In [1]:
```
#Importa os pacotes principais
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
from sklearn.model_selection import train_test_split
%matplotlib inline
```

In [2]:
```
#Carrega o dataset
df = pd.read_csv('train.csv')
```

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

Out[3]:

	ID	var3	var15	imp_ent_var16_ult1	imp_op_var39_comer_ult1	imp_op_var39_comer_ult3	imp
0	1	2	23	0.0	0.0	0.0	
1	3	2	34	0.0	0.0	0.0	
2	4	2	23	0.0	0.0	0.0	
3	8	2	37	0.0	195.0	195.0	
4	10	2	39	0.0	0.0	0.0	

5 rows × 371 columns

In [4]:
```
df['ID'].count()
```

Out[4]:
```
76020
```

In [5]:
```
#Temos uma distribuição bastante heterogênea, com predominância de TARGET 0
df.groupby('TARGET').size()
```

Out[5]:
```
TARGET
0    73012
1     3008
dtype: int64
```

In [7]:
```
#Como a base está muito desbalanceada, precisamos rearranjar sua distribuição. Para isso, vou separar
#duas bases, uma balanceada aleatóriamente e outra com a mesma distribuição da inicial para teste
#final do modelo
dfT0 = df.loc[df['TARGET']==0,:]
dfT1 = df.loc[df['TARGET']==1,:]

dft1train, dfT1test = train_test_split(dfT1, test_size=0.1)
dft0train, dfT0test = train_test_split(dfT0, test_size=0.1)
dft0train = dft0train.sample(frac=0.042)

dfTrain = pd.concat([dft0train,dft1train])
dfTrain = dfTrain.sort_values('ID')

dfTest = pd.concat([dfT0test,dfT1test])
```

In [8]:
```
dfTrain.groupby('TARGET').size()
```

Out[8]:
```
TARGET
0    2760
1    2707
dtype: int64
```

In [9]:
```
dfTest.groupby('TARGET').size()
```

Out[9]:
```
TARGET
0    7302
1     301
dtype: int64
```

In [17]:
```
#Separando o dataset de treino
dadosX = dfTrain.iloc[:,1:-1]
dadosY = dfTrain['TARGET'].values
variables = dfTrain.columns[1:-1]

X_testFinal = dfTest.iloc[:,1:-1]
y_testFinal = dfTest['TARGET'].values
```

- Dado que as colunas são anônimas, a análise exploratória dos dados fica dificultada. Não conseguimos tirar insights dos dados.
- Como temos muitas dimensões, iremos utilizar técnicas de feature selection

