Projeto Final

Grupo:

In [1]: import time

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```
import optuna
import numpy as np
import pandas as pd
                                         from numpy import std
from numpy import mean
import scikitplot as skplt
import matplotlib.pyplot as plt
                                          import warnings
                                          warnings.filterwarnings('ignore')
                                          from random import randint
from tensorflow import keras
                                         from sklearn.neural_network import MLPClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross val_score
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import accuracy_score, recall_score, precision_score, fl_score, roc_auc_score, average_precision_score, plot_confusion_matrix
                                          ds = pd.read csv('TRNcod.xls', delimiter = "\t")
                                         # Shuffle no dataset
ds = ds.sample(frac=1).reset_index(drop=True)
                                       def compute_performance_metrics(y, y_pred_class, y_pred_scores=None):
    accuracy = accuracy_score(y, y_pred_class)
    recall = recall_score(y, y_pred_class)
    precision = precision_score(y, y_pred_class)
    f1 = f1_score(y, y_pred_class)
    performance_metrics = (accuracy, recall, precision, f1)
    if y_pred_scores is not None:
        skplt.metrics.plot_ks_statistic(y, y_pred_scores)
        plt.show()
        y_pred_scores = y_pred_scores[, 1]
        auroc = roc_auc_score(y, y_pred_scores)
        aupr = average_precision_score(y, y_pred_scores)
        performance_metrics = performance_metrics + (auroc, aupr)
        plt.supprecision_score(y, y_pred_scores)
        aupr = average_precision_score(y, y_pred_scores)
        aupr = average_precision_score(y, y_pred_scores)
        performance_metrics + (auroc, aupr)
        plt.suptitle('Acuracia: {:3.3f}\nRecall: {:3.3f}\nPrecision: {:3.3f}\nPrecision: {:3.3f}\nAUROC: {:3.3f}\nAUR
                                        def compute_performance_metrics_sem_plot(y, y_pred_class, y_pred_scores=None):
    accuracy = accuracy_score(y, y_pred_class)
    recall = recall_score(y, y_pred_class)
    precision = precision_score(y, y_pred_class)
    f1 = f1_score(y, y_pred_class)
    performance_metrics = (accuracy, recall, precision, f1)
    if y_pred_scores is not None:
        # skplt.metrics.plot_ks_statistic(y, y_pred_scores)
        # nlt.show()
                                                           # plt.show()
y_pred_scores = y_pred_scores(:, 1)
auroc = roc_auc_score(y, y_pred_scores)
aupr = average_precision_score(y, y_pred_scores)
performance_metrics = performance_metrics + (auroc, aupr)
return_performance_metrics
                                        def compute_performance_metrics_sem_plot2(y, y_pred_class, y_pred_scores, rede_trial):
    accuracy = accuracy_score(y, y_pred_class)
    recall = recall_score(y, y_pred_class)
    precision = precision_score(y, y_pred_class)
    fl = fl_score(y, y_pred_class)
    performance_metrics = (accuracy, recall, precision, fl)
    if y_pred_scores is not None:
        skplt.metrics.plot_ks_statistic(y, y_pred_scores)
    # plt_schore()
                                                          # plt.show()
y_pred_scores = y_pred_scores[:, 1]
auroc = roc_auc_score(y, y_pred_scores)
aupr = average_precision_score(y, y_pred_scores)
performance_metrics = performance_metrics + (auroc, aupr)
plt.title(label=rede_trial, y=0.9)
plt.suptitle('Acurácia: {:3.3f}\nRecall: {:3.3f}\nPrecision: {:3.3f}\nFl: {:3.3f}\nAUROC: {:3.3f}\nAURP: {:3.3f}\nAURP: {:3.3f}\.format(accuracy, recall, precision, fl, aur
plt.savefig(rede_trial, dpi=100)
plt.close()
return performance_metrics
In [ ]: # print([d for d in ds.columns])
```

Tratamento do Dataset

```
# inadimplentes = pd.DataFrame(list(filter(lambda x: x == 1, ds['IND_BOM_1_2'])))
# Selecionando quem é inadimplente
inadimplentes = ds[ds['IND_BOM_1_2'] == 1]
# Selecionando quem é adimplente
adimplente = ds[ds['IND_BOM_1_2'] == 0]

global treino jan
global treino jan
global treino jan
global teste ina
global treino adi
global treino adi
global treino jan
global valid_adi

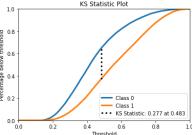
# Dividindo datasets
treino ina = inadimplentes[:int(len(inadimplentes)/2)]
teste ina = inadimplentes[int(len(inadimplentes)/2):int((len(inadimplentes)/2):int(ina == inadimplentes]/int(ten(inadimplentes)/2);
treino_adi = adimplente[:int(len(adimplentes)/2)]
teste adi = adimplente[:int(len(adimplentes)/2)]
teste adi = adimplente[:int(len(adimplente)/2)]
teste adi = adimplente[int(len(adimplente)/2)]
# Equalizando tamanho de datasets treino e validação dos inadimplentes ao de adimplentes
treino jan = treino_ina.loc(treino jan.index.repeat(2)).drop''INDEX', axis=1)
treino_ina('CDTA') = treino_ina.loc(treino jan.index.repeat(2)).drop''INDEX', axis=1)
treino_ina('CDTA') = treino_ina.loc(treino jan.index.repeat(2)).drop''INDEX', axis=1)
treino_ina('CDTA') = treino_ina.loc(treino jan.index.repeat(2)).drop''INDEX'
```

```
treino ina.drop(columns=["COPIA"], axis=1, inplace=True)
 treino adi.drop(columns=['INDEX'], axis=1, inplace=True)
valid_ina["COPIA"] = valid_ina.index.repeat(2)].drop('INDEX', valid_ina.sort_values(by="COPIA", inplace=True, ignore_index=True) valid_ina = valid_ina.iloc[: (len(valid_idi) - len(valid_ina)), valid_ina.drop(columns=["COPIA"], axis=1, inplace=True) # Fim da equalização
 valid_ina = valid_ina.loc[valid_ina.index.repeat(2)].drop('INDEX', axis=1)
valid_ina["COPIA"] = valid_ina.duplicated()
                                                                                     len(valid_ina)), : ]
print('Tamanhos de inadimplentes: \nTreino: {}\nTeste: {}\nValidação: {}\n'.format(len(treino_ina.values), len(teste_ina.values), len(valid_ina.values)))
print('Tamanhos de adimplentes: \nTreino: {}\nTeste: {}\nValidação: {}\n'.format(len(treino_adi.values), len(teste_adi.values), len(valid_adi.values)))
print('Colunas: {}'.format(len([d for d in ds.columns])))
ds.drop(labels="INDEX", axis=1, inplace=True)
Tamanhos de inadimplentes:
Treino: 127549
Teste: 33524
Validação: 63775
Tamanhos de adimplentes:
Treino: 127549
Teste: 63774
Validação: 63775
Colunas: 246
# https://stackoverflow.com/questions/29294983/how-to-calculate-correlation-between-all-columns-and-remove-highly-correlated-on # https://psicometriaonline.com.br/como-testar-a-normalidade-da-amostra-com-kolgomorov-smirnov-e-shapiro-wilk/
     # Create correlation matri
 # corr matrix = ds.corr().abs()
 # # Select upper triangle of correlation matrix
# upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))
 ## Find features with correlation greater than 0.89 # to\_drop = [column \ for \ column \ in \ upper.columns \ if \ any(upper[column] > 0.89)]
 # # Drop features
# # ds.drop(to_drop, axis=1, inplace=True)
 # ds.columns
 # Colunas mais correlacionadas
```

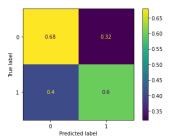
MLP

```
df_treino = treino_ina.drop(axis=1, labels=['IND_BOM_1 1', 'IND_BOM_1 2']).append(treino_adi.drop(axis=1, labels=['IND_BOM_1 1', 'IND_BOM_1 2']))
df_teste = teste_ina.drop(['IND_BOM_1 2', 'IND_BOM_1 1'], axis=1).append(teste_adi.drop(['IND_BOM_1 2', 'IND_BOM_1 1'], axis=1))
df_teste.drop(columns=['INDEX'], axis=1, inplace=True)
df_validacao = valid_ina.drop(['IND_BOM_1 2', 'IND_BOM_1 1'], axis=1).append(valid_adi.drop(['IND_BOM_1 2', 'IND_BOM_1 1'], axis=1))
df_validacao.drop(columns=['INDEX'], axis=1, inplace=True)
      best mlp = []
      def mlp(trial):
                   learning_rate=learning_rate,
hidden_layer_sizes=(neurons,) if layers==1 else (neurons, neurons),
learning_rate_init=learning_rate_init,
early_stopping=True).fit(df_treino, [0]*len(treino_ina)+[1]*len(treino_adi))
                    best_mlp.append(mlp)
                   mlp_pred_class = mlp.predict(df_validacao)
mlp_pred_scores = mlp.predict_proba(df_validacao)
                    accuracy, recall, precision, f1, auroc, aupr = compute_performance_metrics_sem_plot2([0]*len(valid_ina)+[1]*len(valid_adi), mlp_pred_class, mlp_pred_scores, "MLP"
                    return accuracy
     study\_0 = optuna.create\_study(direction="maximize")\\ study\_0.optimize(mlp, n\_trials=64)
     compute_performance_metrics([0]*len(teste_ina)+[1]*len(teste_adi), best_mlp[study_0.best_trial.number].predict(df_teste), best_mlp[study_0.best_trial.number].predictplot_confusion_matrix(best_mlp[study_0.best_trial.number], df_teste, [0]*len(teste_ina)+[1]*len(teste_adi), normalize='true')
plot_confusion_matrix(best_mb[study_0.best_trial.number], df_teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina)+[1]*len(teste_ina
```

