PROJETO: Prevendo Customer Churn em Operadoras de Telecom

Data: 09/03/2020

Problema de negócio: prever se um cliente vai cancelar seu plano SIM ou NÃO.

In [2]:
```
### Bibliotecas

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sea
from sklearn.feature_selection import VarianceThreshold
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Alteração de parâmetros para visualizar dataset com grande números de colunas

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

Carregamento e limpeza dos dados

In [4]:
```
## Leitura do dataset

df = pd.read_csv('C:/FCD/PythonSpark/Projeto_telecom/projeto4_telecom_treino.csv')

df.head(10)
```

Out[4]:

	Unnamed: 0	state	account_length	area_code	international_plan	voice_mail_plan	number_vmail_messages	total_day_mi
0	1	KS	128	area_code_415	no	yes	25	
1	2	OH	107	area_code_415	no	yes	26	
2	3	NJ	137	area_code_415	no	no	0	
3	4	OH	84	area_code_408	yes	no	0	
4	5	OK	75	area_code_415	yes	no	0	
5	6	AL	118	area_code_510	yes	no	0	
6	7	MA	121	area_code_510	no	yes	24	
7	8	MO	147	area_code_415	yes	no	0	
8	9	LA	117	area_code_408	no	no	0	
9	10	WV	141	area_code_415	yes	yes	37	

In [5]:
```
#Verificando Tipos dos atributos

df.dtypes
```

Out[5]:
```
Unnamed: 0                        int64
state                            object
account_length                    int64
area_code                        object
international_plan               object
voice_mail_plan                  object
number_vmail_messages             int64
total_day_minutes               float64
total_day_calls                   int64
total_day_charge                float64
total_eve_minutes               float64
total_eve_calls                   int64
total_eve_charge                float64
total_night_minutes             float64
total_night_calls                 int64
total_night_charge              float64
total_intl_minutes              float64
total_intl_calls                  int64
total_intl_charge               float64
number_customer_service_calls     int64
churn                            object
dtype: object
```

In [6]:
```
# Quantidade linhas x colunas

df.shape
```

Out[6]: (3333, 21)

In [7]:
```
# Verificação de valores null

df.isnull().values.any()

# Verificação valores vazios

df.empty
```

Out[7]: False

In [8]:
```
# Verificando o balanceamento da variável target (churn), na qual, valor 'no' = cliente não desistiu e
# valor 'yes' = cliente desistiu da operada;

churn = pd.DataFrame(df.churn.value_counts())
churn['%_churns']=100*churn['churn']/df.shape[0]
churn

# Constata-se que a variável TARGET está proporcionalmente desbalanceada e,portanto, é necessário o balanceamento dos dados para
# aplicar o algoritimo de machine learning.
```

Out[8]:

	churn	%_churns
no	2850	85.508551
yes	483	14.491449

In [9]:
```
#Remoção da variável 'Unnamed: 0 ', pois trata-se de apenas um indice do dataset;
#Remoção da variável 'number_customer_service_calls', pois refere-se a um número de serviço do cliente(irrelevante para o modelo)
df.drop(['Unnamed: 0'], axis= 1, inplace= True)
df.drop(['number_customer_service_calls'], axis= 1, inplace= True)
```

In [10]:
```
df.head(10)
```

Out[10]:

	state	account_length	area_code	international_plan	voice_mail_plan	number_vmail_messages	total_day_minutes	total
0	KS	128	area_code_415	no	yes	25	265.1	
1	OH	107	area_code_415	no	yes	26	161.6	
2	NJ	137	area_code_415	no	no	0	243.4	
3	OH	84	area_code_408	yes	no	0	299.4	
4	OK	75	area_code_415	yes	no	0	166.7	
5	AL	118	area_code_510	yes	no	0	223.4	
6	MA	121	area_code_510	no	yes	24	218.2	
7	MO	147	area_code_415	yes	no	0	157.0	
8	LA	117	area_code_408	no	no	0	184.5	
9	WV	141	area_code_415	yes	yes	37	258.6	

In [11]:
```
# Limpeza da variável 'area_code'
df.area_code = df.area_code.apply(lambda x: x.split('_')[2])
df.head()
```

Out[11]:

	state	account_length	area_code	international_plan	voice_mail_plan	number_vmail_messages	total_day_minutes	total_day
0	KS	128	415	no	yes	25	265.1	
1	OH	107	415	no	yes	26	161.6	
2	NJ	137	415	no	no	0	243.4	
3	OH	84	408	yes	no	0	299.4	
4	OK	75	415	yes	no	0	166.7	

In [12]:
```
# Convertendo variáveis categóricas para variáveis numéricas (0 e 1): Label Encoding
from sklearn.preprocessing import LabelEncoder