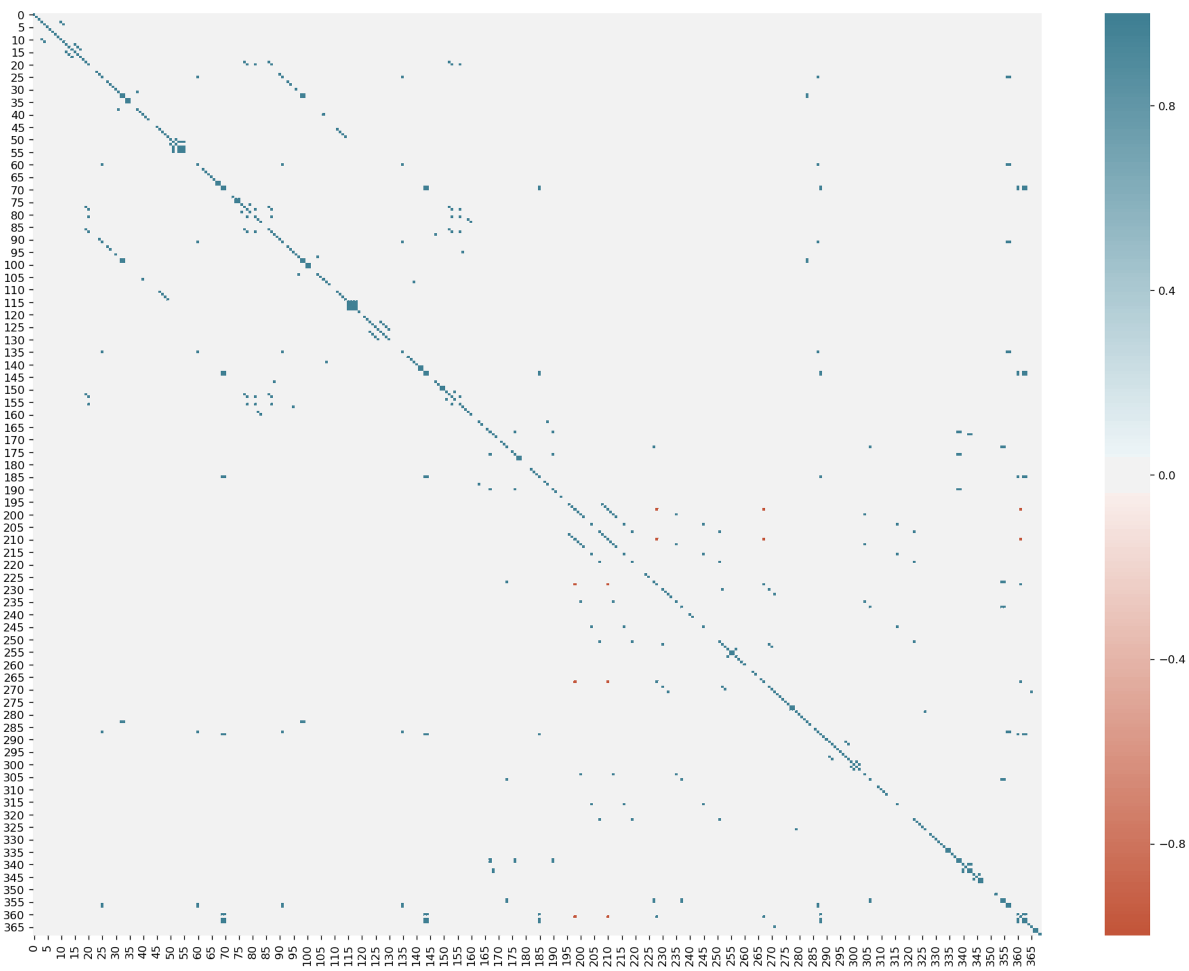
Feature Selection

- Correlação

In [19]:
```
#Cálculo de correlação com separação de valores maiores de 0.95
np.set_printoptions(threshold=np.inf)
dfCorrMatrix = np.corrcoef(dadosX, rowvar = False)
dfCorrMatrix = np.nan_to_num(dfCorrMatrix)
dfCorrMatrix[np.where(np.abs(dfCorrMatrix) < 0.95)] = 0.0
```

```
C:\ProgramData\Anaconda3\lib\site-packages\numpy\lib\function_base.py:2534: R
untimeWarning: invalid value encountered in true_divide
  c /= stddev[:, None]
C:\ProgramData\Anaconda3\lib\site-packages\numpy\lib\function_base.py:2535: R
untimeWarning: invalid value encountered in true_divide
  c /= stddev[None, :]
```

In [20]:
```
#Muitas variáveis possuem correlação maior que 0.95
fig = plt.figure(figsize=(20, 15), dpi = 120)
corrGrafico = sns.heatmap(
    dfCorrMatrix,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200))
```



In [21]:
```
#Removendo as variáveis altamente correlacionadas
fica = []
sai = []
for linha in range(len(dfCorrMatrix)):
    for coluna in range(len(dfCorrMatrix)):
        if dfCorrMatrix[linha,coluna] != 0 and linha != coluna:
            if coluna not in fica:
                sai.append(coluna)
            if linha not in sai:
                fica.append(linha)
```