```
| April | Control | Contro
```



<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f7b8deded30>



Plot da matriz de confusão do melhor classificador dentre os testados acima

Resultados do MLP

```
In [6]: optuna.visualization.plot_optimization_history(study_0)

In [6]: optuna.visualization.plot_slice(study_0)

In [6]: optuna.visualization.plot_param_importances(study_0)
```

Comentários acerca dos resultados do MLP

Random Forest

```
# Cuidado: usar esses parâmetros muito elevados, ou o default (100 estimadores e profundidade ilimitada) vai travar seu computador

# Parâmetros default:
# n_estimators=100, *,
# criterion="gini",
# max_depth=None,
# min_samples_split=2,
# min_samples_leaf=1,
# min_weight_fraction_leaf=0.,
# max_features="auto",
# max_features="auto",
# max_features="auto",
# min_impurity_decrease=0.,
# min_impurity_split=None,
# bootstrap=True,
# oob_score=False,
# n_jobs=None,
# random_state=None,
# random_state=None,
# verbose=0,
# warm_start=False,
# class_weight=None,
# ccp_alpha=0.0,
# max_samples=None
```

Teste de Kolmogorov-Smirnov (KS) e matriz de confusão da Random Forest

Acima, podemos ver os resultados de ambos. O teste de Kolmogorov-Smirnov assemelha-se bastante a uma distribuição normal. A matriz foi bem sucedida para identificar resultados falsos, para casos verdadeiro seu resultado foi pouco acima de 50%.

```
verdadeiro seu resultado foi pouco acima de 50%.
      \label{eq:decomposition} $$ ds_drop(labels=['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1) $$ df_treino = treino_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(treino_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1)) $$ df_validacao = valid_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(valid_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1)) $$ df_validacao.drop(columns=['INDEX'], axis=1, inplace=True) $$ df_validacao
      def rf(trial):
                                                                                                          = trial.suggest_int("max_depth", 16, 64)
= trial.suggest_categorical("criterion", ["gi
= trial.suggest_int("n_estimators", 8, 32)
= trial.suggest_int("min_samples_leaf", 2, 8)
= trial.suggest_int("min_samples_split", 2, 8
                        max depth
                       criterion
                                                                                                                                                                                                                                                                                               ["gini", "entropy"])
                       n_estimators
min_samples_leaf
                       min_samples_split
                     # Código opcional para logar e cronometrar tempo
# print('Random Forest com {} estimadores e profundidade máxima {}, critério {}, min amostras de folhas {} e min divisão de amostras {}\n'.format(
# n_estimators, max_depth, criterion, min_samples_leaf, min_samples_split
# ))
# start = time.time()
                       # n_scores = cross_val_score(random_forest, ds_dropado, ds['IND_BOM_1_2'], scoring='accuracy', n_jobs=1, error_score='raise')
# print('Acurácia e desvio padrão: %.3f (%.3f)' % (mean(n_scores), std(n_scores)))
# print("Tempo: ", format(time.time() - start, '.3f'), 's\n', sep='')
                       best rf.append(random forest)
                       rf_pred_class = random_forest.predict(df_validacao)
rf_pred_scores = random_forest.predict_proba(df_validacao)
                       accuracy, recall, precision, f1, auroc, aupr = compute_performance_metrics_sem_plot2([0]*len(valid_ina)+[1]*len(valid_adi), rf_pred_class, rf_pred_scores, "RF/RF"
                       return accuracy
      \label{eq:study_lemma} \begin{split} & study\_1 = optuna.create\_study(direction="maximize") \\ & study\_1.optimize(rf, n\_trials=64) \end{split}
[I 2021-12-13 09:53:46,701] A new study created in memory with name: no-name-645ee9d7-04f2-49f6-b887-c3745391ff0c
[I 2021-12-13 09:54:27,698] Trial 0 finished with value: 0.6122540180321443 and parameters: {'max_depth': 62, 'criterion': 'gini', 'n_estimators': 20, 'min_samples_l eaf': 4, 'min_samples_split': 8}. Best is trial 0 with value: 0.6122540180321443.
[I 2021-12-13 09:54:47,460] Trial 1 finished with value: 0.6049392395139161 and parameters: {'max_depth': 37, 'criterion': 'gini', 'n_estimators': 10, 'min_samples_l eaf': 5, 'min_samples_split': 6}. Best is trial 0 with value: 0.6122540180321443.
[I 2021-12-13 09:55:08,387] Trial 2 finished with value: 0.5943237945903567 and parameters: {'max_depth': 55, 'criterion': 'entropy', 'n_estimators': 9, 'min_samples_leaf': 3, 'min_samples_split': 2}. Best is trial 0 with value: 0.6175406063684829 and parameters: {'max_depth': 57, 'criterion': 'gini', 'n_estimators': 24, 'min_samples_leaf': 5, 'min_samples_split': 2}. Best is trial 3 with value: 0.6175406063684829.
[I 2021-12-13 09:55:79.799] Trial 4 finished with value: 0.608764063684829.
[I 2021-12-13 09:56:17,799] Trial 4 finished with value: 0.6175406063684829.
[I 2021-12-13 09:56:42,197] Trial 5 finished with value: 0.6175406063684829.
[I 2021-12-13 09:56:42,197] Trial 5 finished with value: 0.6195550372402979 and parameters: {'max_depth': 25, 'criterion': 'gini', 'n_estimators': 13, 'min_samples_leaf': 8, 'min_samples_split': 3}. Best is trial 5 with value: 0.6196550372402979 and parameters: {'max_depth': 22, 'criterion': 'entropy', 'n_estimators': 15, 'min_samples_leaf': 3, 'min_samples_split': 4}. Best is trial 6 with value: 0.621858094864759.
```

```
[1 2021-12-13 09:57:32,041] Trial 7 finished with value: 0.61542943439474 and parameters: {"max_depth": 24, "criterion": "gini, "n_estimators": 11, "min_samples_off: 6, "min_samples_split": 7). Best is trial 6 with value: 0.621858094864759.

### Comparison of the 
       [I 2021-12-13 09:57:32,841] Trial 7 finished with value: 0.6154292434339474 and parameters: {'max_depth': 24, 'criterion': 'gini', 'n_estimators': 11, 'min_samples_l
       [I 2021-12-13 10:13:34,519] Frial Z/ finished with value: 0.6251439811446491 and parameters: {'max_depth': Z/, 'criterion': 'entropy', 'n_estimators': Z9, 'min_sample split': 6}. Best is trial I7 with value: 0.6375668609548804.

[I 2021-12-13 10:14:36,783] Trial 28 finished with value: 0.6289925519404155 and parameters: {'max_depth': Z1, 'criterion': 'entropy', 'n_estimators': Z3, 'min_sample se_leaf': 6, 'min_samples_split': 7}. Best is trial 17 with value: 0.6375668609548804.

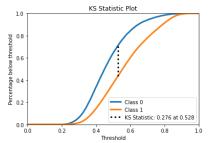
[I 2021-12-13 10:15:06,389] Trial 29 finished with value: 0.6340415523324187 and parameters: {'max_depth': 16, 'criterion': 'entropy', 'n_estimators': 19, 'min_sample se_leaf': 4, 'min_samples_split': 6}. Best is trial 17 with value: 0.6375068600548804.

[I 2021-12-13 10:15:48,125] Trial 30 finished with value: 0.6263347706781655 and parameters: {'max_depth': 23, 'criterion': 'entropy', 'n_estimators': 21, 'min_sample se_leaf': 4, 'min_samples_split': 6}.
es_leaf': 7, 'min_samples_split': 6}. Best is trial 58 with value: 0.6395531164249314.

[I 2021-12-13 10:42:20,026] Trial 62 finished with value: 0.6398086240689925 and parameters: {'max_depth': 16, 'criterion': 'entropy', 'n_estimators': 31, 'min_sample se_leaf': 8, 'min_samples_split': 6}. Best is trial 58 with value: 0.6395531164249314.

[I 2021-12-13 10:43:17,386] Trial 63 finished with value: 0.6343551548412387 and parameters: {'max_depth': 19, 'criterion': 'entropy', 'n_estimators': 32, 'min_sample se_leaf': 10, 'criterion': 'entropy', 'n_estimators': 10, 'criterion': 'entropy', 'n_estimators': 10, 'criterion': 'entropy', 'n_estimat
         es leaf': 8, 'min samples split': 6}. Best is trial 58 with value: 0.6395531164249314.
                                                                                                                                                                                                                                                     Traceback (most recent call last)
         <ipvthon-input-3-23bc67534477> in
                                    indn:input-3-2006/35447/> in <a href="mailto:monographics">monographics</a> in <a href="mai
         redict proba(df teste)
                                    42 plot confusion matrix(best rf[study 1.best trial.number], df teste, [0]*len(teste ina)+[1]*len(teste adi), normalize='true')
        NameError: name 'df teste' is not defined
```

In [4]: df_teste = teste_ina.drop(['IND_BOM_1_2','IND_BOM_1_1'], axis=1).append(teste_adi.drop(['IND_BOM_1_2','IND_BOM_1_1'], axis=1))
 df_teste.drop(columns=['INDEX'], axis=1, inplace=True)
 compute_performance_metrics([0]*len(teste_ina)+[1]*len(teste_adi), best_fistudy_1.best_trial.number].predict(df_teste), best_rf[study_1.best_trial.number].predict_p
 plot_confusion_matrix(best_rf[study_1.best_trial.number], df_teste, [0]*len(teste_ina)+[1]*len(teste_adi), normalize='true')



Out[4]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f0a35b8blc0>

0.40

<Figure size 432x288 with 0 Axes>
-0.60
-0.55
-0.55
-0.45

Predicted label Resultados da Random Forest

In [5]: optuna.visualization.plot optimization history(study 1)

In [6]: optuna.visualization.plot_slice(study_1)

optuna.visualization.plot_param_importances(study_1)

Comentários acerca dos resultados da Random Forest

A profundidade máxima é, sem dúvidas, o maior diferencial entre todos os hiperparâmetros, e menores profundidades são melhores; é possível perceber através do gráfico que quanto maior a profundidade melhor vai ser o desempenho, até atingir-se um limite. A quantidade de estimadores tem um impacto bastante menor, no gráfico, é possível ver que, excluindo-se os outliers, o número de estimadores realmente não interfere bastante no resultado final. A quantidade mínima de samples nas folhas tem impacto ainda menor, pode-se dizer que é inútil alterar este parâmetro.

Teste com profundidade menor

