Data Science com Python

Módulo 5 - Modelagem Regressão

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LEMBRETE: Fazer o import dos datasets usados no ambiente do colab antes de executar os comandos.

Import dos pacotes

```
# Manipulação dados
import pandas as pd

# Visualização de dados
import seaborn as sns
import matplotlib.pyplot as plt

# Quebrar os dados
from sklearn.model_selection import train_test_split

# Feature selection
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import RFE

# Modelos de regressão
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor

# Validação cruzada
from sklearn.model_selection import cross_val_score

# Metricas
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from sklearn.metrics import make_scorer

# Tuning de hiperparametros
from sklearn.model_selection import GridSearchCV
```

```
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', None)
```

Import dos metadados

link da base: https://www.kaggle.com/rashmiranu/banking-dataset-classification?select=new_train.csv

```
meta = pd.read_excel('metadata.xlsx')
```

```
meta
```

	Feature	Feature_Type	
0	age	numeric	
1	job	Categorical,nominal	type of job ('admin.','blue-collar','entrepreneur','l employed','services','stude
2	marital	categorical,nominal	marital status ('divorced','married','single','unknown'; note:
3	education	categorical,nominal	('basic.4y','basic.6y','basic.9y','high.school','illiterate','professiona
4	default	categorical,nominal	ha
5	housing	categorical,nominal	
6	loan	categorical,nominal	h
7	contact	categorical,nominal	contact co
8	month	categorical,ordinal	last contact month
9	dayofweek	categorical,ordinal	last contact da
10	duration	numeric	last contact duration, in seconds . Important note: this attribute
11	campaign	numeric	number of contacts performed during this campaign a
12	pdays	numeric	number of days that passed by after the client was last co mea
13	previous	numeric	number of contacts performed
14	poutcome	categorical,nominal	outcome of the previous marketing ca

Import da base

```
df = pd.read_csv('new_train.csv', sep=',')
```

```
df.head()
```

	age	job	marital	education	default	housing	loan	contact	month
0	49	blue-collar	married	basic.9y	unknown	no	no	cellular	nov
1	37	entrepreneur	married	university.degree	no	no	no	telephone	nov
2	78	retired	married	basic.4y	no	no	no	cellular	jul

Feature engineering - Criando novas variáveis

```
df.corr()
```

	age	duration	campaign	pdays	previous
age	1.000000	-0.001841	0.003302	-0.032011	0.020670
duration	-0.001841	1.000000	-0.075663	-0.047127	0.022538
campaign	0.003302	-0.075663	1.000000	0.053795	-0.079051
pdays	-0.032011	-0.047127	0.053795	1.000000	-0.589601
previous	0.020670	0.022538	-0.079051	-0.589601	1.000000

```
df['poutcome'].value_counts()
```

```
nonexistent    28416
failure         3429
success         1105
Name: poutcome, dtype: int64
```

```
df['previous'].value_counts()
```

```
0    28416
1     3673
2      606
3      175
4       60
5       14
6        5
7        1
Name: previous, dtype: int64
```

Criando uma nova variável que traz a escala de dificuldade de contato, baseando-se em poutcome e previous

```
df['difficulty'] = -1 # para desconhecido
df.loc[(df['poutcome'] == 'success') & (df['previous'].between(0,1)), 'difficulty'] = 0 #
df.loc[(df['poutcome'] == 'success') & (df['previous'].between(2,4)), 'difficulty'] = 1 #
df.loc[(df['poutcome'] == 'success') & (df['previous'].between(5,7)), 'difficulty'] = 2 #
df.loc[(df['poutcome'] == 'nonexistent') & (df['previous'] > 7), 'difficulty'] = 2 # para
df.loc[(df['poutcome'] == 'failure'), 'difficulty'] = 2 # para impossivel
```

```
df['difficulty'].value_counts()
```

```
-1    28416
 2     3446
 0      697
 1      391
Name: difficulty, dtype: int64
```

