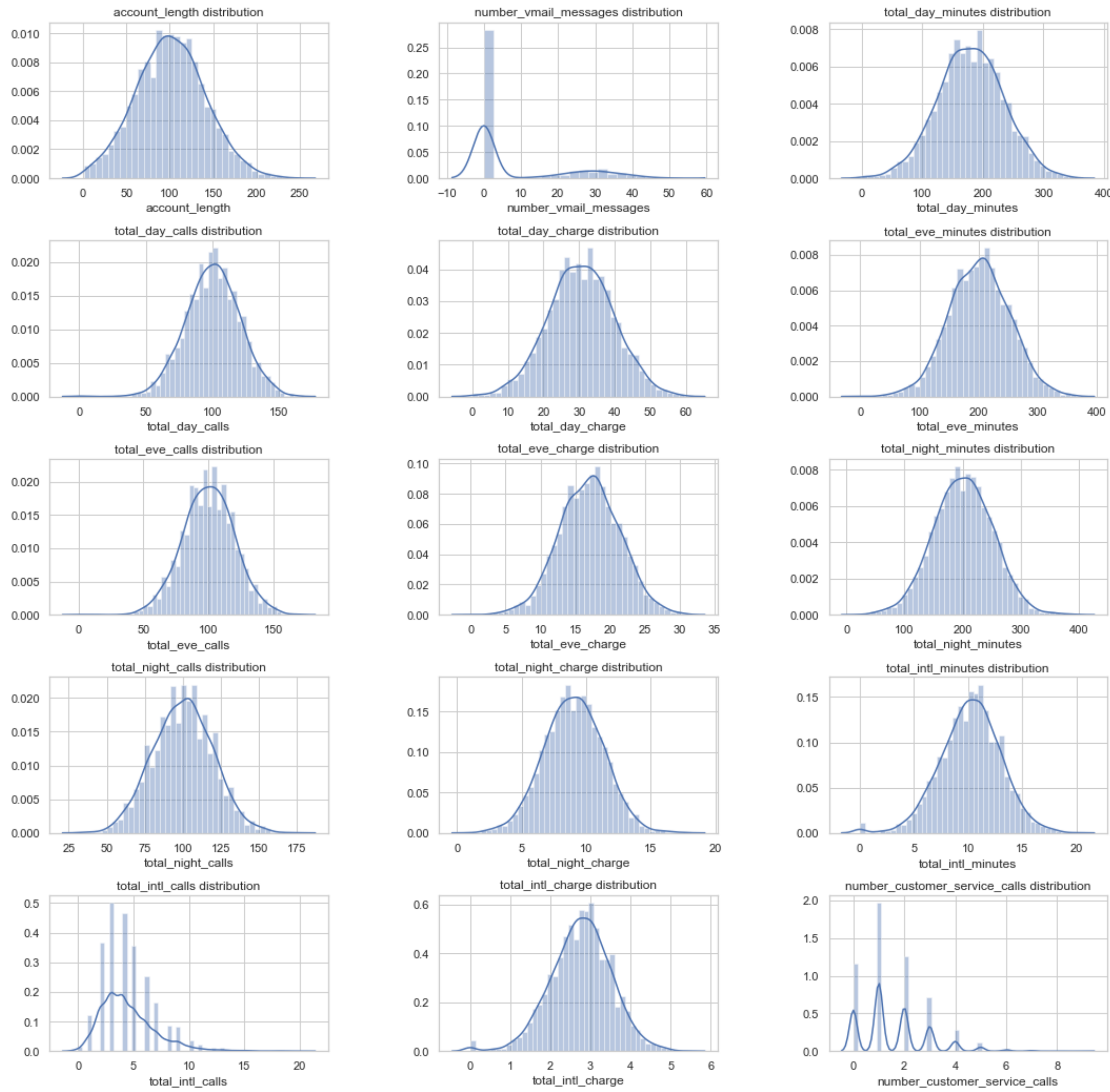
[30]:
```
# voice_mail_plan values and proportion
plt.figure(figsize=(8,4))

df = pd.DataFrame(pd.Categorical(df_train.voice_mail_plan).describe())
display(df)

# voice_mail_plan variable barplot
sns.set(style="whitegrid")
sns.barplot(x=df_train.voice_mail_plan.value_counts().index,
            y=df_train.voice_mail_plan.value_counts().values,
           palette='Set1')

plt.title('Voice mail plan barplot', size=20)
plt.xlabel('Voice mail plan', size=15)
plt.ylabel('Number of records', size=15)
plt.yticks(fontsize=14)
plt.xticks(fontsize=14)
plt.show()
```

```
            counts     freqs
categories
no            2411  0.723372
yes            922  0.276628
```



Most customers do not have voice mail plan. #### Numerical variables ###### Checking numerical features distributions

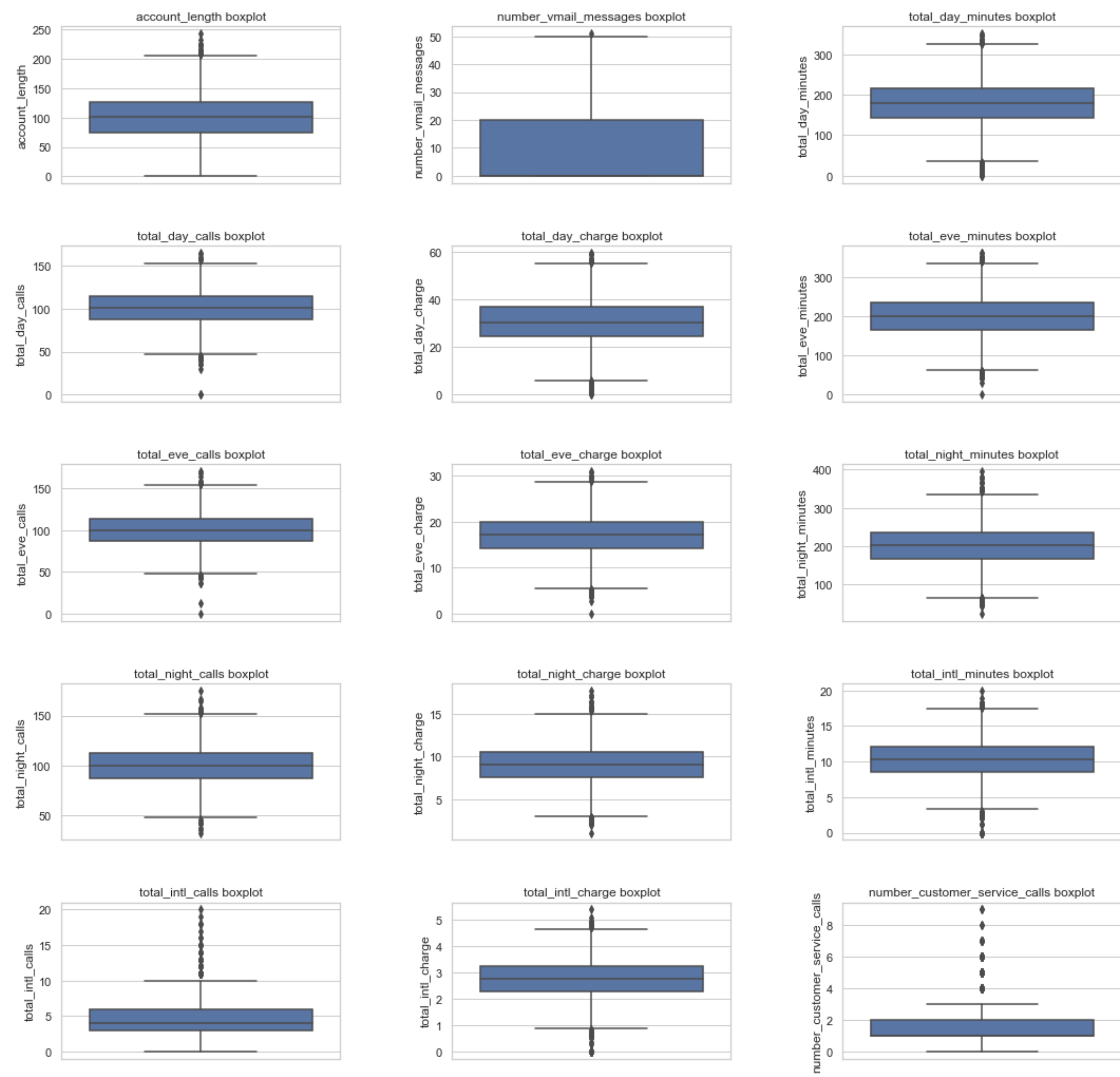
[40]:
```
# Features histograms and kde
df = df_train_num.copy()
fig, axs = plt.subplots(ncols=3, nrows=5)
plt.subplots_adjust(hspace = 0.4, wspace = 0.4)
fig.set_size_inches(18, 18, forward=True)

count = 0

for i in range(5):
    for j in range(3):
        plt.sca(ax=axs[i][j])
        if count < df.shape[1]:
            col = df.columns[count]
            sns.distplot(df[col]).set_title(col +' distribution')
        else:
            break

        count +=1
```



"account_lenght", " total_day_minutes"," total_day_calls"," total_day_charge"," total_eve_minutes"," total_eve_calls"," total_eve_charge"," total_night_minutes"," total_night_calls"," total_night_charge"," total_intl_minutes"," total_intl_charge" seem to have a normal distribution. "number_vmail_messages" has a bimodal distribution; "total_intl_calls" has a exponential distribution and "number_customer_service_calls" has a multimodal distribution.