```
II 2021-12-13 10:51:57,381] A new study created in memory with name: no-name-f0leceaf-879c-435b-b6ec-274994bcbc97
[I 2021-12-13 10:52:39,920] Firal 0 finished with value: 0.6385966287739301 and parameters: ('max_depth': 14, 'criterion': 'entropy', 'n_estimators': 26, 'min_samples sclai': 7, 'min_samples split': 3]. Best is trial 0 with value: 0.6385962873939301.
[I 2021-12-13 10:52:53-76] Firal 1 finished with value: 0.62470632614661 and parameters: ('max_depth': 6, 'criterion': 'entropy', 'n_estimators': 20, 'min_samples_leaf': 4, 'min_samples_split': 7). Best is trial 0 with value: 0.624706327614661 and parameters: ('max_depth': 7, 'criterion': 'entropy', 'n_estimators': 20, 'min_samples_leaf': 4, 'min_samples_split': 7). Best is trial 0 with value: 0.6285960287730301.
[I 2021-12-13 10:53:07-2072] Trial 4 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:07-2072] Trial 4 finished with value: 0.62870674127793 and parameters: ('max_depth': 7, 'criterion': 'entropy', 'n_estimators': 28, 'min_samples_leaf': 6, 'min_samples_split': 8). Best is trial 0 with value: 0.6385960287730301.
[I 2021-12-13 10:53:30-732] Trial 4 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:30-732] Trial 4 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:30-732] Trial 4 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:40-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:40-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:40-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:40-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:40-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:50-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:50-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:50-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13 10:53:50-750] Trial 5 finished with value: 0.6385960287730301.
[I 2021-12-13
```

```
1, 201, 12, 13, 10, 11, 10, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11, 100, 11
                  optuna.visualization.plot optimization history(study 1)
                   optuna.visualization.plot slice(study 1)
                   optuna.visualization.plot param importances(study 1)
            Comentários acerca dos resultados da segunda execução
```

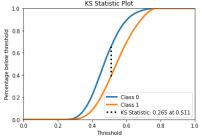
Gradient Boosting

mais rápida (11 minutos a menos) que a primeira (que demorou um total de 50 minutos), então, o teste foi válido.

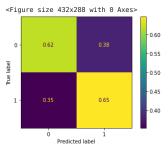
Os resultados foram melhores, é possível perceber uma tendência de crescimento em torno do 16, entretanto, a melhora foi de menos de 1% (a melhora foi de 0.04%). Tendo em vista que esta execução foi

```
# min_impurity_decrease=0.,
# min_impurity_split=None,
# random_state=None,
     # random_state=wone,
# max_features=None, v
# max_leaf_nodes=None,
# warm_start=False,
    # validation_fraction=0.1,
# n_iter_no_change=None,
# tol=1e-4,
    # ccp_alpha=0.0
   ds_dropado = ds.drop(labels=['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1)
df_treino = treino_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(treino_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_validacao = valid_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(valid_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_validacao.drop(columns=['INDEX'], axis=1, inplace=True)
df_teste = teste_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(teste_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_teste.drop(columns=['INDEX'], axis=1, inplace=True)
    best gb = []
    def gb(trial):
                                              = trial.suggest_categorical("loss", ["deviance", "exponential"])
= trial.suggest_int("max_depth", 16, 64)
= trial.suggest_float("subsample", 0.01, 0.7)
= trial.suggest_int("n_estimators", 8, 32)
= trial.suggest_float("learning_rate", 0.01, 0.7)
= trial.suggest_int("min_samples_leaf", 2, 8)
            loss
max_depth
           subsample
              estimators
            # Código opcional para logar execuções
# print('Gradient Boosting com {} estimadores e profundidade máxima {}, critério {}, min amostras de folhas {}, subsample de {} e taxa de aprendizagem {}\n'.form
# n_estimators, max_depth, loss, min_samples_leaf, subsample, learning_rate
           gradient boost = GradientBoostingClassifier(n estimators = n estimators,
                                                                                   max_depth = max_depth,
min_samples_leaf = min_samples_leaf,
learning_rate = learning_rate,
loss = loss,
                                                                                   subsample = subsample).fit(df treino, [0]*len(treino ina)+[1]*len(treino adi))
           best qb.append(gradient boost)
           gb_pred_class = gradient_boost.predict(df_validacao)
gb_pred_scores = gradient_boost.predict_proba(df_validacao)
           accuracy, recall, precision, f1, auroc, aupr = compute_performance_metrics_sem_plot2([0]*len(valid_ina)+[1]*len(valid_adi), gb_pred_class, gb_pred_scores, "GB/GB
    study_2 = optuna.create_study(direction="maximize")
study_2.optimize(gb, n_trials=64)
compute_performance_metrics([0]*len(teste_ina)+[1]*len(teste_adi), best_gb[study_2.best_trial.number].predict(df_teste), best_gb[study_2.best_trial.number].predict_p
plot_confusion_matrix(best_gb[study_2.best_trial.number], df_teste, [0]*len(teste_ina)+[1]*len(teste_adi), normalize='true')
```

```
[1 2011 12 14 16:46:38.765] Trial 35 finished with value: 0.6180243841944335 and parameters: ('loss': 'exponential', 'max_depth': 63, 'subsample': 0.44365568786719
2. n. estimators': 32, 'tearning_rate': 0.1177342007845447, 'mar_samples_leaf': 50, Bert is trial 6 with value: 0.632438655589712: subsample': 0.442266717731904, 'n. estimators': 30, 'tearning_rate': 0.149268737731904, 'n. estimators': 30, 'tearning_rate': 0.149268737731904, 'n. estimators': 30, 'tearning_rate': 0.442268737731904, 'n. estimators': 30, 'tearning_rate': 0.2438366087340, 'mar_samples_leaf': 30, 'tearning_rate': 0.243836637399212. 'subsample': 0.33825268673959
9, 'n. estimators': 27, 'tearning_rate': 0.243836660873404, 'mar_samples_leaf': 0. tearning_rate': 0.243836687399212. 'subsample': 0.33825268673959
12 2011-12-14 17115.7931717a1 30 finished with value: 0.623835394762383 and parameters; ('loss': 'teaponettal', 'mar_depth': 43, 'usbample': 0.37359566083108
12 2011-12-14 1715.199, 1271 7124 40 finished with value: 0.623835394762383 and parameters; ('loss': 'teaponettal', 'mar_depth': 43, 'usbample': 0.18596096420241, 'mar_estimators': 30, 'tearning_rate': 0.1859609643044, 'mar_estimators': 30, 'tea
```



Out[3]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f6168865be0>



Teste de Kolmogorov-Smirnov (KS) e matriz de confusão da Gradient Boosting

Acima, podemos ver os resultados de ambos. O teste de Kolmogorov-Smirnov assemelha-se, assim como a Random Forest, bastante a uma distribuição normal. Mais uma vez (semelhante a Random Forest), a matriz foi bem sucedida para identificar resultados verdadeiros e falsos. Entretanto, o Gradient Boosting peca pela sua lenta execução, a qual apresenta resultados inferiores aos do Random Forest

Resultados do Gradient Boosting

```
In [4]: optuna.visualization.plot_optimization_history(study_2)

In [5]: optuna.visualization.plot_slice(study_2)

In [6]: optuna.visualization.plot_param_importances(study_2)
```

Comentários acerca dos resultados do Gredient Boosting

O learning rate é certamente o mais importante dos hiperparâmetros, vemos que quanto mais próximo a 0 melhor o seu desempenho. Um número maior de estimadores foi o que obteve melhores resultados. Para subsamples, o intervalo ao redor de 0.2 obteve os melhores resultados. O min samples leaf obteve resultados consistentes no valor de 6. Por fim, a profundidade máxima se saiu bem com valores entre 40 e 50, o que foi uma surpresa, pois intuitivamente, imaginávamos que maiores profundidades iriam obter melhores resultados.

Teste de Kolmogorov-Smirnov (KS) e matriz de confusão da Regressão Logística

Acima, podemos ver os resultados de ambos. O teste de Kolmogorov-Smirnov assemelha-se, assim como a Random Forest e Gradient Boosting, bastante a uma distribuição normal. Semelhante aos já supracitados, a matriz foi melhor sucedida para identificar resultados falsos, porém, os resultados caíram na identificação de resultados falsos mas foram os melhores até então para identificar resultados verdadeiros.