number= LabelEncoder()
df.international_plan= number.fit_transform(df.international_plan)
df.voice_mail_plan = number.fit_transform(df.voice_mail_plan)
df.state = number.fit_transform(df.state)
df.churn = number.fit_transform(df.churn)
df.head()
```

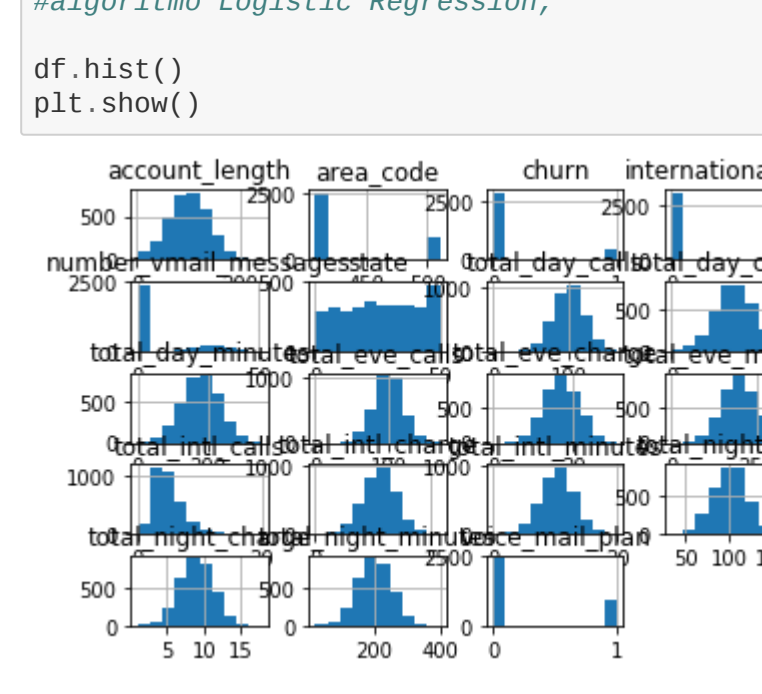
Out[12]:

	state	account_length	area_code	international_plan	voice_mail_plan	number_vmail_messages	total_day_minutes	total_day
0	16	128	415	0	1	25	265.1	
1	35	107	415	0	1	26	161.6	