[42]:
```
# Features boxplot
df = df_train_num.copy()
fig, axs = plt.subplots(ncols=3, nrows=5)
plt.subplots_adjust(hspace = 0.4, wspace = 0.4)
fig.set_size_inches(18, 18, forward=True)

count = 0

for i in range(5):
```

```
    for j in range(3):
        plt.sca(ax=axs[i][j])
        if count < df.shape[1]:
            col = df.columns[count]
            sns.boxplot(y=df[col]).set_title(col +' boxplot')
        else:
            break

        count +=1
```

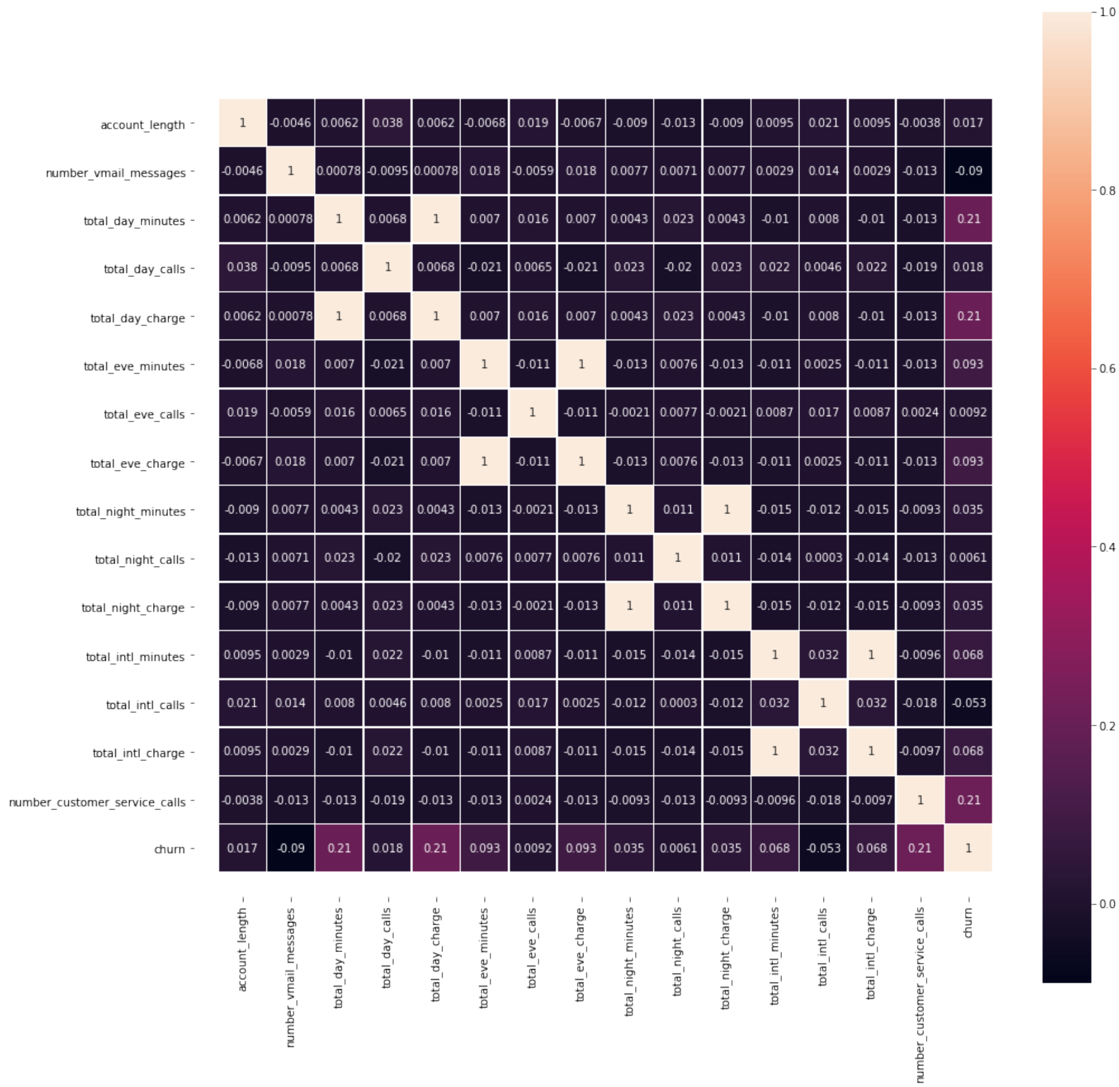


"total_intl_calls" and "number_customer_service" have a large number of outliers. ### Bivariate analysis ###### Checking correlation between numerical variables

[16]:
```
# heat map of correlation values
df = df_train_num.copy()
```

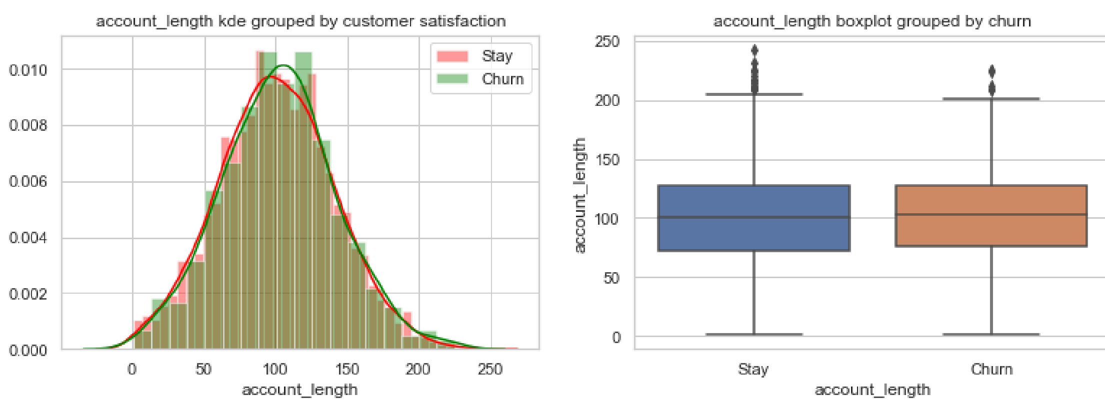
```
df['churn'] = df_train.churn.apply(lambda x: 0 if x=='no' else 1)

corr = df.corr()
fig, ax = plt.subplots(figsize=(16,16))

g = sns.heatmap(corr, annot=True, ax=ax, square=True, linewidth=0.5)

plt.yticks(rotation=0)
g.set_xticklabels(g.get_xticklabels(), rotation=90)
ax.set_ylim([len(corr) + 0.5, 0])
ax.set_xlim([-0.5, len(corr)])
```

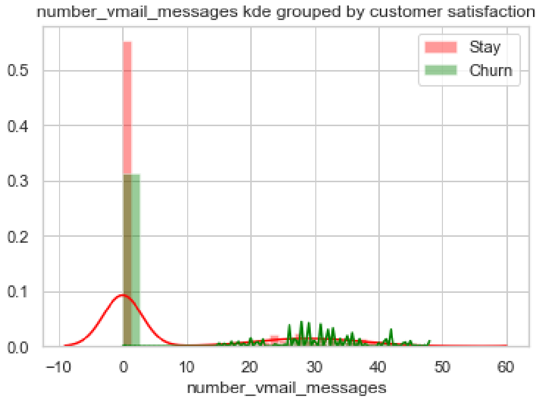
[16]: (-0.5, 16)