```
ds_dropado = ds.drop(labels=['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1)
df_treino = treino_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(treino_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_validacao = valid_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(valid_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_validacao.drop(columns=['INDEX'], axis=1, inplace=True)
df_teste = teste_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(teste_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_teste.drop(columns=['INDEX'], axis=1, inplace=True)
 best rl = []
 def rl(trial):
      rt(ilat):
# penalty = trial.suggest_categorical("penalty", ["none", "l2", "l1", "elasticnet"])
solver = trial.suggest_categorical("solver", ["newton-cg", "lbfgs", "liblinear", "sag", "saga"])
C = trial.suggest_float("C", 0.01, 1.0)
multi_class = "ovr"
       # Código opcional para log
       # print('Regressão Logística com solver {} e C {}\n'.format(
       # solver, C
# ))
       regressao_log = LogisticRegression(max_iter=1000,
                                                       random_state=1,
                                                       solver=solver.
                                                       multi_class=multi_class).fit(df_treino, [0]*len(treino_ina)+[1]*len(treino_adi))
       best_rl.append(regressao_log)
       rl_pred_class = regressao_log.predict(df_validacao)
rl_pred_scores = regressao_log.predict_proba(df_validacao)
       accuracy, recall, precision, f1, auroc, aupr = compute performance metrics sem plot2([0]*len(valid ina)+[1]*len(valid adi), rl pred class, rl pred scores, "LR/L
       return accuracy
 study_3 = optuna.create_study(direction="maximize")
study_3.optimize(rl, n_trials=64)
 compute\_performance\_metrics([0]*len(teste\_ina)+[1]*len(teste\_adi), \ best\_rl[study\_3.best\_trial.number].predict(df\_teste), \ best\_rl[study\_3.best\_trial.number].predict\_pplot\_confusion\_matrix(best\_rl[study\_3.best\_trial.number], \ df\_teste, \ [0]*len(teste\_ina)+[1]*len(teste\_adi), \ normalize='true')
[I 2021-12-13 17:28:29,982] A new study created in memory with name: no-name-ea7c6a75-d17e-45ea-8b7f-6053360cb5ec
[I 2021-12-13 17:28:45,474] Trial θ finished with value: θ.631344570756566 and parameters: {'solver': 'saga', 'C': θ.5849769857357946}. Best is trial θ with value:
0.631344570756566.
[I 2021-12-13 17:29:00,180] Trial 1 finished with value: 0.631485691885535 and parameters: {'solver': 'saga', 'C': 0.2842694673818212}. Best is trial 1 with value:
 0.631485691885535
                          29:24,171] Trial 2 finished with value: 0.6313524108192865 and parameters: {'solver': 'sag', 'C': 0.6668490171508832}. Best is trial 1 with value:
[1 2021-12-13 17:29:45,635] Trial 3 finished with value: 0.6313288906311251 and parameters: {'solver': 'liblinear', 'C': 0.6562292021435742}. Best is trial 1 with va
 [I 2021-12-13 17:29:45]
lue: 0.631485691885535
[I 2021-12-13 17:30:02,812] Trial 4 finished with value: 0.631313210505684 and parameters: {'solver': 'saga', 'C': 0.7034896202550367}. Best is trial 1 with value:
 0.631485691885535.
                          30:19,197] Trial 5 finished with value: 0.6313524108192865 and parameters: {'solver': 'lbfgs', 'C': 0.7197685296802497}. Best is trial 1 with value:
[1 2021-12-13 17:30:19,197] Trial 5 finished with value: 0.6313524108192865 and parameters: {'solver': 'lbfgs', 'C': 0.7197685296802497}. Best is trial 1 with value: 0.631485691885535.
[I 2021-12-13 17:31:29,515] Trial 6 finished with value: 0.6314072912583301 and parameters: {'solver': 'newton-cg', 'C': 0.4162968317742919}. Best is trial 1 with value: 0.631485691885535.
[I 2021-12-13 17:31:46,629] Trial 7 finished with value: 0.6313837710701685 and parameters: {'solver': 'saga', 'C': 0.45572740122819116}. Best is trial 1 with value: 0.631485691885535.
                         .
32:04,158] Trial 8 finished with value: 0.6314151313210505 and parameters: {'solver': 'saga', 'C': 0.4131170914789713}. Best is trial 1 with value:
 [I 2021-12-13 17:32:04,158] Trial 8 finished with value: 0.03141313051000 and parameters: {'solver': 'liblinear', 'C': 0.789271822152566}. Best is trial 1 with value: 0.6313210505684046 and parameters: {'solver': 'liblinear', 'C': 0.789271822152566}. Best is trial 1 with value: 0.6313210505684046 and parameters: {'solver': 'liblinear', 'C': 0.789271822152566}.
LE. 0.031485691885535.

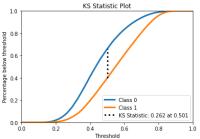
[I 2021-12-13 17:33:26,1

value: 0.631485691885535

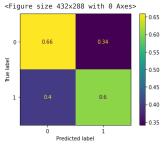
[I 2021-12-13 17:28
                     17:33:26,179] Trial 10 finished with value: 0.6313210505684046 and parameters: {'solver': 'newton-cg', 'C': 0.038839105626143844}. Best is trial 1 with
                              45,271] Trial 11 finished with value: 0.6315013720109761 and parameters: {'solver': 'saga', 'C': 0.20663194752199038}. Best is trial 11 with valu
e: 0.6315013720109761.
                     17:34:03,176] Trial 12 finished with value: 0.631485691885535 and parameters: {'solver': 'saga', 'C': 0.168295196141211}. Best is trial 11 with value:
 0.6315013720109761.
    2021-12-13 17:34:21,116] Trial 13 finished with value: 0.63157/05213041/1 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}. Best is trial 13 with value 2021-12-13 17:34:40,620] Trial 14 finished with value: 0.631172089376715 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}. Best is trial 13 with value 2021-12-13 17:34:40,620] Trial 14 finished with value: 0.631172089376715 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}. Best is trial 13 with value 2021-12-13 17:34:40,620] Trial 14 finished with value: 0.631172089376715 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}. Best is trial 13 with value 2021-12-13 17:34:40,620] Trial 14 finished with value: 0.631172089376715 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}. Best is trial 13 with value 2021-12-13 17:34:40,620] Trial 14 finished with value: 0.631172089376715 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}. Best is trial 13 with value 2021-12-13 17:34:40,620] Trial 14 finished with value: 0.631172089376715 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}. Best is trial 13 with value: 0.631172089376715 and parameters: {'solver': 'sag', 'C': 0.016941920740670358}.
                           0.6315170521364171.
[] 2021-12-13 17:34:58.054| Trial 15 finished with value: 0.6314308114464916 and parameters: {'solver': 'lbfos'. 'C': 0.23564256637746384}. Best is trial 13 with val
    2021-12-13 17:35:17,987] Trial 16 finished with value: 0.6313053704429635 and parameters: {'solver': 'saga', 'C': 0.9932414743438174}. Best is trial 13 with valu 0.6315170521364171. 2021-12-13 17:35:38,429] Trial 17 finished with value: 0.6314229713837711 and parameters: {'solver': 'saga', 'C': 0.1380865293926395}. Best is trial 13 with valu 0.6315170521364171.
ue: 0.6315170521364171
[I 2021-12-13 17:35:56,890] Trial 18 finished with value: 0.6314308114464916 and parameters: {'solver': 'saga', 'C': 0.30825183139007606}. Best is trial 13 with value
    0.6315170521364171
                     17:36:35,659] Trial 19 finished with value: 0.6314621716973736 and parameters: {'solver': 'sag', 'C': 0.0859798302036967}. Best is trial 13 with value:
(1. 2021-12-13 17:36:53,639) Frial 19 Finished with Value: 0.6314151313210505 and parameters: { solver : Sag , C : 0.0539/90502050907}. Best is trial 13 with Value: 0.6314151313210505 and parameters: { 'solver': 'liblinear', 'C': 0.357885375301218}. Best is trial 13 with Value: 0.6315170521364171.
                     17:37:16,157] Trial 21 finished with value: 0.6315092120736966 and parameters: {'solver': 'saga', 'C': 0.2567440157756343}. Best is trial 13 with value
e: 0.6315170521364171.
[I 2021-12-13 17:37:26
                              11. 36,533] Trial 22 finished with value: 0.6315013720109761 and parameters: {'solver': 'saga', 'C': 0.19101557903025057}. Best is trial 13 with valu
0.6315248921991375.
                     17:38:11,501] Trial 24 finished with value: 0.6314229713837711 and parameters: {'solver': 'saga', 'C': 0.33459591611069894}. Best is trial 23 with valu
    0.6315248921991375
                              30,957] Trial 25 finished with value: 0.631297530380243 and parameters: {'solver': 'lbfgs', 'C': 0.5311214530379987}. Best is trial 23 with valu
                     17:39:35,089] Trial 26 finished with value: 0.6314072912583301 and parameters: {'solver': 'newton-cg', 'C': 0.10494444636335767}. Best is trial 23 with
 value: 0.6315248921991375
                     17:39:53,818] Trial 27 finished with value: 0.631485691885535 and parameters: {'solver': 'saga', 'C': 0.2869459413780808}. Best is trial 23 with value:
[1 201-12-13 17:39:53,818] Frial 27 finished with value: 0.631485691885535 and parameters: {'solver': 'saga', 'C': 0.2869459413780808}. Best is trial 23 with value: 0.6315248921991375.
[I 2021-12-13 17:40:11,577] Trial 28 finished with value: 0.6315640925127401 and parameters: {'solver': 'saga', 'C': 0.23216200775438173}. Best is trial 28 with value: 0.6315640925127401.
```

```
[I 2021-12-13 17:40:29.994] Trial 29 finished with value: 0.631375931007448 and parameters: {'solver': 'saga', 'C': 0.569675094227418}. Best is trial 28 with value:
 0.6315640925127401.
   2021-12-13 17:41:07,216] Trial 30 finished with value: 0.6315327322618581 and parameters: {'solver': 'saga', 'C': 0.06388184901496352}. Best is trial 28 with value
   2021-12-13 17:41:07,210] Trial 30 Trialshed with value: 0.631532/322016361 and parameters: { Solver : Saya , C : 0.00360164901490352}. Best is trial 20 with value o.6315640925127401.