2	31	137	415	0	0	0	243.4	
3	35	84	408	1	0	0	299.4	
4	36	75	415	1	0	0	166.7	

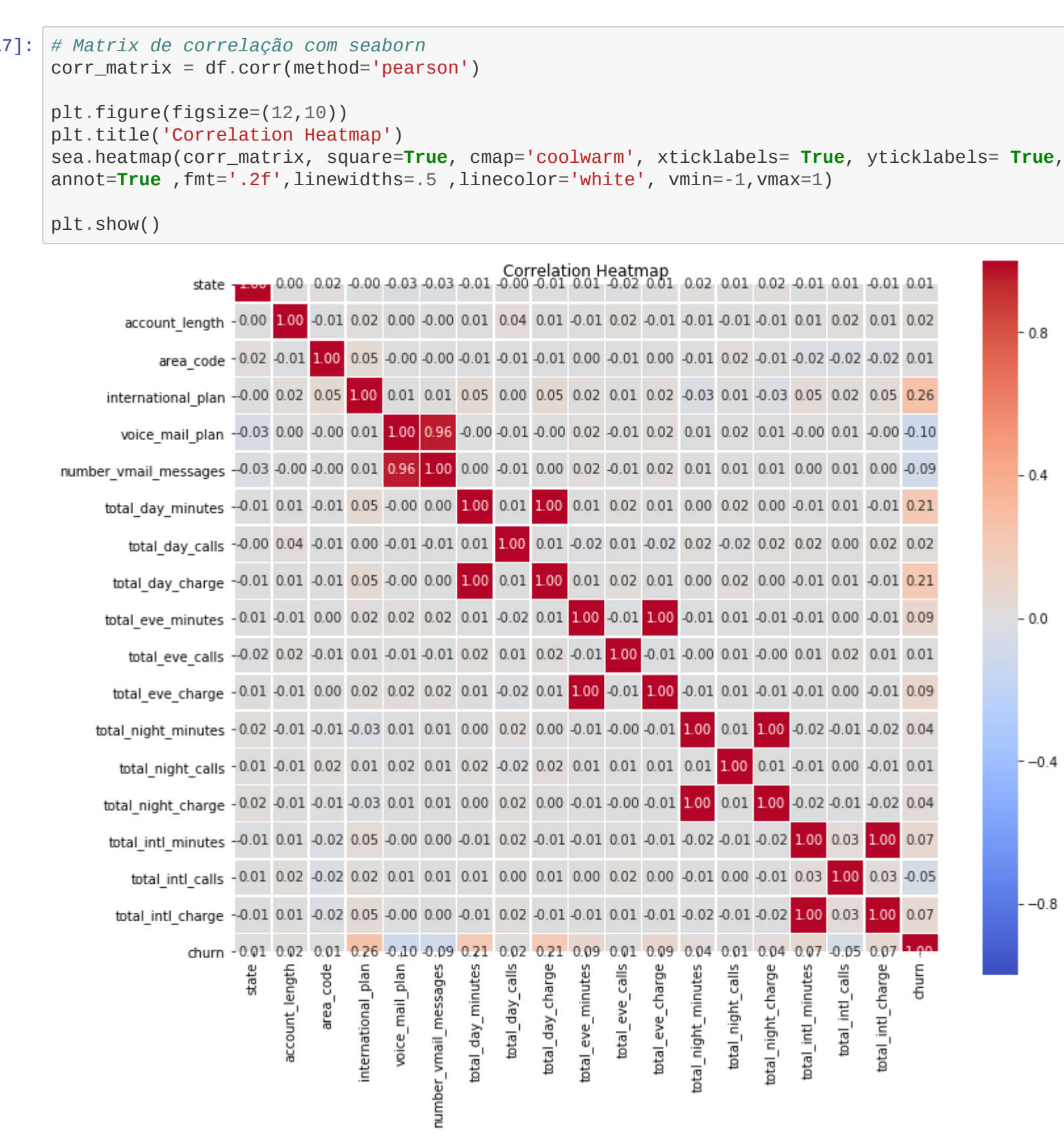
In [13]:
```
#Convertendo 'area_code' to numeric
df.area_code = pd.to_numeric(df['area_code'])
```

Análise exploratória (Estatística descritiva)

In [14]:
```
# Análise de distribuição dos dados através de um Histograma;
# Embora a maior parte dos dados apresentarem distribuição normal, será necessário a padronização dos dados para o
#algoritmo Logistic Regression;