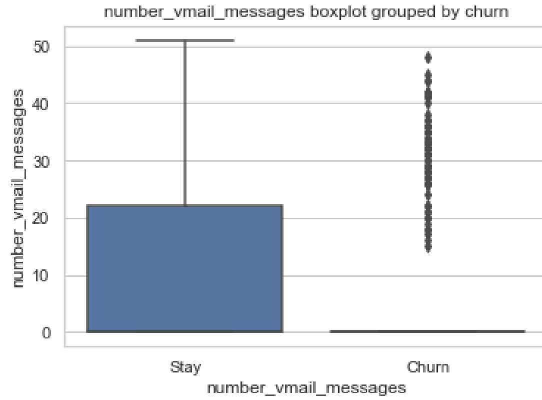


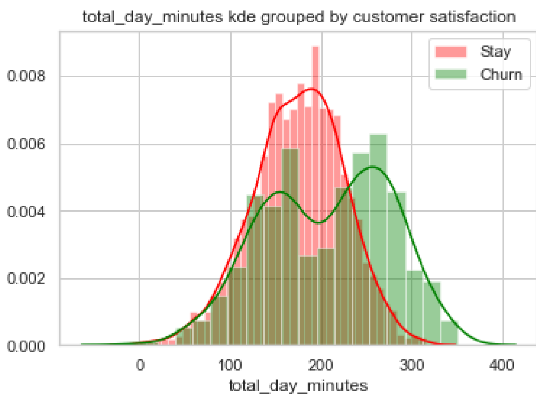
There is a high correlation between the following pairs of variables: "total_day_minutes" and "total_day_charge", "total_night_minutes" and "total_night_charge", "total_eve_minutes" and "total_eve_charge", "total_intl_minutes" and "total_intl_charge". ###### Getting numerical features distribuition grouped by target variable (churn)

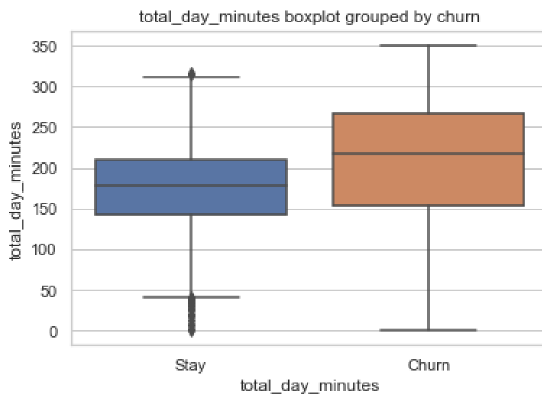
[50]:
```
# Getting numerical features distribuition grouped by churn variable
df = df_train_num
df['churn'] = df_train.churn.copy()

for col in df.drop("churn", axis=1).columns:
    fig, axs = plt.subplots(ncols=2)
    fig.set_size_inches(13, 4, forward=True)
    sns.distplot(df[df.churn == 'no'][col], color='red', label='Stay',␣
 ↪ax=axs[0], bins = 40)
    sns.distplot(df[df.churn == 'yes'][col], color='green', label='Churn',␣
 ↪ax=axs[0], bins = 18)
    axs[0].legend()
    axs[0].set_xlabel(col)
    axs[0].set_title(col + ' kde grouped by customer satisfaction')
    sns.boxplot(y=col, x="churn", data = df, ax=axs[1])
    axs[1].set_xlabel(col)
    axs[1].set_xticklabels(['Stay', 'Churn'])
    axs[1].set_title(col + ' boxplot grouped by churn')
    plt.show()
```

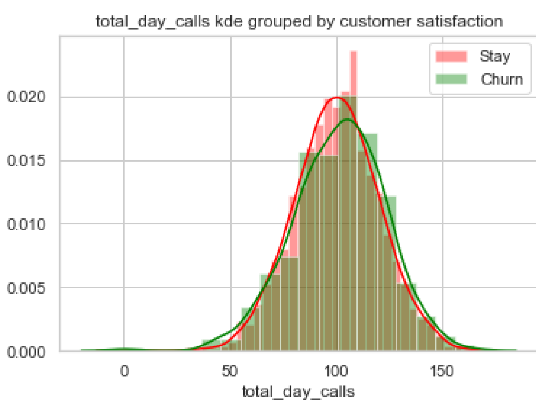


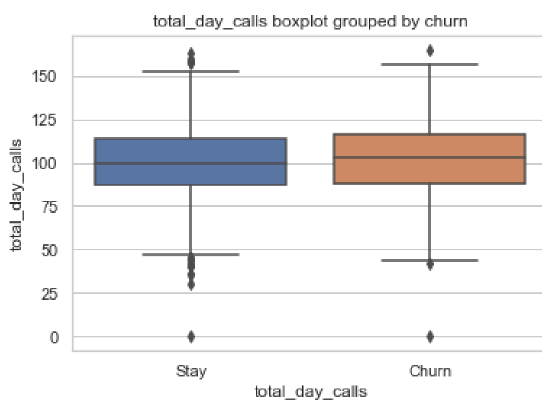

number_vmail_messages kde grouped by customer satisfaction
Stay
Churn
number_vmail_messages

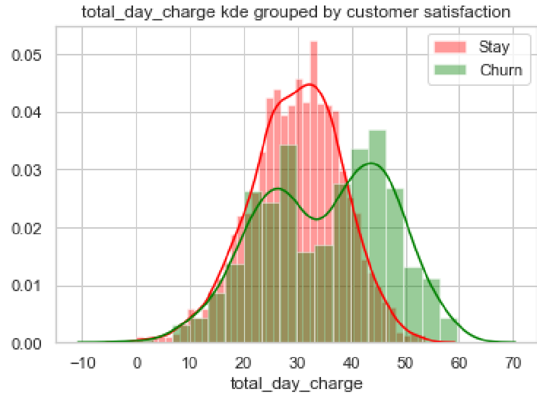

number_vmail_messages boxplot grouped by churn
number_vmail_messages
Stay
Churn
number_vmail_messages

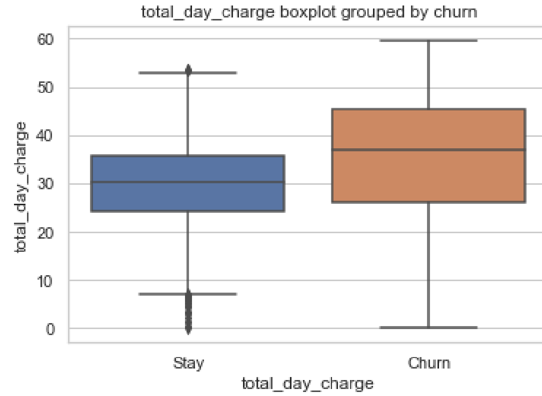

total_day_minutes kde grouped by customer satisfaction
Stay
Churn
total_day_minutes

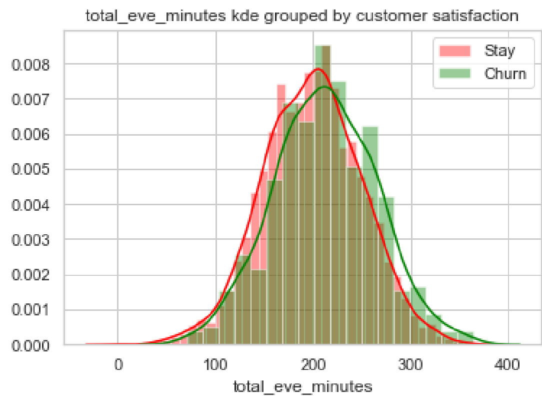

total_day_minutes boxplot grouped by churn
total_day_minutes
Stay
Churn
total_day_minutes

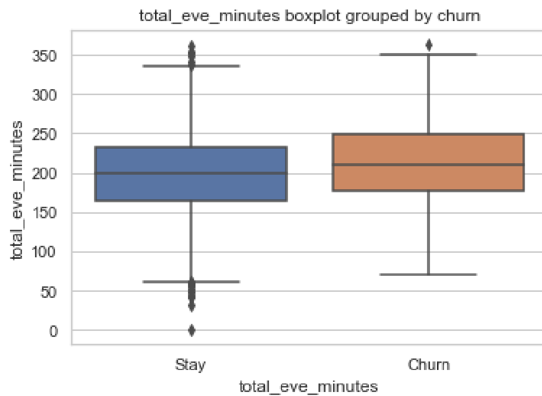

total_day_calls kde grouped by customer satisfaction
Stay
Churn
total_day_calls

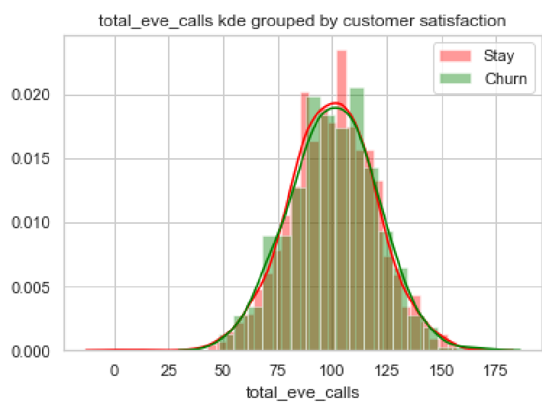

total_day_calls boxplot grouped by churn
total_day_calls
Stay
Churn
total_day_calls