2021-12-13 17:41:45,511] Trial 31 finished with value: 0.6314778518228146 and parameters: {'solver': 'saga', 'C': 0.0527578981823673}. Best is trial 20 with value o.6315640925127401.
         12-13 17:42:00.5701 Trial 32 finished with value: 0.6314229713837711 and parameters: {'solver': 'saga'. 'C': 0.13968279418122004}. Best is trial 28 with value
   0.6315640925127401
                  :42:11,718] Trial 33 finished with value: 0.6315484123872991 and parameters: {'solver': 'saga', 'C': 0.229259702423482}. Best is trial 28 with value:
0.6315640925127401
                     :22,377] Trial 34 finished with value: 0.6314151313210505 and parameters: {'solver': 'saga', 'C': 0.3855739753054221}. Best is trial 28 with valu
   2021-12-13 17:42:22
0.6315640925127401
                   0.6315640925127401
[I 2021-12-13 17:43:01,93
value: 0.631564092512740
                   43:01,973] Trial 36 finished with value: 0.631109368874951 and parameters: {'solver': 'liblinear', 'C': 0.016512103852271226}. Best is trial 28 with
   2021-12-13 17:43:13,006] Trial 37 finished with value: 0.6315013720109761 and parameters: {'solver': 'saga', 'C': 0.27216893174449597}. Best is trial 28 with value 0.6315640925127401.
               17:43:24,899] Trial 38 finished with value: 0.631313210505684 and parameters: {'solver': 'lbfqs', 'C': 0.46842789059036777}. Best is trial 28 with value
   0.6315640925127401
                      36,948] Trial 39 finished with value: 0.6314151313210505 and parameters: {'solver': 'saga', 'C': 0.14468623959222282}. Best is trial 28 with valu
                   44:12,358] Trial 40 finished with value: 0.6314308114464916 and parameters: {'solver': 'newton-cg', 'C': 0.3444907385797983}. Best is trial 28 with
[I 2021-12-13 17:44:12,358 value: 0.6315640925127401
                   44:23,687] Trial 41 finished with value: 0.6315484123872991 and parameters: {'solver': 'saga', 'C': 0.22114137732095895}. Best is trial 28 with value
   0.6315640925127401.
2021-12-13 17:44:34,980] Trial 42 finished with value: 0.6315640925127401 and parameters: {'solver': 'saga', 'C': 0.23180877186234763}. Best is trial 28 with value
   2021-12-13 17:44:34
0.6315640925127401.
               17:44:46,306] Trial 43 finished with value: 0.6315013720109761 and parameters: {'solver': 'saga', 'C': 0.1789596585249374}. Best is trial 28 with value
   0.6315640925127401
                      0.6315640925127401
                      n.
25,814] Trial 45 finished with value: 0.6314151313210505 and parameters: {'solver': 'saga', 'C': 0.31241240553059696}. Best is trial 28 with valu
         12-13 17:45:37,859] Trial 46 finished with value: 0.6314151313210505 and parameters: {'solver': 'saga', 'C': 0.41471476891886294}. Best is trial 28 with valu
   0.6315640925127401
                   45:49,167] Trial 47 finished with value: 0.6315170521364171 and parameters: {'solver': 'saga', 'C': 0.21215788966190618}. Best is trial 28 with valu
[1 2021-12-13 17:45:49][07] First 47 Finished with value: 0.0315170521504171 and parameters. { Solver: Saya , C: 0.212157053001900187. Best is trial 28 with value [1 2021-12-13 17:46:05,066] Trial 48 finished with value: 0.6314464915719326 and parameters: { 'solver': 'liblinear', 'C': 0.12443291331195848}. Best is trial 28 with value: 0.6315640925127401.
         12-13 17:46:15.9861 Trial 49 finished with value: 0.6313994511956096 and parameters: {'solver': 'saga'. 'C': 0.4623321889705078}. Best is trial 28 with value
   0.6315640925127401
  . 0.031304092312401. [2021-12-13 17:46:35,975] Trial 50 finished with value: 0.6313053704429635 and parameters: {'solver': 'sag', 'C': 0.8537853763331291}. Best is trial 28 with value: .6315640925127401. [2021-12-13 17:46:48,625] Trial 51 finished with value: 0.6314935319482556 and parameters: {'solver': 'saga', 'C': 0.2618101050476938}. Best is trial 28 with value: 0.6314935319482556 and parameters: {'solver': 'saga', 'C': 0.2618101050476938}.
   0.6315640925127401.
   2021-12-13 17:46:59.931] Trial 52 finished with value: 0.6315640925127401 and parameters: {'solver': 'saga'. 'C': 0.23150423611955934}. Best is trial 28 with value
   0.6315640925127401
                       11,233] Trial 53 finished with value: 0.631485691885535 and parameters: {'solver': 'saga', 'C': 0.17387524321300313}. Best is trial 28 with valu
                  27-72. 47:22,525] Trial 54 finished with value: 0.6315092120736966 and parameters: {'solver': 'saga', 'C': 0.21581937086086203}. Best is trial 28 with valu
   0.6315640925127401
   2021-12-13 17:47:33,328] Trial 55 finished with value: 0.6314151313210505 and parameters: {'solver': 'saga', 'C': 0.3860063462522674}. Best is trial 28 with value:
   0.6315640925127401
2021-12-13 17:48-2
                        .
,245] Trial 56 finished with value: 0.631454331634653 and parameters: {'solver': 'newton-cg', 'C': 0.2972336940778451}. Best is trial 28 with v
               17:48:32.5301 Trial 57 finished with value: 0.6315248921991375 and parameters: {'solver': 'saga'. 'C': 0.2187454883791752}. Best is trial 28 with value
   0.6315640925127401.
[I 2021-12-13 17:48:44,854] Trial 58 finished with value: 0.6313916111328891 and parameters: {'solver': 'lbfgs', 'C': 0.17720251004516163}. Best is trial 28 with val
    0.6315640925127401.
2021-12-13 17:49:17,619] Trial 59 finished with value: 0.6313210505684046 and parameters: {'solver': 'saga', 'C': 0.040364038465462396}. Best is trial 28 with val
         12-13 17:49:28.9541 Trial 60 finished with value: 0.6315327322618581 and parameters: {'solver': 'saga', 'C': 0.2503863913752739}. Best is trial 28 with value
   0.6315640925127401
               17:49:39,781] Trial 61 finished with value: 0.6314151313210505 and parameters: {'solver': 'saga', 'C': 0.3223366806518014}. Best is trial 28 with value
   0.6315640925127401.
2021-12-13 17:49:51,095] Trial 62 finished with value: 0.6315170521364171 and parameters: {'solver': 'saga', 'C': 0.2419893551273464}. Best is trial 28 with value 0.6315640925127401.
         .12-13 17:50:02.0261 Trial 63 finished with value: 0.6313994511956096 and parameters: {'solver': 'saga'. 'C': 0.36343712697564384}. Best is trial 28 with value
e: 0.6315640925127401.
```



Out[3]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f4ald2ab160>



Resultados da Regressão Logística

```
In [4]: optuna.visualization.plot_optimization_history(study_3)
```

```
in [5]: optuna.visualization.plot_slice(study_3)
```

In [6]: optuna.visualization.plot param importances(study 3)

Comentários acerca dos resultados da Regressão Logística

Vimos que há uma tendência de resultados melhores na região de 0.2 até 0.26 para a variável C. Vamos afunilar e gerar mais testes nesse intervalo