df.hist()
plt.show()
```



In [17]:
```
# Matrix de correlação com seaborn
corr_matrix = df.corr(method='pearson')

plt.figure(figsize=(12,10))
plt.title('Correlation Heatmap')
sea.heatmap(corr_matrix, square=True, cmap='coolwarm', xticklabels= True, yticklabels= True,
annot=True ,fmt='.2f',linewidths=.5 ,linecolor='white', vmin=-1,vmax=1)

plt.show()
```

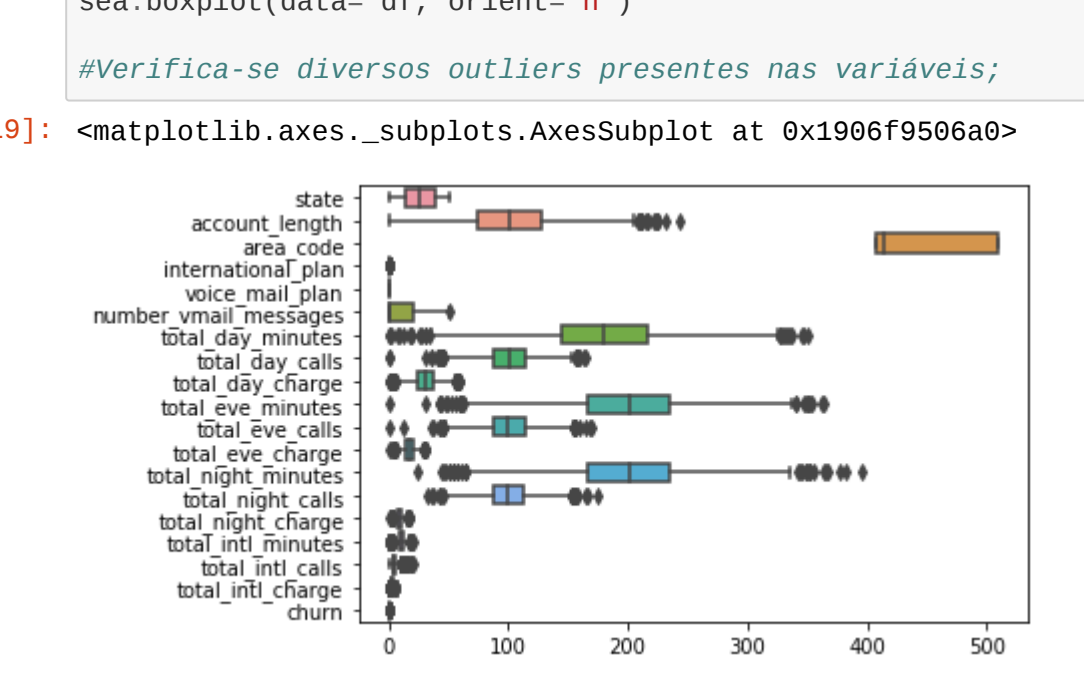


In [18]:
```
#Correlação com a variável target 'churn'
cor_target = abs(corr_matrix["churn"])

#Selecting highly correlated features

# A correlação entre a variável target e as demais é baixa; apenas 4 variáveis mostraram uma correlação de apenas >=20 %.

relevant_features = cor_target[cor_target>0.2]
relevant_features
```

Out[18]:
```
international_plan     0.259852
total_day_minutes      0.205151
total_day_charge       0.205151
churn                  1.000000
Name: churn, dtype: float64
```

In [19]:
```
### Boxplot

sea.boxplot(data= df, orient='h')

#Verifica-se diversos outliers presentes nas variáveis;
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x1906f9506a0>



Pré-Processamento

Feature Selection - Seleção Univariada

In [20]:
```
# Extração de Variáveis com Testes Estatísticos Univariados

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2


#Separando input e output
x= df.iloc[:,0:18]
y=df.iloc[:,18]

# Função para seleção de variáveis (4)
best_var = SelectKBest(score_func = chi2, k = 4)

# Executa a função de pontuação em (X, y) e obtém os recursos selecionados
fit = best_var.fit(x, y)

# Reduz X para os recursos selecionados
features = fit.transform(x)

# Resultados
print('\nNúmero original de features:', x.shape[1])
print('\nNúmero reduzido de features:', features.shape[1])
print('\nFeatures (Variáveis Selecionadas): \n\n', features)
```

```
Número original de features: 18

Número reduzido de features: 4

Features (Variáveis Selecionadas):

 [[ 25.    265.1   45.07 197.4 ]
 [ 26.    161.6   27.47 195.5 ]
 [  0.    243.4   41.38 121.2 ]
 ...
 [  0.    180.8   30.74 288.8 ]
 [  0.    213.8   36.35 159.6 ]
 [ 25.    234.4   39.85 265.9 ]]
```

In [21]:
```
# As 4 variáveis mais relevantes conforme o teste univariado (qui-quadrado), foram:

#number_vmail_messages;total_day_minutes, total_day_charges,total_eve_minutes

df_new = pd.DataFrame(data=features)
df_new.head()
```

Out[21]:

	0	1	2	3
0	25.0	265.1	45.07	197.4
1	26.0	161.6	27.47	195.5
2	0.0	243.4	41.38	121.2
3	0.0	299.4	50.90	61.9
4	0.0	166.7	28.34	148.3