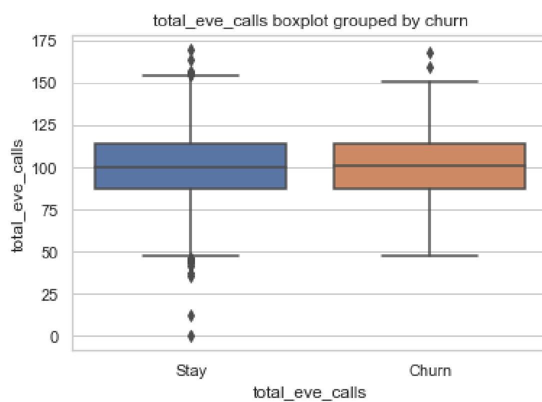

total_day_charge kde grouped by customer satisfaction
Stay
Churn
total_day_charge

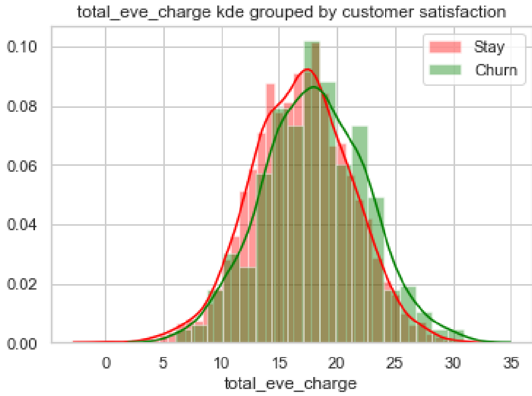

total_day_charge boxplot grouped by churn
total_day_charge
Stay
Churn
total_day_charge

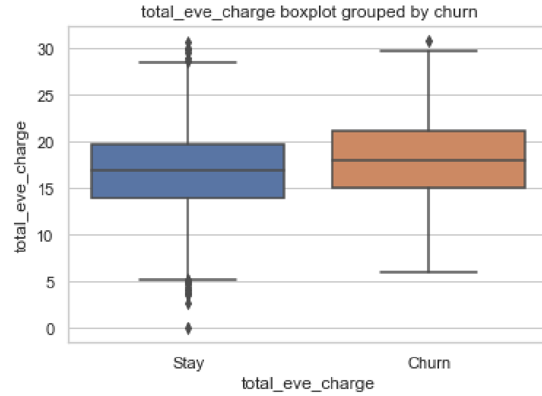

total_eve_minutes kde grouped by customer satisfaction
Stay
Churn
total_eve_minutes

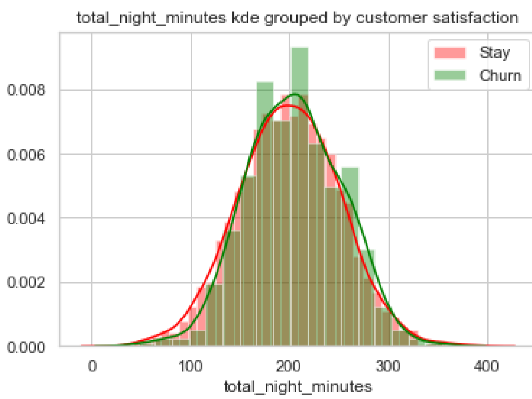

total_eve_minutes boxplot grouped by churn
total_eve_minutes
Stay
Churn
total_eve_minutes

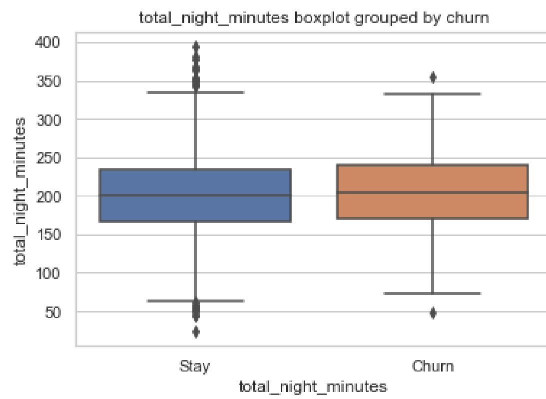

total_eve_calls kde grouped by customer satisfaction
Stay
Churn
total_eve_calls

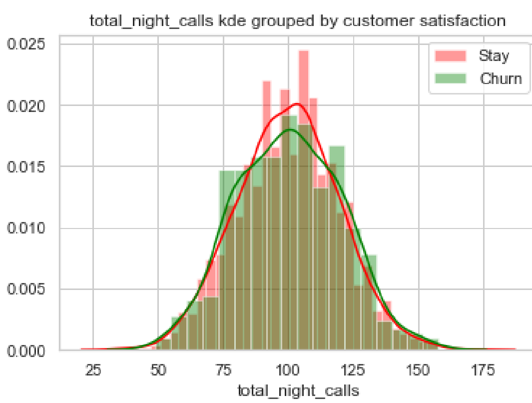

total_eve_calls boxplot grouped by churn
total_eve_calls
Stay
Churn
total_eve_calls

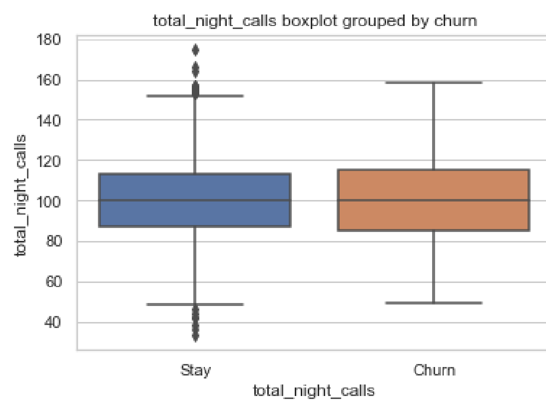

total_eve_charge kde grouped by customer satisfaction
Stay
Churn
0.10
0.08
0.06
0.04
0.02
0.00
0
5
10
15
20
25
30
35
total_eve_charge

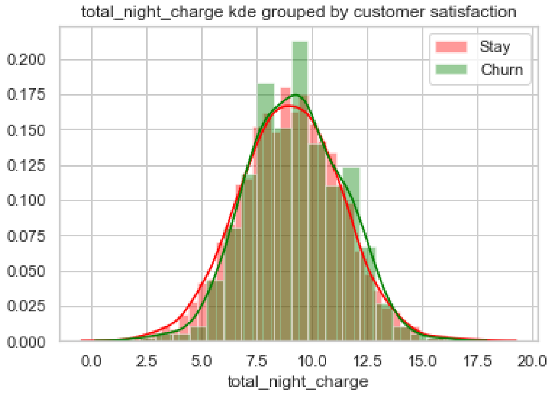

total_eve_charge boxplot grouped by churn
total_eve_charge
30
25
20
15
10
5
0
Stay
Churn
total_eve_charge

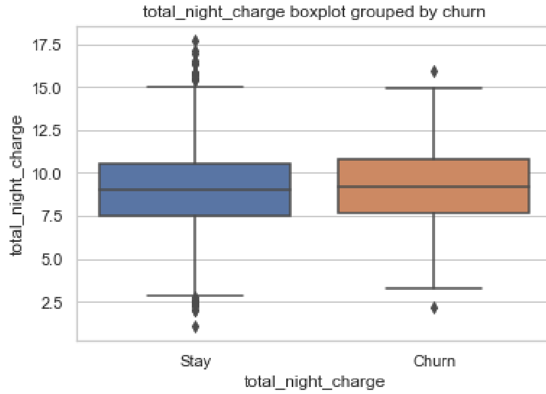

total_night_minutes kde grouped by customer satisfaction
Stay
Churn
0.008
0.006
0.004
0.002
0.000
0
100
200
300
400
total_night_minutes

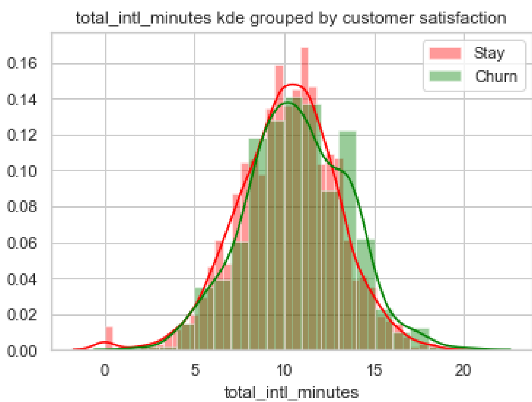

total_night_minutes boxplot grouped by churn
total_night_minutes
400
350
300
250
200
150
100
50
Stay
Churn
total_night_minutes

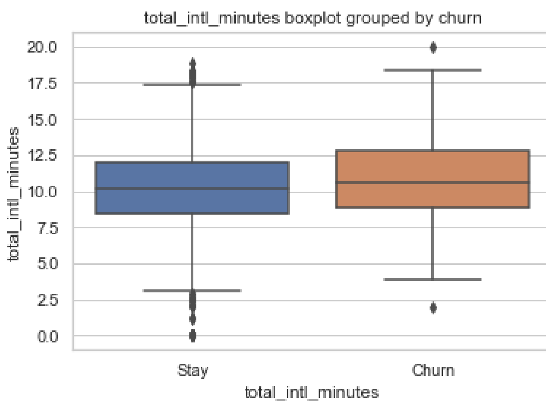

total_night_calls kde grouped by customer satisfaction
Stay
Churn
0.025
0.020
0.015
0.010
0.005
0.000
25
50
75
100
125
150
175
total_night_calls