In [22]:
```
print('Um total de %d variáveis foram removidas' % len(set(sai)))
dadosXv1 = dadosX.drop(dadosX.columns[sai], axis=1)
X_testFinalv1 = X_testFinal.drop(X_testFinal.columns[sai], axis=1)
```

```
Um total de 112 variáveis foram removidas
```

In [23]:
```
dadosXv1.shape
```

Out[23]:
```
(5467, 257)
```

- Teste do ChiSquare

In [24]:
```
from sklearn.feature_selection import chi2
```

In [25]:
```
#Calcula a estatística ChiSquare
colunasMantem = list(set(np.where(dadosXv1 < 0)[1]))
dadosX2 = dadosXv1.values
dadosX2[np.where(dadosX2 < 0)] = 0
chitests = chi2(dadosX2,dadosY)
```

In [26]:
```
#Filtra valores p maiores que 15% para elimina-los
chitests = np.nan_to_num(chitests)
chiColunas = list(np.where(chitests[1] > 0.15)[0])
chiColunas = [x for x in chiColunas if x not in colunasMantem]
```

In [27]:
```
print('Um total de %d variáveis foram removidas' % len(chiColunas))
dadosXv2 = dadosXv1.drop(dadosXv1.columns[chiColunas], axis=1)
X_testFinalv2 = X_testFinalv1.drop(X_testFinalv1.columns[chiColunas], axis=1)
```

```
Um total de 21 variáveis foram removidas
```

In [28]:
```
dadosXv2.shape
```

Out[28]:
```
(5467, 236)
```

- Seleção por árvore de decisão

In [29]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel
```

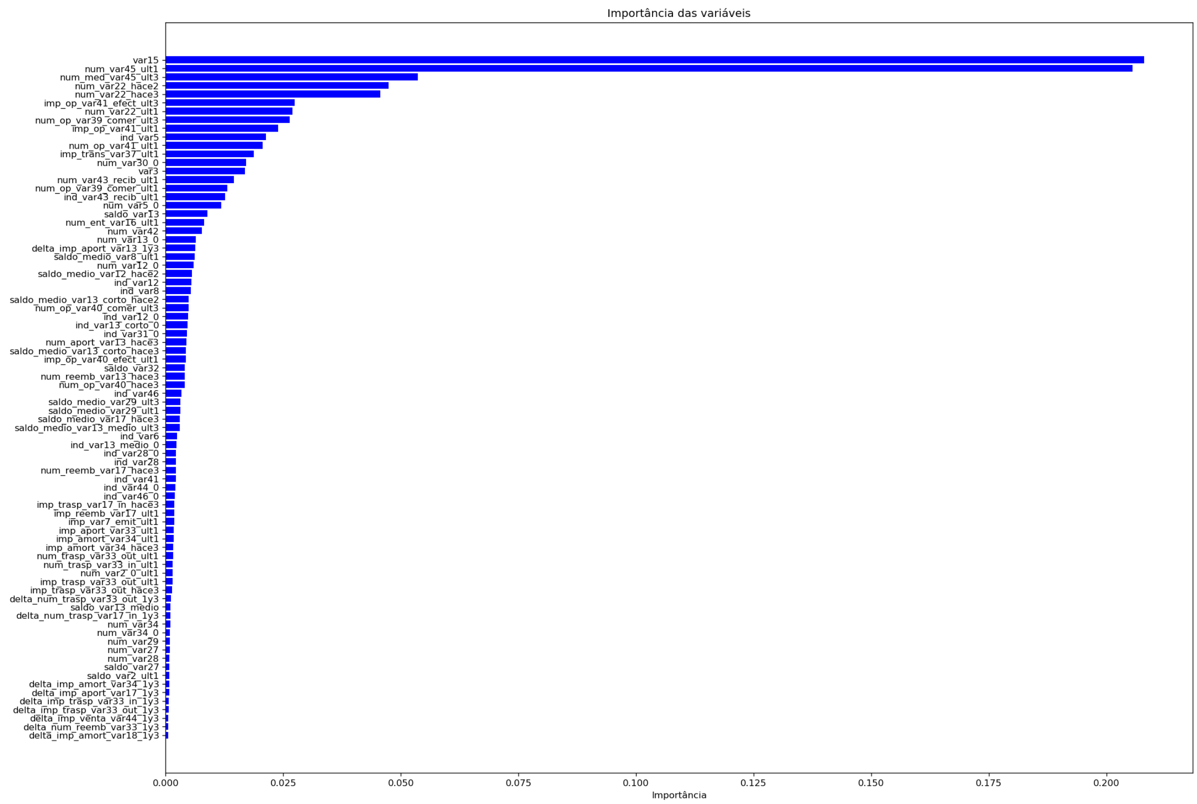
```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\weight_boosting.p
y:29: DeprecationWarning: numpy.core.umath_tests is an internal NumPy module
and should not be imported. It will be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