Feature Selection - Recursive Feature Elimination

In [22]:
```
# Import dos módulos

from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
import warnings
warnings.filterwarnings('ignore')

# Criação do modelo
modelo = LogisticRegression()

# RFE
rfe = RFE(modelo, 3)
fit = rfe.fit(x, y)


# Print dos resultados
print("Variáveis Preditoras:", x.columns[0:18])
print("Variáveis Selecionadas: %s" % fit.support_)
print("Ranking dos Atributos: %s" % fit.ranking_)
print("Número de Melhores Atributos: %d" % fit.n_features_)
```

```
Variáveis Preditoras: Index(['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'],
      dtype='object')
Variáveis Selecionadas: [False False False  True  True False False False False False False Fa
lse
 False False False False  True False]
Ranking dos Atributos: [11 16  5  1  1  4  3  8 12  7 10 14 13  9 15  2  1  6]
Número de Melhores Atributos: 3
```

In [ ]:
```
# 4 Melhores variáveis conforme método RFE: 'international_plan',voice_mail_plan''total_intl
_calls','total_eve_charge'
```

Feature Selection - Ensemble

In [23]:
```
# Importância do Atributo com o Extra Trees Classifier

# Import dos Módulos

from sklearn.ensemble import ExtraTreesClassifier

# Criação do Modelo - Feature Selection
modelo = ExtraTreesClassifier()
modelo.fit(x, y)

# Print dos Resultados
print(x.columns[0:18])
print(modelo.feature_importances_)
```

```
Index(['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'],
      dtype='object')
[0.0432953  0.04293907 0.02710827 0.07184055 0.01872    0.01800938
 0.12242037 0.04776417 0.13252386 0.0623604  0.04331638 0.06140953
 0.04592336 0.04526765 0.04754067 0.05329694 0.06058713 0.05567697]
```

In [24]:
```
#Ordenando o resultado do maior para o menor
# As 3 variáveis mais importante neste método foram:
# 'total_day_charge','total_day_minutes', 'international_plan'

df_importance = modelo.feature_importances_
df_importance = pd.DataFrame(data=df_importance)
df_importance.sort_values(by=[0], ascending= False)
```

Out[24]:

	0
8	0.132524
6	0.122420
3	0.071841
9	0.062360
11	0.061410
16	0.060587
17	0.055677
15	0.053297
7	0.047764
14	0.047541
12	0.045923
13	0.045268
10	0.043316
0	0.043295
1	0.042939
2	0.027108
4	0.018720
5	0.018009

PCA (Principal Component Analysis)

In [25]:
```
# Feature Extraction

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Gerando outro dataset de treino

#Separando input e output
x1= df.iloc[:,0:18]
y=df.iloc[:,18]

## Padronizando os dados

scaler= StandardScaler().fit(x1)
standardx = scaler.transform(x1)


# Seleção de atributos
pca = PCA(.95)
pca = PCA(n_components = 4)

pca.fit(standardx)
fit_pca = pca.transform(standardx)

pca_df = pd.DataFrame(data = fit_pca, columns = ['principal component 1', 'principal compone
nt 2', 'principal component 3',
                                                'principal component 4'])

#Print
pca_df
```

Out[25]:

	principal component 1	principal component 2	principal component 3	principal component 4
0	1.841795	-0.251173	-1.168298	-2.050583
1	-0.460939	-0.311583	0.800381	-2.969701
2	-1.509282	-0.630053	-2.693775	0.343338
3	0.593548	-2.572033	-3.749474	1.381734
4	-1.068688	-0.823577	-0.635462	0.762775
...	...	...	...	...
3328	1.260652	-0.569365	1.702145	-2.497620
3329	0.080122	-0.844403	-1.567299	0.820277
3330	-0.435639	1.998808	0.026402	-0.656141
3331	0.798615	-0.055045	-1.292827	2.745441
3332	1.076641	1.398818	-0.343993	-3.115884

3333 rows × 4 columns

Modelo de Machine Learning: Logistic Regression / PCA

In [26]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
import warnings
warnings.filterwarnings('ignore')