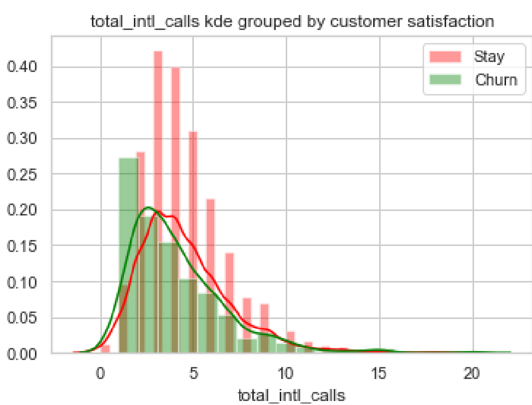

total_night_calls boxplot grouped by churn
total_night_calls
180
160
140
120
100
80
60
40
Stay
Churn
total_night_calls

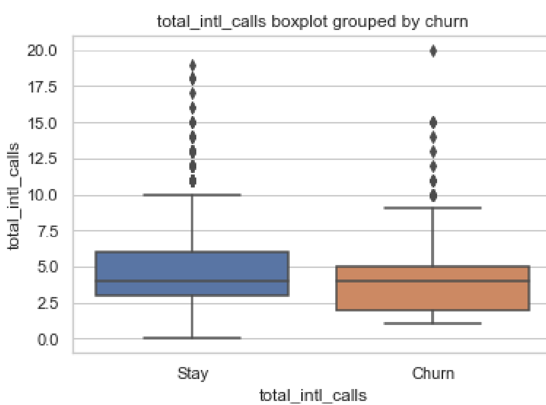

total_night_charge kde grouped by customer satisfaction
Stay
Churn
total_night_charge

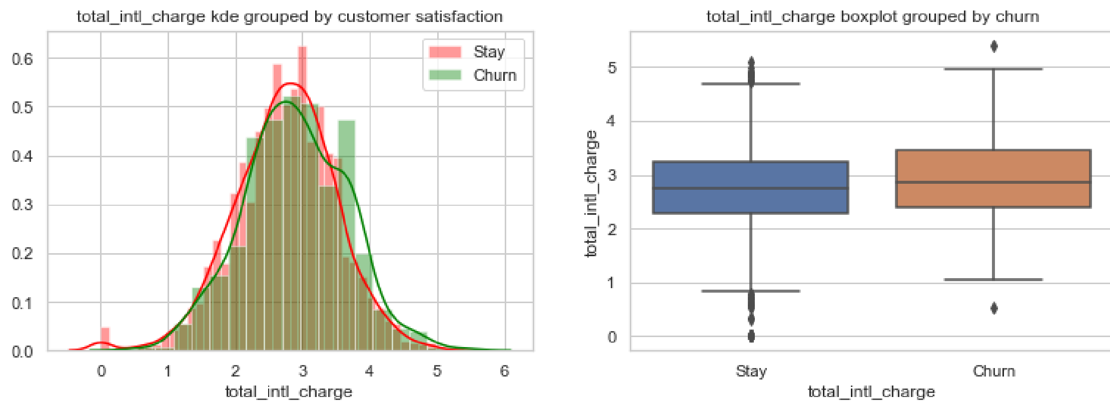

total_night_charge boxplot grouped by churn
total_night_charge
Stay
Churn
total_night_charge

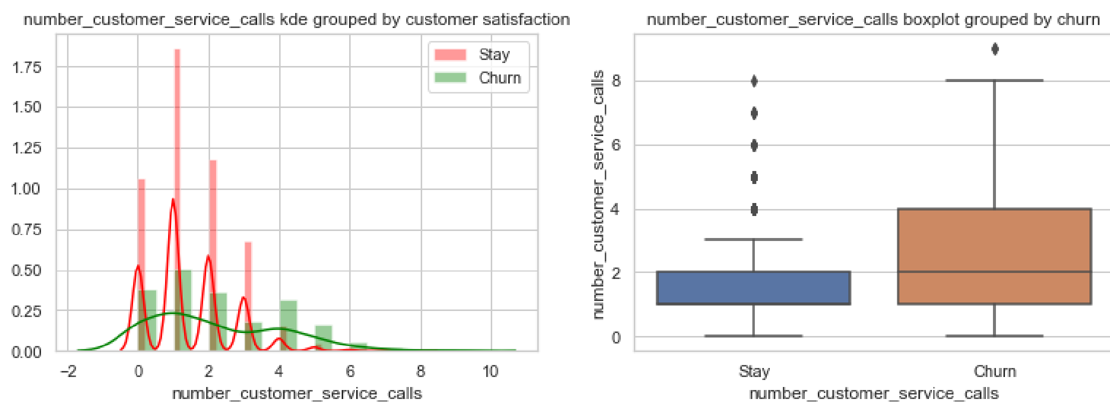

total_intl_minutes kde grouped by customer satisfaction
Stay
Churn
total_intl_minutes


total_intl_minutes boxplot grouped by churn
total_intl_minutes
Stay
Churn
total_intl_minutes


total_intl_calls kde grouped by customer satisfaction
Stay
Churn
total_intl_calls


total_intl_calls boxplot grouped by churn
total_intl_calls
Stay
Churn
total_intl_calls

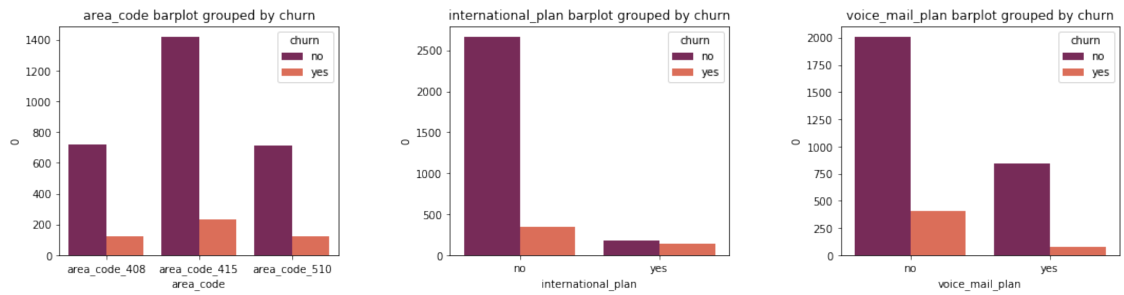




Getting categorical features barplot grouped by churn variable

[87]:
```
# categorical variables boxplot grouped by churn
df = df_train_cat.drop('state', axis=1)
df['churn'] = df_train.churn.copy()

fig, axs = plt.subplots(ncols=3)
plt.subplots_adjust(hspace = 0.4, wspace = 0.4)
fig.set_size_inches(18, 4, forward=True)

count = 0


for j in range(3):
    plt.sca(ax=axs[j])
    if count < df.shape[1]:
        col = df.columns[count]
        df_g = pd.DataFrame(df.groupby([col, 'churn']).size()).reset_index()
        sns.barplot(x=col, y=0, hue="churn", data=df_g, palette="rocket")
```

```
        axs[j].set_xlabel(col)
        axs[j].set_title(col + ' barplot grouped by churn')
    else:
        break
    count +=1
```

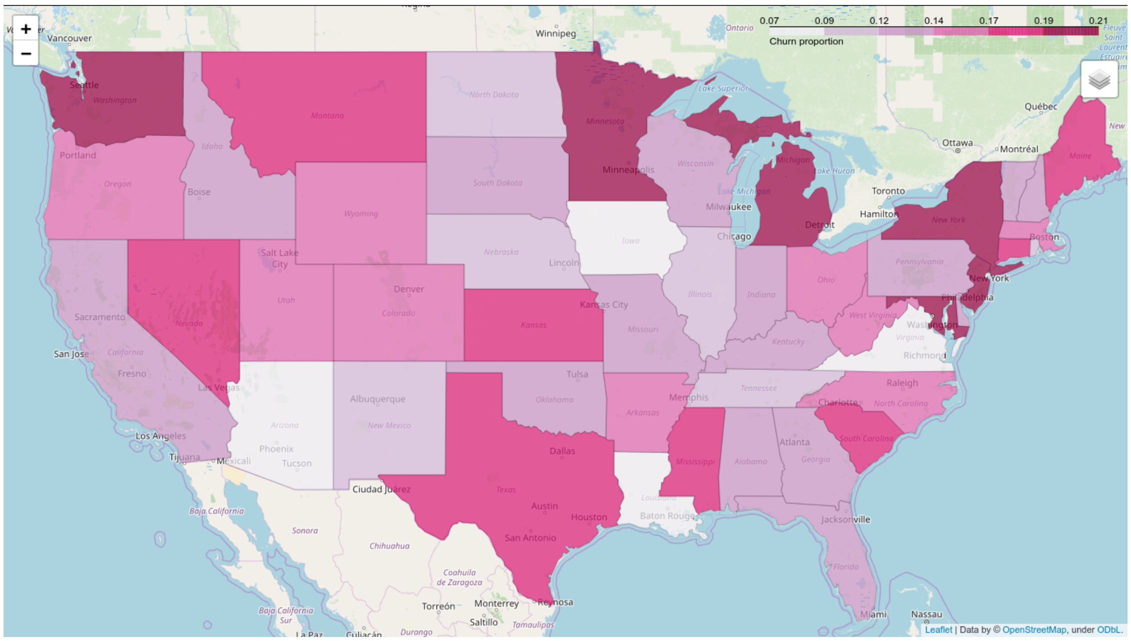


Most of the customers who remained do not have an international plan. ###### Churn by state