ABT

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y', 'difficulty'],
      dtype='object')
```

```
df.isnull().sum()
```

```
age            0
job            0
marital        0
education      0
default        0
housing        0
loan           0
contact        0
month          0
day_of_week    0
duration       0
campaign       0
pdays          0
previous       0
poutcome       0
y              0
difficulty     0
dtype: int64
```

```
df.columns
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y', 'difficulty'],
      dtype='object')
```

```
df.dtypes
```

```
age             int64
job            object
marital        object
education      object
default        object
housing        object
loan           object
```

```
contact        object
month          object
day_of_week    object
duration        int64
campaign        int64
pdays           int64
previous        int64
poutcome       object
y              object
difficulty      int64
dtype: object
```

Separando as variáveis explicativas da variável resposta

```
explicativas = df.drop(columns=['age'])
```

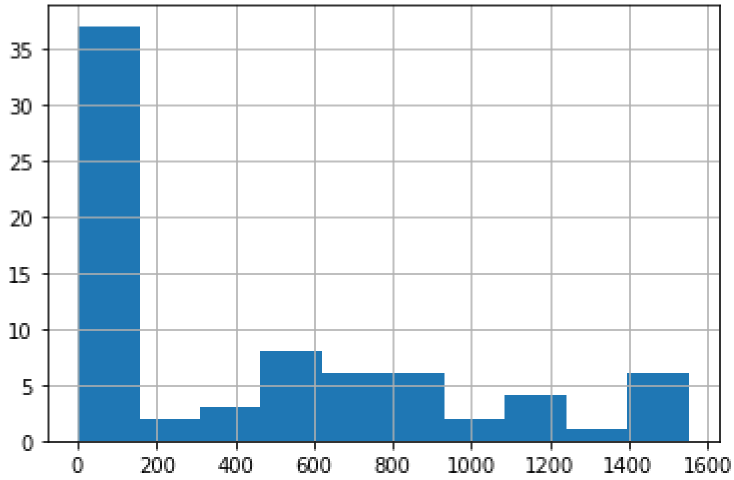
```
var_resp = df['age']
```

```
var_resp.head()
```

```
0    49
1    37
2    78
3    36
4    59
Name: age, dtype: int64
```

```
var_resp.value_counts().hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1f0ab2ca90>
```




```
explicativas.head()
```

	job	marital	education	default	housing	loan	contact	month	day_
0	blue-collar	married	basic.9y	unknown	no	no	cellular	nov	
1	entrepreneur	married	university.degree	no	no	no	telephone	nov	
3	admin	married	university.degree	no	yes	no	telephone	may	

Tratamento de enconding das variáveis categóricas

```
expl_cat = explicativas[['job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'month','poutcome','difficulty']]
```

```
expl_num = explicativas[['duration', 'campaign', 'pdays', 'previous']]
```

```
expl_cat_encoding = pd.get_dummies(expl_cat, prefix_sep='_', columns=expl_cat.columns,
                                   drop_first=True)
```

```
expl_cat_encoding.head()
```

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employe
0	1	0	0	0	0	
1	0	1	0	0	0	
2	0	0	0	0	1	
3	0	0	0	0	0	
4	0	0	0	0	1	

```
explicativas_tratada = expl_num.merge(expl_cat_encoding, left_index=True, right_index=True
```

```
explicativas_tratada.shape
```

```
(32950, 46)
```

Resultado a ser considerado na modelagem

```
explicativas_tratada.head()
```

	duration	campaign	pdays	previous	job_blue-collar	job_entrepreneur	job_housemaid
0	227	4	999	0	1	0	0
1	202	2	999	1	0	1	0
2	1148	1	999	0	0	0	0

Feature selection

Seleção de variáveis usando DecisionTreeRegressor para variáveis categóricas