# Criando o modelo
modelo = LogisticRegression()

# Definindo os valores para os folds
num_folds = 10

# Separando os dados em folds
kfold = KFold(num_folds, True, random_state= 10)

# Criando o modelo
modelo = LogisticRegression()
resultado = cross_val_score(modelo, fit_pca, y, cv = kfold)

# Usamos a média e o desvio padrão
print("Acurácia Final: %.2f%%" % (resultado.mean() * 100.0))
```

```
Acurácia Final: 85.69%
```

In [27]:
```
# Exclusão de variáveis que apresentaram menor correlação ou importância conforme as técnica
s de feature selection realizadas

x.drop(['state'], axis=1, inplace= True)
x.drop(['area_code'], axis=1, inplace= True)
x.drop(['account_length'], axis=1, inplace= True)
x.drop(['total_day_calls'], axis=1, inplace= True)
x.drop(['total_eve_calls'], axis=1, inplace= True)
x.drop(['total_night_calls'], axis=1, inplace= True)
x.drop(['total_night_charge'], axis=1, inplace= True)
x.drop(['total_intl_calls'], axis=1, inplace= True)
x.drop(['total_intl_charge'], axis=1, inplace= True)
```

In [28]:
```
## Padronizando os dados

scaler= StandardScaler().fit(x)
standard = scaler.transform(x)
```

Modelo de Machine Learning: Logistic Regression

In [34]:
```
# Modelo Logistic regression utilizando divisão dos dados de forma estática, 70% dados de tr
eino e 30% dados para teste

# Import dos módulos

from sklearn.metrics import roc_auc_score
from sklearn.metrics import classification_report
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import warnings
warnings.filterwarnings('ignore')

# Criação do modelo

# Criando os conjuntos de dados de treino e de teste
teste_size = 0.30


# Dividindo os dados em treino e teste
x_treino, x_teste, y_treino, y_teste = train_test_split(standard, y, test_size = teste_size,
random_state=27)

# Criando o modelo
model = LogisticRegression()
model.fit(x_treino, y_treino)


# Previsão do modelo
pred = model.predict(x_teste)

#Acurácia
score = model.score(x_teste, y_teste )
print( "\nAcurácia Final: %.2f%%" % (score * 100.00))

print('\nAUC: %.2f%%' % (roc_auc_score(pred, y_teste) * 100))

report = classification_report(y_teste, pred)
print(report)
```

```
Acurácia Final: 86.30%

Accuracy Score: 86.30%

AUC: 66.34%
              precision    recall  f1-score   support

           0       0.89      0.96      0.92       871
           1       0.44      0.21      0.28       129

    accuracy                           0.86      1000
   macro avg       0.66      0.58      0.60      1000
weighted avg       0.83      0.86      0.84      1000
```

In [35]:
```
# Previsão probabilística do modelo

previsoes = model.predict_proba(x_teste)
previsoes = pd.DataFrame(previsoes)

print(previsoes)
```

```
            0         1
0    0.895550  0.104450
1    0.906524  0.093476
2    0.944873  0.055127
3    0.859314  0.140686
4    0.796612  0.203388
..        ...       ...
995  0.800552  0.199448
996  0.959192  0.040808
997  0.905393  0.094607
998  0.896119  0.103881
999  0.903923  0.096077

[1000 rows x 2 columns]
```

In [39]:
```
# Logistic Regression utilizando cross-validation

#Separando input e output

x2= df.iloc[:,0:18]
y2=df.iloc[:,18]

# Criando o modelo
modelo = LogisticRegression()

# Definindo os valores para os folds
num_folds = 10

# Separando os dados em folds
kfold = KFold(num_folds, True, random_state = 8)

# Criando o modelo
modelo = LogisticRegression()
resultado = cross_val_score(modelo, x2, y2, cv = kfold)


# Acurácia
print("Acurácia Final: %.2f%%" % (resultado.mean() * 100.0))
```

```
Acurácia Final: 85.75%
```

In [43]:
```
# Balanceamento dos dados (SMOTE)
from imblearn.over_sampling import SMOTE

x1= df.iloc[:,0:18]
y1=df.iloc[:,18]