[11]:
```
# Map graph exibing churn proportion
# Load the shape of the zone (US states)
state_geo = os.path.join('', 'us-states.json')

# state data
state_data = pd.DataFrame({'state': df_train[df_train.churn == 'yes'].state.
 ↪value_counts().index,
                           'churn_prop': df_train[df_train.churn == 'yes'].
 ↪state.value_counts().values/ \
                           df_train.state.value_counts().values})

state_data

# Initialize the map:
m = folium.Map(location=[37, -102], zoom_start=5)

# Add the color for the chloropleth:
m.choropleth(
 geo_data=state_geo,
 name='Churn proportion by state',
 data=state_data,
 columns=['state', 'churn_prop'],
 key_on='feature.id',
 fill_color='PuRd',
 fill_opacity=0.7,
 line_opacity=0.2,
 legend_name='Churn proportion'
)
folium.LayerControl().add_to(m)
```

```
# Save to html
m.save('#churn_proportion.html')

display(m)

# # Loading map image
# Image(filename='churn_proportion_by_state.png')
```

[11]:



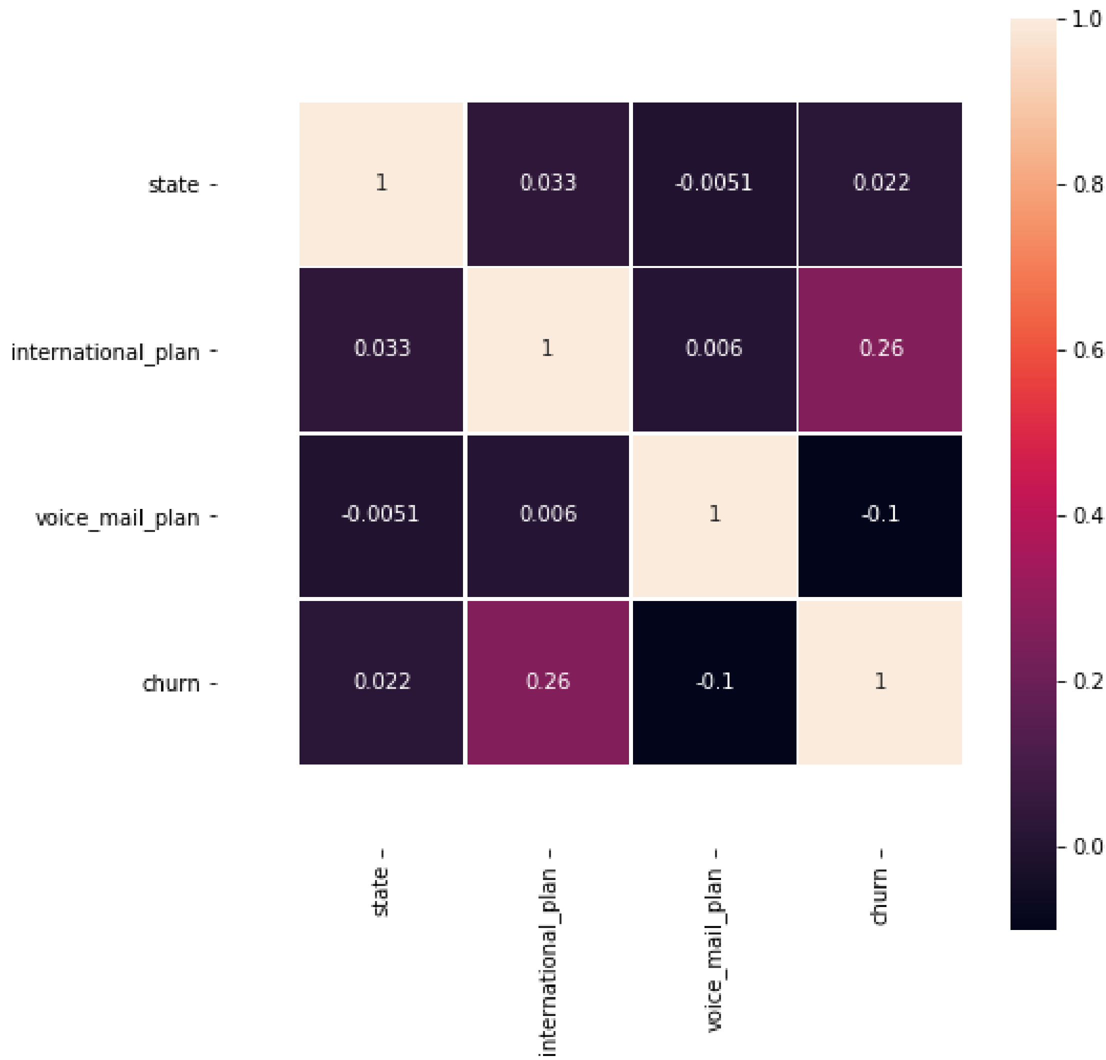
Checking categorical features

[88]:
```
df_new_train_cat = df_train_cat.copy()

# Converting to binary
df_new_train_cat.international_plan = df_new_train_cat.international_plan.
 ↪apply(lambda x: 0 if x=='no' else 1)
df_new_train_cat.voice_mail_plan = df_new_train_cat.voice_mail_plan.
 ↪apply(lambda x: 0 if x=='no' else 1)
df_new_train_cat.churn = df_new_train_cat.churn.apply(lambda x: 0 if x=='no'␣
 ↪else 1)

dic = {}
count = 1

# Changing state variable
for state in df_new_train_cat.state.unique():
    dic[state] = count
```

```
    count += 1

df_new_train_cat.state = df_new_train_cat.state.apply(lambda x: dic[x])

# Changing area_code variable
df_new_train_cat.area_code[df_new_train_cat.area_code == 'area_code_408'] = 1
df_new_train_cat.area_code[df_new_train_cat.area_code == 'area_code_510'] = 2
df_new_train_cat.area_code[df_new_train_cat.area_code == 'area_code_415'] = 3
```