```
In [7]: def rl(trial):
                                                                                                                                    "elasticnet"])
"'roar". "sag", "saga"])
                     # penalty = trial.suggest_categorical("penalty", ["none", "l2", "l1", "elasticn
solver = trial.suggest_categorical("solver", ["newton-cg", "lbfgs", "liblinear"
C = trial.suggest_float("C", 0.19, 0.26)
multi_class = "ovr"
                     regressao log = LogisticRegression(max iter=1000.
                                                                       random_state=1,
solver=solver,
                                                                       multi_class=multi_class).fit(df_treino, [0]*len(treino_ina)+[1]*len(treino_adi))
                     best rl.append(regressao log)
                     rl_pred_class = regressao_log.predict(df_validacao)
rl_pred_scores = regressao_log.predict_proba(df_validacao)
                     accuracy, recall, precision, f1, auroc, aupr = compute performance metrics sem plot([0]*len(valid ina)+[1]*len(valid adi), rl pred class, rl pred scores)
               study_3 = optuna.create_study(direction="maximize")
              study 3.optimize(rl, n trials=64)
             [I 2021-12-13 17:53:19,003] A new study created in memory with name: no-name-ce42977e-cad4-43c8-a88c-clc38867c807
[I 2021-12-13 17:53:30,829] Trial 0 finished with value: 0.6315327322618581 and parameters: {'solver': 'saga', 'C': 0.24683243924552206}. Best is trial 0 with value:
             [1 2021-12-13 17:53:50,029] Iffat 0 [initiated with value: 0.0315327322016361 and parameters: { Solver: Saya , C: 0.24063243924532209}, best is triat 0 with value: 0.6315327322618581 and parameters: { Solver: 'liblinear', 'C': 0.2464369495349933}. Best is trial 0 with v
             alue: 0.6315327322618581.
                                    17:54:47,903] Trial 2 finished with value: 0.6315405723245786 and parameters: {'solver': 'newton-cg', 'C': 0.23096729387561515}. Best is trial 2 with v
             alue: 0.6315405723245786.
             II 2021-12-13 17:55:00,556] Trial 3 finished with value: 0.6315327322618581 and parameters: {'solver': 'saga', 'C': 0.2502997486409192}. Best is trial 2 with value: 0.6315405723245786.
II 2021-12-13 17:55:48,734] Trial 4 finished with value: 0.6315092120736966 and parameters: {'solver': 'newton-cg', 'C': 0.20775547948277212}. Best is trial 2 with value: 0.6315092120736966 and parameters: {'solver': 'newton-cg', 'C': 0.20775547948277212}.
             alue: 0.6315405723245786
                                        2249700.
55:609,787] Trial 5 finished with value: 0.6315170521364171 and parameters: {'solver': 'saga', 'C': 0.2124200236063185}. Best is trial 2 with value:
             [I 2021-12-13 17.56
0.6315405723245786
                                          oc. 13,063] Trial 6 finished with value: 0.6315092120736966 and parameters: {'solver': 'saga', 'C': 0.1963930960061364}. Best is trial 2 with value:
              [I 2021-12-13 17:56:13,063] Trial 6 finished with value: 0.0313367306938455 and parameters: {'solver': 'lbfgs', 'C': 0.21235618670109935}. Best is trial 2 with value: 0.6313367306938455 and parameters: {'solver': 'lbfgs', 'C': 0.21235618670109935}. Best is trial 2 with value: 0.6313367306938455 and parameters: {'solver': 'lbfgs', 'C': 0.21235618670109935}. Best is trial 2 with value: 0.6313367306938455 and parameters: {'solver': 'lbfgs', 'C': 0.21235618670109935}. Best is trial 2 with value: 0.6313367306938455 and parameters: {'solver': 'lbfgs', 'C': 0.21235618670109935}.
             e: 0.6315405723245786. [I 2021-12-13 17:56:59,338] Trial 8 finished with value: 0.6315092120736966 and parameters: {'solver': 'sag', 'C': 0.25813895016555877}. Best is trial 2 with value: 0.6315405723245786. [I 2021-12-13 17:58:04,165] Trial 9 finished with value: 0.6315092120736966 and parameters: {'solver': 'newton-cg', 'C': 0.20316898685680146}. Best is trial 2 with value: 0.6315405723245786. [I 2021-12-13 17:58:54,780] Trial 10 finished with value: 0.6315405723245786 and parameters: {'solver': 'newton-cg', 'C': 0.22778793145687184}. Best is trial 2 with
             value: 0.6315405723245786.
[I 2021-12-13 18:00:40,429] Trial 12 finished with value: 0.6315405723245786 and parameters: {'solver': 'newton-cg', 'C': 0.2336088773707623}. Best is trial 2 with value: 0.6315405723245786.
[I 2021-12-13 18:00:40,429] Trial 12 finished with value: 0.6315405723245786 and parameters: {'solver': 'newton-cg', 'C': 0.2279261916805474}. Best is trial 2 with value: 0.6315405723245786 and parameters: {'solver': 'newton-cg', 'C': 0.2279261916805474}. Best is trial 2 with value: 0.6315405723245786 and parameters: {'solver': 'newton-cg', 'C': 0.2279261916805474}.
             alue: 0.6315405723245786.
[I 2021-12-13 18:01:22,170] Trial 13 finished with value: 0.6315405723245786 and parameters: {'solver': 'newton-cg', 'C': 0.23512507970331903}. Best is trial 2 with
             value: 0.6315405723245786.
[I 2021-12-13 18:02:11,794] Trial 14 finished with value: 0.6315248921991375 and parameters: {'solver': 'newton-cg', 'C': 0.2212772126531317}. Best is trial 2 with value: 0.63153495723245786.
[I 2021-12-13 18:02:29,754] Trial 15 finished with value: 0.6315327322618581 and parameters: {'solver': 'liblinear', 'C': 0.22220047554576147}. Best is trial 2 with
               value: 0.6315405723245786
             [I 2021-12-13 18:02:41,781] Trial 16 finished with value: 0.6313680909447276 and parameters: {'solver': 'lbfgs', 'C': 0.23870672131520754}. Best is trial 2 with value
                 0.6315405723245786
                                             07,009] Trial 17 finished with value: 0.6315640925127401 and parameters: {'solver': 'sag', 'C': 0.23832960730630523}. Best is trial 17 with valu
                  2021-12-13 18:03:28,454] Trial 18 finished with value: 0.6315092120736966 and parameters: {'solver': 'sag', 'C': 0.25890860331921356}. Best is trial 17 with value
                 0.6315640925127401
                  2021-12-13 18:03:51,667] Trial 19 finished with value: 0.6315484123872991 and parameters: {'solver': 'sag', 'C': 0.2401800322848446}. Best is trial 17 with value:
             [1 2021-12-13 18:03:51,007] Trial 19 Tillished with Value: 0.05154041230/2991 and parameters: { Solver: Sag , C: 0.2401000522040440}. Dest is trial 17 with Value: 0.051540925127401.
[I 2021-12-13 18:04:15,591] Trial 20 finished with value: 0.0515405723245786 and parameters: {'solver': 'sag', 'C': 0.24104428209603428}. Best is trial 17 with value: 0.05315640925127401.
                         -12-13 18:04:37,834] Trial 21 finished with value: 0.6315405723245786 and parameters: {'solver': 'sag', 'C': 0.2417431880495569}. Best is trial 17 with value:
             0.6315640925127401.
                                   16:05:01.687] Trial 22 finished with value: 0.6315484123872991 and parameters: {'solver': 'sag', 'C': 0.22379859313737488}. Best is trial 17 with valu
                 2021-12-13 16:05:01;007; Filet 22 intrinse with value: 0.6315248921991375 and parameters: {'solver': 'sag', 'C': 0.22026105693489417}. Best is trial 17 with value: 0.631548921991375 and parameters: {'solver': 'sag', 'C': 0.2536171285242527}. Best is trial 17 with value: 0.631540925127401.
                         -12-13 18:05:47,359] Trial 24 finished with value: 0.6315092120736966 and parameters: {'solver': 'saq', 'C': 0.2536171285242527}. Best is trial 17 with value:
             0.6315640925127401.
[I 2021-12-13 18:06:10,405] Trial 25 finished with value: 0.6315484123872991 and parameters: {'solver': 'sag', 'C': 0.23775937954220988}. Best is trial 17 with value.
                 0.6315640925127401
             e: 0.031040923127401.

[I 2021-12-13 18:06:35,660] Trial 26 finished with value: 0.6315248921991375 and parameters: {'solver': 'sag', 'C': 0.2175890470774522}. Best is trial 17 with value: 0.6315640925127401.

[I 2021-12-13 18:06:59,570] Trial 27 finished with value: 0.6315092120736966 and parameters: {'solver': 'sag', 'C': 0.24573443801061115}. Best is trial 17 with value: 0.6315092120736966 and parameters: {'solver': 'sag', 'C': 0.24573443801061115}.
                 0.6315640925127401
                                        07:23,476] Trial 28 finished with value: 0.6315484123872991 and parameters: {'solver': 'sag', 'C': 0.2340819591755565}. Best is trial 17 with value:
                0.6315719325754606.
                                   18:08:10,189] Trial 30 finished with value: 0.6315092120736966 and parameters: {'solver': 'sag', 'C': 0.25197453496046585}. Best is trial 29 with valu
                 0.6315719325754606
             e: 0.6315/19325/34000.
[I 2021-12-13 18:08:35,262] Trial 31 finished with value: 0.6315484123872991 and parameters: {'solver': 'sag', 'C': 0.23282664125706914}. Best is trial 29 with value: 0.6315719325754606.
[I 2021-12-13 18:08:52,585] Trial 32 finished with value: 0.6315484123872991 and parameters: {'solver': 'liblinear', 'C': 0.2312379023723466}. Best is trial 29 with
               value: 0.6315719325754606
                                    18:09:09,639] Trial 33 finished with value: 0.6315327322618581 and parameters: {'solver': 'liblinear', 'C': 0.22844020304631202}. Best is trial 29 with
             Value: 0.6315719325754696.

[I 2021-12-13 18:09:32,935] Trial 34 finished with value: 0.6315092120736966 and parameters: {'solver': 'sag', 'C': 0.24489411551753681}. Best is trial 29 with value: 0.6315719325754696.

[I 2021-12-13 18:09:49,699] Trial 35 finished with value: 0.6315484123872991 and parameters: {'solver': 'liblinear', 'C': 0.23157341024317407}. Best is trial 29 with
              value: 0.6315719325754606.
```

```
[I 201-12-13 18:10:06,543] Trial 36 finished with value: 0.6315327322618581 and parameters: {'solver': 'liblinear', 'C': 0.23601376815604988}. Best is trial 29 with value: 0.6315719325754606. [I 2021-12-13 18:10:22,526] Trial 37 finished with value: 0.6315248921991375 and parameters: {'solver': 'liblinear', 'C': 0.24723329622367238}. Best is trial 29 with value: 0.6315719325754606.
          -12-13 18:10:47.4451 Trial 38 finished with value: 0.6315248921991375 and parameters: {'solver': 'sag'. 'C': 0.24206920159005874}. Best is trial 29 with value
[I 2021
   0.6315719325754606
                          58,955] Trial 39 finished with value: 0.6315092120736966 and parameters: {'solver': 'saga', 'C': 0.21477802999147932}. Best is trial 29 with valu
   0.6315719325754606
   2021-12-13 18:11:11,393] Trial 40 finished with value: 0.6315013720109761 and parameters: {'solver': 'lbfgs', 'C': 0.2233535218428334}. Best is trial 29 with valu 0.6315719325754606.
[I 2021-12-13 18:11:36.181] Trial 41 finished with value: 0.6315719325754606 and parameters: {'solver': 'sag'. 'C': 0.23695225760055608}. Best is trial 29 with value
in 301-12-13 18:11:50,001 | Trial 41 finished with value: 0.0313/1322335000 and parameters. { solver': 'say', C': 0.23016013645390984}. Best is trial 29 with value: 0.0315719325754606.