In [30]:
```
modelo = RandomForestClassifier()
modelo = modelo.fit(dadosXv2,dadosY)
```

In [31]:
```
#Filtrando as importâncias para melhora vizualização
importances = modelo.feature_importances_
indices = np.argsort(importances)
variablesv2 = dadosXv2.columns
ind=[]
for i in indices:
    ind.append(variablesv2[i])

ind = np.asarray(ind)
limite = np.where(importances > 0.0005)[0]
importances = importances[limite]
indices2 = np.argsort(importances)
ind = ind[limite]
```

In [32]:
```
# Plot da Importância das variáveis
fig = plt.figure(figsize=(20, 15), dpi = 120)
plt.title('Importância das variáveis')
plt.barh(range(len(indices2)), importances[indices2], color = 'b', align = 'ce
nter')
plt.yticks(range(len(indices2)),ind)
plt.xlabel('Importância')
plt.show()
```



In [33]:
```
#Vamos selecionar os 60 melhores features para iniciar a modelagem preditiva e
verificar se atendem
#o requerimento mínimo de 70% de acurácia
dadosXv3 = dadosXv2.iloc[:,indices[-61:-1]]
X_testFinalv3 = X_testFinalv2.iloc[:,indices[-61:-1]]
```

In [34]:
```
dadosXv3.shape
```

Out[34]:
```
(5467, 60)
```

In [35]:
```
#Dataset que utilizaremos para a modelagem preditiva
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()

dadosMP = dadosXv3
dadosMPN = min_max_scaler.fit_transform(dadosMP)
#dadosMPN = preprocessing.scale(dadosMP)
```

In [36]:
```
#Importa pacotes para modelagem preditiva
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

Modelo preditivo

- Regressão Logística

In [37]:
```
import statsmodels.api as sm
from sklearn import linear_model
```

In [38]:
```
modeloRL_sm=sm.Logit(dadosY,dadosMPN)
modeloRL_smResult=modeloRL_sm.fit()
modeloRL_smResult.summary2()
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: inf
         Iterations: 35