# Criando os conjuntos de dados de treino e de teste
teste_size = 0.30


# Dividindo os dados em treino e teste
x_train, x_test, y_train, y_test = train_test_split(x1, y1, test_size = teste_size, random_s
tate=27)


sm = SMOTE(random_state=27)
x_train, y_train = sm.fit_sample(x_train, y_train)
```

In [51]:
```
### Logistic Regression após balanceamento da variável target churn (técnica SMOTE)

smote = LogisticRegression(solver='liblinear',C=0.01, penalty='l2', random_state= 22).fit(x_
train, y_train)

smote_pred = smote.predict(x_test)


print("\nAccuracy Score: %.2f%%" % (accuracy_score(smote_pred, y_test) * 100))


print('\nAUC: %.2f%%' % (roc_auc_score(smote_pred, y_teste) * 100))

report = classification_report(smote_pred,y_teste)
print(report)

matrix2 = confusion_matrix(y_test, smote_pred)
print('\nConfusion matrix: \n', matrix2)
```

```
Accuracy Score: 63.70%

AUC: 57.83%
              precision    recall  f1-score   support

           0       0.63      0.94      0.75       582
           1       0.71      0.22      0.34       418

    accuracy                           0.64      1000
   macro avg       0.67      0.58      0.54      1000
weighted avg       0.66      0.64      0.58      1000


Confusion matrix:
 [[545 326]
 [ 37  92]]
```

In [47]:
```
# Random Forest

from sklearn.ensemble import RandomForestClassifier

# train model
rfc = RandomForestClassifier(n_estimators=10).fit(x_treino, y_treino)


rfc_pred = rfc.predict(x_teste)


print("\nAccuracy Score: %.2f%%" % (accuracy_score(rfc_pred, y_teste) * 100))


print("\nAUC Score: %.2f%%" % (roc_auc_score(rfc_pred, y_teste) * 100))

report2 = classification_report(rfc_pred, y_teste)
matrix3 = confusion_matrix(y_teste, rfc_pred)
print(report2)
print('\nConfusion matrix: \n',matrix3)
```

```
Accuracy Score: 92.20%

AUC Score: 86.98%
              precision    recall  f1-score   support

           0       0.98      0.93      0.96       917
           1       0.52      0.81      0.63        83

    accuracy                           0.92      1000
   macro avg       0.75      0.87      0.79      1000
weighted avg       0.94      0.92      0.93      1000


Confusion matrix:
 [[855  16]
 [ 62  67]]
```

Otimização dos parâmetros para o modelo Logistic Regression (Hyperparameter tuning)

In [48]:
```
# Import das bilbiotecas

#Otimizando o modelo usando o GridSearchCV

from sklearn.model_selection import GridSearchCV

# Definindo os valores que serão testados
valores_grid = {'penalty': ['l1','l2'], 'C': [0.001,0.01,0.1,1,10,100,1000]}

# Criando o modelo
modelo = LogisticRegression()

# Criando o grid
grid = GridSearchCV(estimator = modelo, param_grid = valores_grid)
grid.fit(x_treino, y_treino)

# Print do resultado
print("Acurácia: %.2f" % (grid.best_score_ * 100))
print("Melhores Parâmetros do Modelo:\n", grid.best_estimator_)
```

```
Acurácia: 85.43
Melhores Parâmetros do Modelo:
 LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [50]:
```
# Criando o modelo com novos parâmetros:

# Acurácia aumentou de 86.30% para 87%;

# AUC aumentou de AUC: 66.34% para 68.71%

model = LogisticRegression(C=0.01, penalty='l2', random_state= 20)
model.fit(x_treino, y_treino)


# Previsão do modelo
pred = model.predict(x_teste)

#Acurácia
score = model.score(x_teste, y_teste )
print( "\nAcurácia Final: %.2f%%" % (score * 100.00))

print('\nAUC: %.2f%%' % (roc_auc_score(pred, y_teste) * 100))

report = classification_report(y_teste, pred)
print(report)
```

```
Acurácia Final: 87.00%

AUC: 68.71%
              precision    recall  f1-score   support

           0       0.89      0.98      0.93       871
           1       0.49      0.16      0.24       129

    accuracy                           0.87      1000
   macro avg       0.69      0.57      0.58      1000
weighted avg       0.83      0.87      0.84      1000
```