[I 2021-12-13 18:11:52,887] Trial 42 finished with value: 0.0315484123872991 and parameters: { 'solver': 'liblinear', 'C': 0.23016013645390984}. Best is trial 29 with value: 0.0315719325754606.

[I 2021-12-13 18:12:09,310] Trial 43 finished with value: 0.0315327322618581 and parameters: { 'solver': 'liblinear', 'C': 0.22985042634483688}. Best is trial 29 with value: 0.031571932575400.
value: 0.6315719325754606
          -12-13 18:12:32,569] Trial 44 finished with value: 0.6315719325754606 and parameters: {'solver': 'sag', 'C': 0.23656835024485606}. Best is trial 29 with valu
   0.6315719325754606
   2021-12-13 18:12:44,052] Trial 45 finished with value: 0.6315327322618581 and parameters: {'solver': 'saga', 'C': 0.2489927140039956}. Best is trial 29 with valu 0.6315719325754606.
2021-12-13 18:13:08,158] Trial 46 finished with value: 0.6315484123872991 and parameters: {'solver': 'sag', 'C': 0.22624251586718486}. Best is trial 29 with valu
   0.6315719325754606.
              -13 18:13:32,783] Trial 47 finished with value: 0.6315797726381811 and parameters: {'solver': 'sag', 'C': 0.23708588227231753}. Best is trial 47 with valu
   0.6315797726381811
                           18:14:18,722] Trial 49 finished with value: 0.6315719325754606 and parameters: {'solver': 'sag', 'C': 0.2372060807103527}. Best is trial 47 with value:
0.6315797726381811.
                       14:42,986] Trial 50 finished with value: 0.6315797726381811 and parameters: {'solver': 'sag', 'C': 0.23664838991030696}. Best is trial 47 with value
e: 0.6315797726381811
```

```
[I 2021-12-13 18:15:07.265] Trial 51 finished with value: 0.6315640925127401 and parameters: {'solver': 'sag', 'C': 0.2354383883269074}. Best is trial 47 with value:
 0.6315797726381811
 0.0015/97/200111. [1] Trial 52 finished with value: 0.6315719325754606 and parameters: {'solver': 'sag', 'C': 0.23610408821306403}. Best is trial 47 with value.
[1 2021-12-13 16:15:59,99] Tract 26 (INISSIGN MACHINES) AND TRACE (INISSION MACHINES) AND TRACE 
      . 0.0313/9//20301011.
2021-12-13 18:16:33,287] Trial 55 finished with value: 0.6315484123872991 and parameters: {'solver': 'sag', 'C': 0.22594710511617722}. Best is trial 47 with valu 0.6315797726381811.
 ue: 0.6315797726381811
E: 0.6315797.
[I 2021-12-13 18:16:22
E: 0.6315797726381811.
E: 7021-12-13 18:17:16
                                 18:16:55.513] Trial 56 finished with value: 0.6315092120736966 and parameters: {'solver': 'sag', 'C': 0.24407676624418756}. Best is trial 47 with valu
 e: 0.6315797726381811.
[I 2021-12-13 18:17:16,827] Trial 57 finished with value: 0.6315248921991375 and parameters: {'solver': 'sag', 'C': 0.24859897970991518}. Best is trial 47 with value.
                                              41,445] Trial 58 finished with value: 0.6315797726381811 and parameters: {'solver': 'sag', 'C': 0.23733509116013135}. Best is trial 47 with valu
      2021-12-13 18:18:05,986] Trial 59 finished with value: 0.6315767726381811.
2021-12-13 18:18:05,986] Trial 59 finished with value: 0.6315562524500196 and parameters: {'solver': 'sag', 'C': 0.24027629709865264}. Best is trial 47 with value.
      2021-12-13 18:18:05,986] Trial 59 finished with value: 0.031302224300150 Unit parameters: {'solver': 'saga', 'C': 0.23347016311973762}. Best is trial 47 with value: 0.6315640925127401 and parameters: {'solver': 'saga', 'C': 0.23347016311973762}.
      0.6315797/26381811. 2021-12-13 18:18:45,128] Trial 61 finished with value: 0.6315405723245786 and parameters: {'solver': 'sag', 'C': 0.23674017787132007}. Best is trial 47 with value: 0.6315797726381811. 2021-12-13 18:19:12,200] Trial 62 finished with value: 0.6315640925127401 and parameters: {'solver': 'sag', 'C': 0.23920829130306664}. Best is trial 47 with value: 0.6315640925127401 and parameters: {'solver': 'sag', 'C': 0.23920829130306664}.
       0.6315797726381811.
                                         19:38,259] Trial 63 finished with value: 0.6315640925127401 and parameters: {'solver': 'saq', 'C': 0.23483146826742954}. Best is trial 47 with value
 e: 0.6315797726381811.
```

Comentários acerca dos resultados da Regressão Logística 2

Os resultados foram pouco distintos dos anteriores, dado que o algoritmo melhorou apenas 0.001%, ou seja, o teste mostrou que atingimos o seu melhor com os parâmetros anteriores.

Ensemble de MLP

```
from numpy import mean
     from numpy import std
     from sklearn.datasets import make classification
    from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_score
from sklearn.meighbors import RepeatedStratifiedKFold
from sklearn.enjsbors import KNeighborsClassifier
from sklearn.ensemble import VotingClassifier
     from matplotlib import pyplot
    import scikitplot as skplt
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score, roc_auc_score, average_precision_score, plot_confusion_matrix
from sklearn.model_selection import cross_val_predict
   ds_dropado = ds.drop(labels=['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1)
df_treino = treino_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(treino_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_validacao = valid_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(valid_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_validacao.drop(columns=['INDEX'], axis=1, inplace=True)
df_teste = teste_ina.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1).append(teste_adi.drop(['IND_BOM_1_2', 'IND_BOM_1_1'], axis=1))
df_teste.drop(columns=['INDEX'], axis=1, inplace=True)
                              Z, y = df_treino, [0]*len(treino_ina)+[1]*len(treino_adi)
return X, y
    def get dataset()
  def get_voting():
    models = list()
    models.append(('mlp0', MLPClassifier(verbose=True, max_iter=10000, early_stopping=True, hidden_layer_sizes=(13), solver='lbfgs', learning_rate='constant', ac
    models.append(('mlp1', MLPClassifier(verbose=True, max_iter=10000, early_stopping=True, hidden_layer_sizes=(3,), solver='sgd', learning_rate='adaptive', acti
    models.append(('mlp2', MLPClassifier(verbose=True, max_iter=10000, early_stopping=True, hidden_layer_sizes=(5,), solver='sgd', learning_rate='constant', acti
    ensemble = VotingClassifier(verbose=True, estimators=models, voting='soft').fit(get_dataset()[0], get_dataset()[1])
  def get_models():
    models = dict()
    models['mlp0'] = MLPClassifier(max_iter=10000, early_stopping=True)
    models['mlp1'] = MLPClassifier(max_iter=10000, early_stopping=True)
    models['mlp2'] = MLPClassifier(max_iter=10000, early_stopping=True)
    models['soft_voting'] = get_voting()
                               return models
   def compute_performance_metrics_sem_plot2(y, y_pred_class, y_pred_scores, rede_trial):
    accuracy = accuracy_score(y, y_pred_class)
    recall = recall_score(y, y_pred_class)
    precision = precision_score(y, y_pred_class)
    f1 = f1_score(y, y_pred_class)
    performance_metrics = (accuracy, recall, precision, f1)
    if y_pred_scores is not None:
    skoll_metrics_plot ks_statistic(y_v_pred_scores)
                               skplt.metrics.plot_ks_statistic(y, y_pred_scores)
                              skplt.metrics.plot_ks_statistic(y, y_pred_scores)
# plt.show()
y_pred_scores = y_pred_scores[:, 1]
auroc = roc_auc_score(y, y_pred_scores)
aupr = average_precision_score(y, y_pred_scores)
performance_metrics = performance_metrics + (auroc, aupr)
plt.title(label=rede_trial, y=0.9)
plt.suptitle('Acurácia: {:3.3f}\nRecall: {:3.3f}\nRecall: {:3.3f}\nPrecision: {:3.3f}\nPrecision: {:3.3f}\nAUROC: {:3.3f}\nAUROC
                  return performance metrics
    def evaluate model(model, X, y)
                               .uate_model(model, X, Y):
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
scores = cross_val_predict(model, X, y, cv=cv, n_jobs=-1, method='predict')
scores_proba = cross_val_predict(model, X, y, cv=cv, n_jobs=-1, method='predict_proba')
compute_performance_metrics_sem_plot2(y, scores, scores_proba, 'Ensamble/Ensamble')
                               return scores
   # Dataset de treino
X, y = get_dataset()
          Modelos de ensamble
    models = get_models()
    # Avaliar cada modelo e armazenar seus resultados
results, names = list(), list()
    pyplot.boxplot(evaluate model(get voting(), ds.drop(axis=1, labels=['IND BOM 1 1', 'IND BOM 1 2']), ds['IND BOM 1 1']), labels=names, showmeans=True)
Iteration 7, loss = 0.64290993
Validation score: 0.623167
```

Verlander, 6, lose = 0.6408117
Verlander, 6, lose = 0.6408117
Verlander, 6, lose = 0.6408117
Verlander, 6, lose = 0.6408007
Verlander, 6, lose = 0.6408007 Iteration 69, loss = 0.62945152 Validation score: 0.639632 Iteration 70, loss = 0.62946220 Validation score: 0.640220