C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\discrete\discrete_mode
l.py:1674: RuntimeWarning: overflow encountered in exp
  return 1/(1+np.exp(-X))
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\discrete\discrete_mode
l.py:1724: RuntimeWarning: divide by zero encountered in log
  return np.sum(np.log(self.cdf(q*np.dot(X,params))))
C:\ProgramData\Anaconda3\lib\site-packages\statsmodels\base\model.py:508: Con
vergenceWarning: Maximum Likelihood optimization failed to converge. Check ml
e_retvals
  "Check mle_retvals", ConvergenceWarning)
```

Out[38]:

Model:	Logit	Pseudo R-squared:	-inf
Dependent Variable:	y	AIC:	inf
Date:	2020-02-13 23:04	BIC:	inf
No. Observations:	5467	Log-Likelihood:	-inf
Df Model:	58	LL-Null:	-3789.2
Df Residuals:	5408	LLR p-value:	1.0000
Converged:	0.0000	Scale:	1.0000
No. Iterations:	35.0000		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
x1	-0.8054	0.5317	-1.5146	0.1299	-1.8476	0.2368
x2	-9.6267	5.4281	-1.7735	0.0761	-20.2656	1.0122
x3	-639734.0910	33216722.9025	-0.0193	0.9846	-65743314.6643	64463846.4823
x4	-17.1009	9.6474	-1.7726	0.0763	-36.0095	1.8078
x5	2.3798	0.8233	2.8906	0.0038	0.7662	3.9934
x6	-103746.2184	5411636.1508	-0.0192	0.9847	-10710358.1713	10502865.7346
x7	-1.7690	1.4760	-1.1985	0.2307	-4.6620	1.1239
x8	-41.5774	10.3208	-4.0285	0.0001	-61.8057	-21.3491
x9	-17287.9876	878851.0115	-0.0197	0.9843	-1739804.3180	1705228.3428
x10	-0.2544	0.3261	-0.7800	0.4354	-0.8935	0.3848
x11	0.3389	0.3200	1.0591	0.2896	-0.2883	0.9661
x12	1.9221	1.0951	1.7552	0.0792	-0.2243	4.0684
x13	19813.7027	3111371.9770	0.0064	0.9949	-6078363.3149	6117990.7202
x14	-51867.6065	2677208.4059	-0.0194	0.9845	-5299099.6612	5195364.4482
x15	-0.8467	1.0081	-0.8399	0.4010	-2.8226	1.1291
x16	6119.1591	958676.1243	0.0064	0.9949	-1872851.5174	1885089.8356
x17	-0.1123	0.1742	-0.6447	0.5191	-0.4537	0.2291
x18	1.0797	5.6640	0.1906	0.8488	-10.0216	12.1811
x19	52987.6684	8320390.7537	0.0064	0.9949	-16254678.5462	16360653.8831
x20	0.1167	1.1632	0.1004	0.9201	-2.1632	2.3966
x21	0.3374	0.2303	1.4650	0.1429	-0.1140	0.7889
x22	7.9673	4.1019	1.9423	0.0521	-0.0724	16.0069
x23	-2.9592	3.4222	-0.8647	0.3872	-9.6666	3.7482
x24	-0.6820	1.0136	-0.6728	0.5011	-2.6686	1.3047
x25	-34.7615	5521.8489	-0.0063	0.9950	-10857.3864	10787.8634
x26	-1.6344	0.8540	-1.9139	0.0556	-3.3082	0.0394
x27	4.4588	2.9531	1.5099	0.1311	-1.3292	10.2468
x28	-6.9594	3.0946	-2.2489	0.0245	-13.0248	-0.8940

x29	0.0668	0.6463	0.1034	0.9177	-1.1999	1.3336
x30	0.7098	1.7134	0.4143	0.6787	-2.6483	4.0679
x31	-7.5832	11.0734	-0.6848	0.4935	-29.2866	14.1202
x32	6.1847	4.7557	1.3005	0.1934	-3.1363	15.5056
x33	-5.1156	2.9976	-1.7066	0.0879	-10.9908	0.7596
x34	1.7231	7.7025	0.2237	0.8230	-13.3735	16.8197
x35	657028.3010	33982169.2021	0.0193	0.9846	-65946799.4516	67260856.0536
x36	-9.4999	6.1978	-1.5328	0.1253	-21.6474	2.6476
x37	1.2132	7.3636	0.1648	0.8691	-13.2193	15.6456
x38	5.4309	8.5237	0.6372	0.5240	-11.2752	22.1369
x39	0.7907	0.4004	1.9746	0.0483	0.0059	1.5755
x40	8.5938	8.6765	0.9905	0.3219	-8.4118	25.5993
x41	-2.8544	6.0970	-0.4682	0.6397	-14.8042	9.0954
x42	1.3427	9453262.1455	0.0000	1.0000	-18528051.9989	18528054.6842
x43	-1.7821	1.6282	-1.0945	0.2738	-4.9734	1.4092
x44	0.9766	10803728.1667	0.0000	1.0000	-21174917.1289	21174919.0822
x45	1.2417	14179893.2170	0.0000	1.0000	-27792078.7682	27792081.2516
x46	2.0163	2.2108	0.9120	0.3618	-2.3168	6.3494
x47	-0.2488	1.7670	-0.1408	0.8880	-3.7120	3.2144
x48	-1.3480	0.1991	-6.7701	0.0000	-1.7382	-0.9577
x49	-0.1806	0.1051	-1.7184	0.0857	-0.3866	0.0254
x50	7078.6099	1111692.5844	0.0064	0.9949	-2171798.8174	2185956.0372
x51	1.9516	20932223.3228	0.0000	1.0000	-41026401.8775	41026405.7807
x52	-0.9880	5.2632	-0.1877	0.8511	-11.3037	9.3276
x53	0.3925	1.9810	0.1981	0.8429	-3.4902	4.2753
x54	-3.5814	3.5157	-1.0187	0.3083	-10.4720	3.3092
x55	-1.2118	0.3418	-3.5449	0.0004	-1.8817	-0.5418
x56	2.4385	4.4426	0.5489	0.5831	-6.2687	11.1458
x57	2.4932	2.9728	0.8387	0.4017	-3.3334	8.3198
x58	-53114.9048	8340412.1815	-0.0064	0.9949	-16400022.3968	16293792.5872
x59	-1.3738	2.6504	-0.5184	0.6042	-6.5685	3.8208
x60	-11.8960	2.2827	-5.2114	0.0000	-16.3700	-7.4221

In [39]:
```
# Montando o modelo
modeloRL = linear_model.LogisticRegression()
X_train, X_test, y_train, y_test = train_test_split(dadosMPN, dadosY, test_siz
e=0.3)
modeloRL.fit(X_train,y_train)