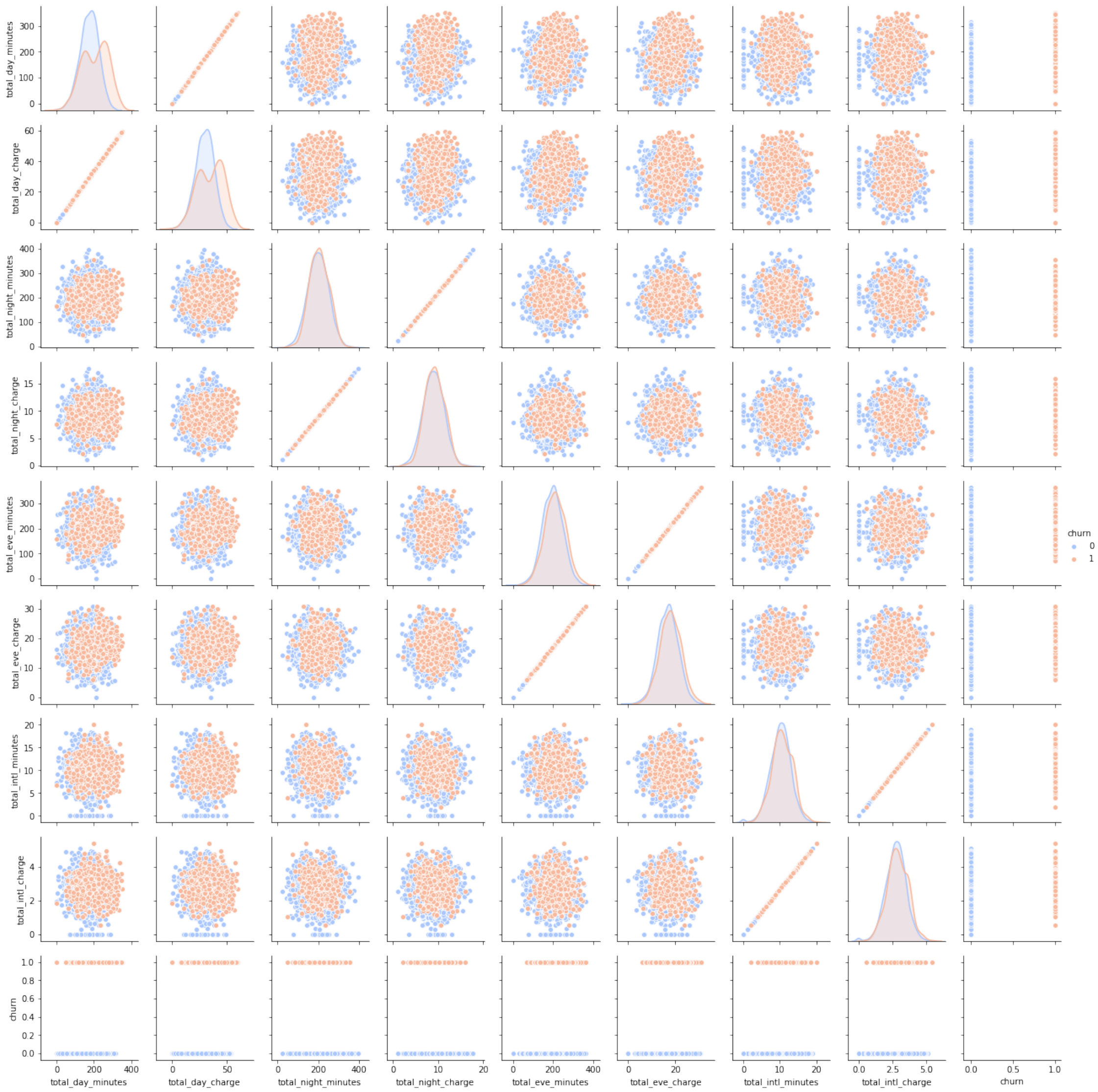
[89]:
```
# heat map of correlation values
df = df_new_train_cat.copy()

corr = df.corr()
fig, ax = plt.subplots(figsize=(8,8))

g = sns.heatmap(corr, annot=True, ax=ax, square=True, linewidth=0.5)

plt.yticks(rotation=0)
g.set_xticklabels(g.get_xticklabels(), rotation=90)
ax.set_ylim([len(corr) + 0.5, 0])
ax.set_xlim([-0.5, len(corr)])
```

[89]:
```
(-0.5, 4)
```



1.2.2 Multivariate analysis

[17]:
```
# pairplot matrix grouped by churn variable
df = df_train[["total_day_minutes", "total_day_charge", "total_night_minutes",
                   "total_night_charge", "total_eve_minutes",␣
 ↪"total_eve_charge",
                   "total_intl_minutes", "total_intl_charge", "churn"]].copy()

df['churn'] = df_train.churn.apply(lambda x: 0 if x=='no' else 1)

g = sns.pairplot(df, hue='churn', palette='coolwarm')
g.fig.set_size_inches(18,18)
```



[90]:
```
# df_new_train_cat = df_train_cat
df_new_train_cat = df_train_cat.copy()
df_new_train_cat.international_plan = df_new_train_cat.international_plan.
↪apply(lambda x: 0 if x=='no' else 1)
df_new_train_cat.voice_mail_plan = df_new_train_cat.voice_mail_plan.
↪apply(lambda x: 0 if x=='no' else 1)
df_new_train_cat.churn = df_new_train_cat.churn.apply(lambda x: 0 if x=='no'␣
↪else 1)
```

[91]:
```
df_new_train_cat.head()
```

[91]:

	state	area_code	international_plan	voice_mail_plan	churn
0	KS	area_code_415	0	1	0
1	OH	area_code_415	0	1	0

```
2     NJ  area_code_415                    0                 0       0
3     OH  area_code_408                    1                 0       0
4     OK  area_code_415                    1                 0       0
```

[96]:
```
# Checking relation between categorical variables grouped by churn
values = df_train_cat[['state', 'international_plan', 'voice_mail_plan',␣
↪'churn']] \
        .groupby(['international_plan', 'voice_mail_plan', 'churn']).count()


dic = {'international_plan': [],
      'voice_mail_plan': [],
      'churn': [],
      'count': []}


for a_tuple in values.index:
    dic['international_plan'].append(a_tuple[0])
    dic['voice_mail_plan'].append(a_tuple[1])
    dic['churn'].append(a_tuple[2])
    dic['count'].append(values.loc[a_tuple].values[0])

display(pd.DataFrame(dic).sort_values(by ='count', ascending=False))
```

	international_plan	voice_mail_plan	churn	count
0	0	0	0	1878
2	0	1	0	786
1	0	0	1	302
4	1	0	0	130
5	1	0	1	101
6	1	1	0	56
3	0	1	1	44
7	1	1	1	36

1.3 Feature Engineering

Converting train categorical variables to numerical

[92]:
```
# converting test categorical variables to numerical
train_data = df_train.drop('id', axis=1).copy()

# Converting to binary
train_data.international_plan = train_data.international_plan.apply(lambda x: 0␣
↪if x=='no' else 1)
train_data.voice_mail_plan = train_data.voice_mail_plan.apply(lambda x: 0 if␣
↪x=='no' else 1)
train_data.churn = train_data.churn.apply(lambda x: 0 if x=='no' else 1)
```

```
dic = {}
count = 1

# Changing state variable
for state in train_data.state.unique():
    dic[state] = count
    count += 1

train_data.state = train_data.state.apply(lambda x: dic[x])

# Changing area_code variable
train_data.area_code[train_data.area_code == 'area_code_408'] = 1
train_data.area_code[train_data.area_code == 'area_code_510'] = 2
train_data.area_code[train_data.area_code == 'area_code_415'] = 3

# Saving dataset
train_data.to_csv("data/train_data.csv", index=False)
```

Converting test categorical variables to numerical

[93]:
```
# converting test categorical variables to numerical
test_data = df_test.drop('id', axis=1).copy()

# Converting to binary
test_data.international_plan = test_data.international_plan.apply(lambda x: 0␣
 ↪if x=='no' else 1)
test_data.voice_mail_plan = test_data.voice_mail_plan.apply(lambda x: 0 if␣
 ↪x=='no' else 1)
test_data.churn = test_data.churn.apply(lambda x: 0 if x=='no' else 1)

dic = {}
count = 1

# Changing state variable
for state in test_data.state.unique():
    dic[state] = count
    count += 1

test_data.state = test_data.state.apply(lambda x: dic[x])

# Changing area_code variable
test_data.area_code[test_data.area_code == 'area_code_408'] = 1
test_data.area_code[test_data.area_code == 'area_code_510'] = 2
test_data.area_code[test_data.area_code == 'area_code_415'] = 3

# Saving dataset
test_data.to_csv("data/test_data.csv", index=False)
```

Removing high correlated features

[94]:
```
high_corr_features = [col for col in train_data.columns if 'minute' in col]
high_corr_features

less_corr_train_data = train_data.drop(high_corr_features, axis=1).copy()
less_corr_test_data = test_data.drop(high_corr_features, axis=1).copy()

less_corr_train_data.to_csv("data/less_corr_train_data.csv", index=False)
less_corr_test_data.to_csv("data/less_corr_test_data.csv", index=False)
```

Standardizing train and test data

[97]:
```
# Applying StandardData to scaled data
# Train data
df = less_corr_train_data.drop(['churn', 'international_plan',␣
↪'voice_mail_plan'], axis=1).copy()

StandardData = pd.DataFrame(StandardScaler().fit_transform(df), \
                            columns = df.columns)

stand_train_data = StandardData
stand_train_data['international_plan'] = less_corr_train_data.
↪international_plan.copy()
stand_train_data['voice_mail_plan'] = less_corr_train_data.voice_mail_plan.
↪copy()
stand_train_data['churn'] = less_corr_train_data.churn.copy()

# Test data
df = less_corr_test_data.drop(['churn', 'international_plan',␣
↪'voice_mail_plan'], axis=1).copy()

StandardData = pd.DataFrame(StandardScaler().fit_transform(df), \
                            columns = df.columns)

stand_test_data = StandardData
stand_test_data['international_plan'] = less_corr_test_data.international_plan.
↪copy()
stand_test_data['voice_mail_plan'] = less_corr_test_data.voice_mail_plan.copy()
stand_test_data['churn'] = less_corr_test_data.churn.copy()

# Saving data
stand_train_data.to_csv("data/stand_train_data.csv", index=False)
stand_test_data.to_csv("data/stand_test_data.csv", index=False)
```