```
Iteration 71, loss = 0.62946774
Validation score: 0.639200
Validation score did not improve more than tol=0.000100 for 10 consecutive epochs. Setting learning rate to 0.000469
Iteration 72, loss = 0.62926121
Validation score: 0.640141
Iteration 73, loss = 0.62923734
Validation score: 0.640651
Iteration 74, loss = 0.62925218
Validation score: 0.639318
Iteration 75, loss = 0.62925183
Validation score: 0.639318
Iteration 76, loss = 0.6292518
Validation score: 0.639632
Iteration 77, loss = 0.6292457
Validation score: 0.639475
Iteration 77, loss = 0.6292392
Validation score: 0.639004
Iteration 78, loss = 0.62923556
Validation score: 0.639357
Iteration 79, loss = 0.62924380
Validation score: 0.639200
Iteration 80, loss = 0.62922735
      Validation score: 0.639357
Iteration 79, loss = 0.62924380
Validation score: 0.639200
Iteration 80, loss = 0.62922735
Validation score: 0.639632
Iteration 81, loss = 0.62922839
Validation score: 0.639533
Iteration 82, loss = 0.62924091
Validation score: 0.639436
Validation score: 0.639436
Validation score: 0.639436
Validation score: 0.6294091
Validation score: 0.6294091
Validation score: 0.6294091
Validation score: 0.639436
Validation score: 0.639436
Iteration 83, loss = 0.6291979
Validation score: 0.639436
Iteration 84, loss = 0.62919390
Validation score: 0.639279
Iteration 85, loss = 0.62919404
Validation score: 0.639318
Iteration 86, loss = 0.62919404
Validation score: 0.639632
Iteration 87, loss = 0.62919444
Validation score: 0.639632
Iteration 88, loss = 0.62919444
Validation score: 0.63959
Iteration 89, loss = 0.62919442
Validation score: 0.63959
Iteration 91, loss = 0.6291941
Validation score: 0.63959
Iteration 92, loss = 0.62919917
Validation score: 0.639592
Iteration 93, loss = 0.62919917
Validation score: 0.639592
Iteration 94, loss = 0.62919261
Validation score: 0.639592
Iteration 95, loss = 0.62919261
Validation score: 0.639591
Iteration 97, loss = 0.62919261
Validation score: 0.639591
Iteration 97, loss = 0.62918211
Validation score: 0.639514
Iteration 96, loss = 0.62918211
Validation score: 0.639514
Iteration 97, loss = 0.62918211
Validation score: 0.639514
Iteration 97, loss = 0.62918211
Validation score: 0.639535
Validation score: 0.639514
Iteration 97, loss = 0.62918214
Validation score: 0.639436
Iteration 98, loss = 0.62918214
Validation score: 0.639436
Iteration 99, loss = 0.62918215
Validation score: 0.639436
Iteration 99, loss = 0.62918219
Validation score: 0.639436
Iteration 99, loss = 0.62918215
Validation score: 0.639436
Iteration 99, loss = 0.62918215
Validation score: 0.639514

Validation score: 0.639514

Validation score: 0.639517

Validation score: 0.639518

Validation score: 0.639519

Va
```

Iteration 71. loss = 0.62946774

```
Validation score: 0.634379
Iteration 6, loss = 0.63713540
Validation score: 0.636417
Iteration 7, loss = 0.63587003
Validation score: 0.638965
Iteration 8, loss = 0.63523851
Validation score: 0.639279
Iteration 9, loss = 0.63523851
Validation score: 0.638769
Iteration 10, loss = 0.6338769
Iteration 11, loss = 0.63355689
Validation score: 0.638769
Iteration 11, loss = 0.63325881
Validation score: 0.63988
Iteration 12, loss = 0.6328981
Validation score: 0.639788
Iteration 13, loss = 0.63276923
Validation score: 0.639788
Iteration 14, loss = 0.6321231
Iteration 15, loss = 0.6321231
Iteration 15, loss = 0.632120204
Validation score: 0.634024
Iteration 15, loss = 0.63127821
Validation score: 0.640624
Iteration 16, loss = 0.63189610
Validation score: 0.639553
Iteration 19, loss = 0.63127024
Validation score: 0.639553
Iteration 20, loss = 0.63127024
Validation score: 0.633558
Iteration 12, loss = 0.63395796
Validation score: 0.6395796
Validation score: 0.6395796
Validation score: 0.6395796
Validation score: 0.6395796
Validation score: 0.640576
Iteration 24, loss = 0.630853893
Validation score: 0.640576
Iteration 24, loss = 0.63085836
Iteration 25, loss = 0.63085838
Iteration 27, loss = 0.63085838
Iteration 27, loss = 0.63085891
Validation score: 0.640576
Iteration 26, loss = 0.63085891
Validation score: 0.640576
Iteration 26, loss = 0.63086402
Validation score: 0.640577
Valuation Score: 0.634143

Iteration 19, loss = 0.63267721

Validation score: 0.637475

Iteration 20, loss = 0.63276467

Validation score: 0.634888
```

Validation score: 0.634379

```
Validation cares 6.6407017
Validation cares 6.64
```

```
Validation score: 0.637279
Iteration 83, loss = 0.63240200
Iteration 83, loss = 0.63240200
Iteration 83, loss = 0.63240200
Validation score: 0.637279
Validation score: 0.637279
Validation score: 0.637279
Validation score: 0.637270
Validation score: 0.637310
Iteration 86, loss = 0.63240207
Validation score: 0.637310
Iteration 87, loss = 0.63240207
Validation score: 0.637310
Iteration 87, loss = 0.63240207
Validation score: 0.637310
Iteration 89, loss = 0.63240207
Validation score: 0.637310
Iteration 99, loss = 0.6284178
Validation score: 0.637310
Validatio
                         Validation score: 0.63491
Iteration 5, loss = 0.640300904
Validation score: 0.633438
Iteration 6, loss = 0.63849581
Validation score: 0.636025
Iteration 7, loss = 0.63868180
Validation score: 0.637123
Iteration 8, loss = 0.6357663
Validation score: 0.637967
Iteration 9, loss = 0.634747405
Validation score: 0.637967
Iteration 10, loss = 0.634747
Iteration 11, loss = 0.6332759
Iteration 11, loss = 0.6332753
Validation score: 0.636613
Iteration 11, loss = 0.63327643
Validation score: 0.638260
Iteration 11, loss = 0.63277643
Validation score: 0.637467
Iteration 11, loss = 0.63277643
Validation score: 0.637946
Iteration 12, loss = 0.63264798
Validation score: 0.637946
Iteration 14, loss = 0.6325555
Iteration 15, loss = 0.63186203
Validation score: 0.637828
Iteration 16, loss = 0.63186203
Validation score: 0.637789
Iteration 17, loss = 0.6311886
Validation score: 0.639749
Iteration 18, loss = 0.6311886
Validation score: 0.639161
Iteration 19, loss = 0.6311669
Validation score: 0.639161
Iteration 12, loss = 0.63085528
Validation score: 0.639396
Iteration 22, loss = 0.630855528
Validation score: 0.6399710
Iteration 22, loss = 0.630855459
Validation score: 0.640964
Validation score: 0.640964
Validation score: 0.640913
Iteration 27, loss = 0.63019344
Validation score: 0.639161
Iteration 27, loss = 0.63019344
Validation score: 0.639168
Validation score: 0.640965
Validation score: 0.6391795
Validation score: 0.6391868
Validation score: 0.6391868
Validation score: 0.63919344
Validation score: 0.639868
Validation score: 0.63919344
Validation score: 0.639868
Validation score: 0.639868
Validation score: 0.63919344
Validation score: 0.639868
Iteration 28, loss = 0.639059591
Validation score: 0.639164544
Validation score: 0.6398446651
Iteration 29, loss = 0.6390595944
Validation score: 0.638848
Iteration 30, loss = 0.62967966
Validation score: 0.638848
Iteration 31, loss = 0.62959930
```

```
Traceback (most recent call last)
<ipython-input-4-0cc2ceb51439> in <module>
    75 results, names = list(), list()
 76
---> 77 pyplot.boxplot(evaluate_model(get_voting(), ds.drop(axis=1, labels=['IND_BOM_1_1', 'IND_BOM_1_2']), ds['IND_BOM_1_1']), labels=names, showmeans=True)
78 pyplot.show()
<ipython-input-4-0cc2ceb51439> in evaluate_model(model, X, y)
   60 def evaluate_model(model, X, y):
   61    cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
---> 62    scores = cross_val_predict(model, X, y, cv=cv, n_jobs=-1, method='predict')
   63    scores_proba = cross_val_predict(model, X, y, cv=cv, n_jobs=-1, method='predict_proba')
   64    compute_performance_metrics_sem_plot2(y, scores, scores_proba, 'Ensamble/Ensamble')
 64
       65
                          # extra_args > 0
  -/.local/lib/python3.8/site-packages/sklearn/model_selection/_validation.py in cross_val_predict(estimator, X, y, groups, cv, n_jobs, verbose, fit_params, pre_dispat
      method)
843
                 test_indices = np.concatenate([test for _, test in splits])
if not _check_is_permutation(test_indices, _num_samples(X)):
    raise ValueError('cross_val_predict only works for partitions')
      844
                 # If classification methods produce multiple columns of output,
ValueError: cross val predict only works for partitions
```

Utilizando o sistema de Voting Classifier com 3 MLPs, obtivemos o resultado de validação médio: 63,88%.

Validation score: 0.640259