# Acurácia
acuracia = cross_val_score(modeloRL, X_train, y_train, cv = 5, scoring = 'roc_
auc', n_jobs = -1)
print('Acurácia média: %0.2f' % np.mean(acuracia))

predicoes = modeloRL.predict(X_test)
# Classification report
print(classification_report(y_test, predicoes))
# Confusion Matrix
print(confusion_matrix(y_test, predicoes))
```

```
Acurácia média: 0.75
             precision    recall  f1-score   support

          0       0.67      0.72      0.69       787
          1       0.72      0.68      0.70       854

avg / total       0.70      0.70      0.70      1641

[[563 224]
 [273 581]]
```

- KNN

In [40]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [41]:
```
# Divisão dos dados de treino em dados de treino e dados de validação
X_trainSmall, X_valid, y_trainSmall, y_valid = train_test_split(X_train, y_tra
in, test_size = 0.1)
```

In [42]:
```
# Range de valores de k que iremos testar
valoresK = range(1, 50, 2)
acuracias = []
```

In [43]:
```
# Testando os valores de K
for k in valoresK:
    modeloKNN = KNeighborsClassifier(n_neighbors = k)
    modeloKNN.fit(X_trainSmall, y_trainSmall)

    acuracia = modeloKNN.score(X_valid, y_valid)
    print("k = %d, %.2f%%" % (k, acuracia * 100))
    acuracias.append(acuracia)
```