Applying MinMaxScaler to train and test data

[98]:
```
# Applying MinMaxData to scaled data
# Train data
df = less_corr_train_data.drop(['churn', 'international_plan',␣
 ↪'voice_mail_plan'], axis=1).copy()

MinMaxData = pd.DataFrame(MinMaxScaler().fit_transform(df), \
                          columns = df.columns)

minmax_train_data = MinMaxData
minmax_train_data['international_plan'] = less_corr_train_data.
 ↪international_plan.copy()
minmax_train_data['voice_mail_plan'] = less_corr_train_data.voice_mail_plan.
 ↪copy()
minmax_train_data['churn'] = less_corr_train_data.churn.copy()

# Test data
df = less_corr_test_data.drop(['churn', 'international_plan',␣
 ↪'voice_mail_plan'], axis=1).copy()

MinMaxData = pd.DataFrame(MinMaxScaler().fit_transform(df), \
                          columns = df.columns)

minmax_test_data = MinMaxData
minmax_test_data['international_plan'] = less_corr_test_data.international_plan.
 ↪copy()
minmax_test_data['voice_mail_plan'] = less_corr_test_data.voice_mail_plan.copy()
minmax_test_data['churn'] = less_corr_test_data.churn.copy()

# Saving data
minmax_train_data.to_csv("data/minmax_train_data.csv", index=False)
minmax_test_data.to_csv("data/minmax_test_data.csv", index=False)
```

1.4 Training models

To predict Customer Churn, I chose to use Logistic Regression to get information on whether customers are going to cancel their plan and their likelihood. ### Balancing data

[115]:
```
# Defining features
Xo_train, Xo_test, yo_train, yo_test = less_corr_train_data.drop("churn",␣
 ↪axis=1).copy(), \
                                       less_corr_test_data.drop("churn",␣
 ↪axis=1).copy(), \
                                       less_corr_train_data.churn.copy(),␣
 ↪less_corr_test_data.churn.copy()
```

1.4.1 Logistic Regression

[146]:
```
# LogisticRegression algorithm
lr = LogisticRegression(C=1e5)

# training model
lr.fit(Xo_train, yo_train)

# prediction
churn_prob = lr.predict(Xo_test)
pred = churn_prob.round()

# Evaluating prediction
print (confusion_matrix(yo_test,pred))
print (classification_report(yo_test,pred))

# Save the model as a pickle in a file
# joblib.dump(lr, 'lr.pkl')
```

```
[[1418   25]
 [ 192   32]]
              precision    recall  f1-score   support

           0       0.88      0.98      0.93      1443
           1       0.56      0.14      0.23       224

    accuracy                           0.87      1667
   macro avg       0.72      0.56      0.58      1667
weighted avg       0.84      0.87      0.83      1667
```

[146]:
```
['lr.pkl']
```

1.5 Trying to optimizate model

1.5.1 Logistic regression optimization

Selecting most important features

[149]:
```
# selecting most important features
k = 9

X = less_corr_train_data.drop("churn", axis=1).copy()
y = less_corr_train_data.churn.copy()

selectChi2 = SelectKBest(chi2, k=k).fit(X, y)
selectF_classif = SelectKBest(f_classif, k=k).fit(X, y)

selected = selectChi2.get_support() & selectF_classif.get_support()
```

```
features = [col for col, i in zip(X.columns, selected) if i]

print("{} most important features: ".format(len(features)), features)
```

```
7 most important features:  ['international_plan', 'voice_mail_plan',
'number_vmail_messages', 'total_day_charge', 'total_eve_charge',
'total_intl_calls', 'number_customer_service_calls']
```

Training model using less variables

[172]:
```
X_train, y_train = less_corr_train_data[features].copy(), less_corr_train_data.
 ↪churn.copy()
X_test, y_test = less_corr_test_data[features].copy(), less_corr_test_data.
 ↪churn.copy()

# LogisticRegression algorithm
lr = LogisticRegression(C=1e5)

# training model
lr.fit(X_train, y_train)

# prediction
churn_prob = lr.predict(X_test)
pred = churn_prob.round()

# Evaluating prediction
print (confusion_matrix(y_test,pred))
print (classification_report(y_test,pred))
print(accuracy_score(y_test,pred))
```

```
[[1410   33]
 [ 184   40]]
              precision    recall  f1-score   support

           0       0.88      0.98      0.93      1443
           1       0.55      0.18      0.27       224

    accuracy                           0.87      1667
   macro avg       0.72      0.58      0.60      1667
weighted avg       0.84      0.87      0.84      1667

0.8698260347930414
```

Using standard deviation dataset

[171]:
```
# Defining features
Xsd_train, Xsd_test, ysd_train, ysd_test = stand_train_data.drop("churn",␣
 ↪axis=1).copy(), \
```

```
                                            stand_test_data.drop("churn", axis=1).
 ↪copy(), \
                                            stand_train_data.churn.copy(),␣
 ↪stand_test_data.churn.copy()

# LogisticRegression algorithm
lr = LogisticRegression(C=1e5)

# training model
lr.fit(Xsd_train, ysd_train)

# prediction
churn_prob = lr.predict(Xsd_test)
pred = churn_prob.round()

# Evaluating prediction
print (confusion_matrix(ysd_test,pred))
print (classification_report(ysd_test,pred))

print(accuracy_score(ysd_test,pred))

# Save the model as a pickle in a file
joblib.dump(lr, 'lr.pkl')
```

```
[[1407   36]
 [ 181   43]]
              precision    recall  f1-score   support

           0       0.89      0.98      0.93      1443
           1       0.54      0.19      0.28       224

    accuracy                           0.87      1667
   macro avg       0.72      0.58      0.61      1667
weighted avg       0.84      0.87      0.84      1667

0.8698260347930414
```

optimization using GridSearch

[155]:
```
#Results dataframe
cols = ['Case', 'LogReg']

resul = pd.DataFrame(columns=cols)
resul.set_index("Case",inplace=True)

resul.loc['Standard'] = [0]
resul.loc['GridSearch'] = [0]
resul.loc['RandomSearch'] = [0]
```

```
resul.loc['Hyperopt'] = [0]
```

[164]:
```
#Models creation
lr = LogisticRegression(solver='liblinear')


# Standard parameters
lr.fit(Xsd_train,ysd_train.values.ravel())
resul.iloc[0, 0] = lr.score(Xsd_test,ysd_test)
```

[174]:
```
# GridSearch parameters
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RepeatedStratifiedKFold

#Logistic Regrresion
solvers = ['newton-cg', 'lbfgs', 'liblinear']
penalty = ['l2']
c_values = [100, 10, 1.0, 0.1, 0.01]
lr_grid = dict(solver=solvers,penalty=penalty,C=c_values)

grid = lr_grid

cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3,
                             random_state=1)

grid_search = GridSearchCV(estimator=lr,
              param_grid=grid, n_jobs=-1, cv=cv,
              scoring='accuracy',error_score=0)

grid_clf_acc = grid_search.fit(Xsd_train, ysd_train)

resul.iloc[1,0] = grid_clf_acc.score(Xsd_test,ysd_test)

# Save the model as a pickle in a file
joblib.dump(grid_search, 'grid_search.pkl')
```

[174]:
```
['grid_search.pkl']
```

optimization using RandomSearch

[165]:
```
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV

cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3,
                             random_state=1)

n_iter_search = 3

random_search = RandomizedSearchCV(lr, param_distributions=grid,
                                   n_iter=n_iter_search, cv=cv)
```

```
random_search.fit(Xsd_train, ysd_train)
resul.iloc[2,0] = random_search.score(Xsd_test,ysd_test)
```

[166]:
```
resul.head()
```

[166]:
```
                  LogReg
Case
Standard        0.870426
GridSearch      0.871626
RandomSearch    0.869826
Hyperopt               0
```

1.5.2 Final model

GridSearch exibed the best result. The final model presents accuracy of 0.87. The results are shown in the table below including churn probability predicted by model.

[191]:
```
# Final model
pred = grid_search.predict(Xsd_test).round()

churn_prob = grid_search.predict_proba(Xsd_test)[:,1]

result = pd.DataFrame({'real_churn': ysd_test, 'predicted_churn': pred,
                      'probability': churn_prob})

print (confusion_matrix(ysd_test,pred))
print (classification_report(ysd_test,pred))
print(accuracy_score(ysd_test,pred))
```

```
[[1410   33]
 [ 181   43]]
              precision    recall  f1-score   support

           0       0.89      0.98      0.93      1443
           1       0.57      0.19      0.29       224

    accuracy                           0.87      1667
   macro avg       0.73      0.58      0.61      1667
weighted avg       0.84      0.87      0.84      1667

0.871625674865027
```

[197]:
```
display(result)
```

```
      real_churn  predicted_churn  probability
0              0                0     0.066634
1              0                0     0.051263
```

```
2              0                0    0.239797
3              0                0    0.133904
4              0                0    0.063361
...          ...              ...         ...
1662           0                0    0.183550
1663           1                0    0.402079
1664           0                0    0.051855
1665           0                0    0.031570
1666           0                0    0.004603

[1667 rows x 3 columns]
```

[198]:

```
result.to_csv("data/result.csv", index=False)
```