```
k = 1, 57.44%
k = 3, 63.19%
k = 5, 63.71%
k = 7, 63.45%
k = 9, 62.92%
k = 11, 65.01%
k = 13, 65.54%
k = 15, 64.49%
k = 17, 64.23%
k = 19, 63.45%
k = 21, 63.71%
k = 23, 64.49%
k = 25, 63.97%
k = 27, 63.97%
k = 29, 64.49%
k = 31, 63.97%
k = 33, 64.23%
k = 35, 63.19%
k = 37, 63.71%
k = 39, 63.45%
k = 41, 63.45%
k = 43, 63.97%
k = 45, 63.97%
k = 47, 63.45%
k = 49, 63.71%
```

In [44]:
```
#Criando o modelo final
maiorK = np.argmax(acuracias)
modeloFinal = KNeighborsClassifier(n_neighbors = valoresK[maiorK])
```

In [45]:
```
# Treinamento do modelo
modeloFinal.fit(X_train, y_train)

# Acurácia
acuracia = cross_val_score(modeloFinal, X_train, y_train, cv = 5, scoring = 'r
oc_auc', n_jobs = -1)
print('Acurácia média: %0.2f' % np.mean(acuracia))

predicoes = modeloFinal.predict(X_test)
# Classification report
print(classification_report(y_test, predicoes))
# Confusion Matrix
print(confusion_matrix(y_test, predicoes))
```

```
Acurácia média: 0.74
             precision    recall  f1-score   support

          0       0.66      0.72      0.69       787
          1       0.72      0.66      0.69       854

avg / total       0.69      0.69      0.69      1641

[[568 219]
 [294 560]]
```

- Arvore de decisão

In [46]:
```
modeloRF = RandomForestClassifier(n_estimators=50)
modeloRF.fit(X_train, y_train)

# Acurácia
acuracia = cross_val_score(modeloRF, X_train, y_train, cv = 5, scoring = 'roc_
auc', n_jobs = -1)
print('Acurácia média: %0.2f' % np.mean(acuracia))

predicoes = modeloRF.predict(X_test)
# Classification report
print(classification_report(y_test, predicoes))
# Confusion Matrix
print(confusion_matrix(y_test, predicoes))
```

```
Acurácia média: 0.73
             precision    recall  f1-score   support

          0       0.64      0.71      0.67       787
          1       0.70      0.63      0.67       854

avg / total       0.67      0.67      0.67      1641

[[557 230]
 [313 541]]
```

- Árvores de decisão AdaBoost

In [47]:
```
from sklearn.ensemble import AdaBoostClassifier
```

In [48]:
```
modeloAB = AdaBoostClassifier(n_estimators=100)
modeloAB.fit(X_train, y_train)

# Acurácia
acuracia = cross_val_score(modeloAB, X_train, y_train, cv = 5, scoring = 'roc_auc', n_jobs = -1)
print('Acurácia média: %0.2f' % np.mean(acuracia))

predicoes = modeloAB.predict(X_test)
# Classification report
print(classification_report(y_test, predicoes))
# Confusion Matrix
print(confusion_matrix(y_test, predicoes))
```

```
Acurácia média: 0.76
             precision    recall  f1-score   support

          0       0.71      0.69      0.70       787
          1       0.72      0.74      0.73       854

avg / total       0.72      0.72      0.72      1641

[[545 242]
 [222 632]]
```

- Árvores de decisão Gradient Boosting

In [49]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

In [50]:
```
modeloGB = GradientBoostingClassifier(n_estimators = 100, learning_rate = 0.2)
modeloGB.fit(X_train, y_train)

# Acurácia
acuracia = cross_val_score(modeloGB, X_train, y_train, cv = 5, scoring = 'roc_auc', n_jobs = -1)
print('Acurácia média: %0.2f' % np.mean(acuracia))

predicoes = modeloGB.predict(X_test)
# Classification report
print(classification_report(y_test, predicoes))
# Confusion Matrix
print(confusion_matrix(y_test, predicoes))
```

```
Acurácia média: 0.77
             precision    recall  f1-score   support

          0       0.71      0.73      0.72       787
          1       0.74      0.73      0.74       854

avg / total       0.73      0.73      0.73      1641

[[574 213]
 [234 620]]
```

Como o modelo de árvore de decisão Gradiente Boosting apresentou o melhor resultado, vamos para a etapa de tunning dos hyperparameters

In [51]:
```
from sklearn.model_selection import GridSearchCV
```

In [52]:
```
#Procurando os melhores parâmetros
parameters = {'n_estimators':[10,50,100,150,200],'learning_rate':[0.1,0.2,0.3,0.5],'max_depth':[2,3,5]}
modeloGB = GradientBoostingClassifier()
modeloGBGS = GridSearchCV(modeloGB, parameters, scoring='roc_auc')
modeloGBGS.fit(X_train, y_train)
```

Out[52]:
```
GridSearchCV(cv=None, error_score='raise',
       estimator=GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'n_estimators': [10, 50, 100, 150, 200], 'learning_rate': [0.1, 0.2, 0.3, 0.5], 'max_depth': [2, 3, 5]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc_auc', verbose=0)
```

In [53]:
```
modeloGBGS.best_score_
```

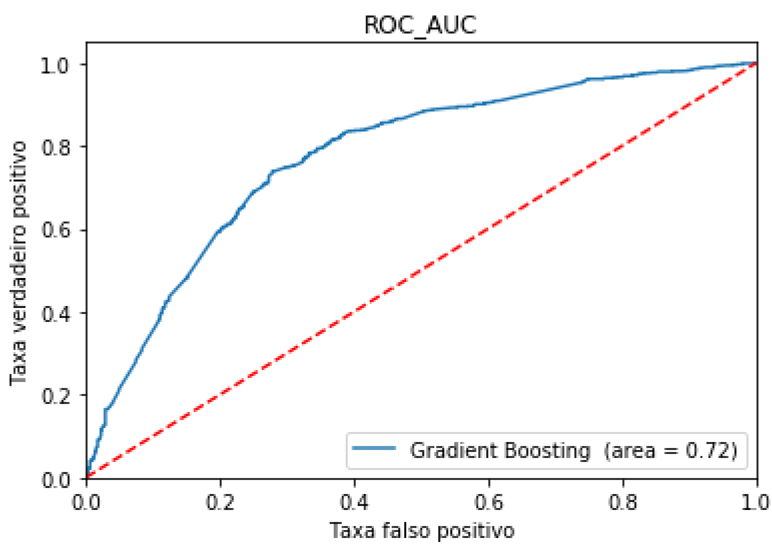
Out[53]: 0.778629751544058

In [54]:
```
modeloGBGS.best_params_
```

Out[54]: {'learning_rate': 0.1, 'max_depth': 2, 'n_estimators': 100}

In [55]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
```

In [56]:
```
#Montando a roc_auc
GB_roc_auc = roc_auc_score(y_test, modeloGBGS.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, modeloGBGS.predict_proba(X_test)[:,1
])
plt.plot(fpr, tpr, label='Gradient Boosting  (area = %0.2f)' % GB_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('Taxa falso positivo')
plt.ylabel('Taxa verdadeiro positivo')
plt.title('ROC_AUC')
plt.legend(loc="lower right")
plt.show()
```



In [57]:
```
#Por último, iremos utilizar a base de teste final, com dados nunca vistos pel
o modelo e
#que possue a mesma distribuição inicial do dataset
predicoes = modeloGBGS.predict(X_testFinalv3)
# Classification report
print(classification_report(y_testFinal, predicoes))
# Confusion Matrix
print(confusion_matrix(y_testFinal, predicoes))
```

```
             precision    recall  f1-score   support

          0       0.96      0.85      0.90      7302
          1       0.05      0.18      0.08       301

avg / total       0.93      0.83      0.87      7603

[[6237 1065]
 [ 247   54]]
```

In [ ]:
```
#Quando o teste é feito mantendo a distribuição inicial, o número de falsos po
sitivos cresce muito
```