```
dt = DecisionTreeRegressor(random_state=42)

tree_selector = SelectFromModel(dt, max_features=5)
tree_selector.fit(expl_cat_encoding, var_resp)
tree_support = tree_selector.get_support()
tree_feature = expl_cat_encoding.loc[:, tree_support].columns.tolist()
tree_feature
```

```
['job_retired', 'marital_single', 'default_unknown', 'housing_yes', 'loan_yes']
```

Seleção de variáveis usando RandomForestRegressor para vars numéricas

```
rfe_selector = RFE(estimator=RandomForestRegressor(random_state=42),
                   n_features_to_select=5,
                   step=1)

rfe_selector.fit(expl_num, var_resp)
rfe_support = rfe_selector.get_support()
rfe_feature = expl_num.loc[:, rfe_support].columns.tolist()
rfe_feature
```

```
['duration', 'campaign', 'pdays', 'previous']
```

Base a ser considerada pós feature selection

```
expl_num_feature = expl_num[['duration', 'campaign', 'pdays', 'previous']]
```

```
expl_cat_feature = expl_cat_encoding[['job_retired', 'marital_single', 'default_unknown',
```

```
explicativas_modelagem = expl_num_feature.merge(expl_cat_feature, left_index=True, right_i
```

```
explicativas_modelagem.head()
```

	duration	campaign	pdays	previous	job_retired	marital_single	default_unknown
0	227	4	999	0	0	0	1
1	202	2	999	1	0	0	0
2	1148	1	999	0	1	0	0
3	120	2	999	0	0	0	0
4	368	2	999	0	1	0	0

Quebra do dataset entre treino e teste

```
x_treino, x_teste, y_treino, y_teste = train_test_split(explicativas_modelagem,
                                                        var_resp,
                                                        test_size=0.3,
                                                        random_state=42)
```

O algoritmo

```
tree = DecisionTreeRegressor(random_state=42)
```

```
tree
```

```
DecisionTreeRegressor(random_state=42)
```

```
rf = RandomForestRegressor(n_estimators=400,
                           random_state=42)
```

```
rf
```

```
RandomForestRegressor(n_estimators=400, random_state=42)
```

cross validation

```
tree_cross = cross_val_score(estimator=tree,
                             X=x_treino,
                             y=y_treino,
                             cv=3,
                             scoring=make_scorer(mean_absolute_error))
```

```
tree_cross
```

```
array([9.04407074, 9.05239799, 8.9375735 ])
```

```
resultado = cross_val_score(estimator=rf,
                            X=x_treino,
```

```
                                y=y_treino,
                                cv=3,
                                scoring=make_scorer(mean_absolute_error))
```

```
resultado
```

```
array([7.55056409, 7.55194655, 7.59332758])
```

```
tree.fit(x_treino, y_treino)
```

```
DecisionTreeRegressor(random_state=42)
```

```
mean_absolute_error(y_treino, tree.predict(x_treino))
```

```
2.530197445929074
```

```
rf.fit(x_treino, y_treino)
```

```
RandomForestRegressor(n_estimators=400, random_state=42)
```

```
mean_absolute_error(y_treino, rf.predict(x_treino))
```

```
3.989521284731999
```

Analisando overfitting

```
mean_absolute_error(y_teste, rf.predict(x_teste))
```

```
7.524939169740626
```

```
y_teste.head()
```

```
20628    28
4344     38
20933    41
4641     38
4638     35
Name: age, dtype: int64
```

```
rf.predict(x_teste)
```

```
array([42.396     , 43.47320696, 36.41666667, ..., 27.97383929,
       35.92128472, 43.92775   ])
```

Tuning de hiperparametros

```
# dicionario da random Forest
```

```
rf_grid_dc = {
    'n_estimators':[50,100,200],
    'bootstrap':[True,False],
    'random_state':[42]
}

rf_grid_dc
```

```
{'bootstrap': [True, False],
 'n_estimators': [50, 100, 200],
 'random_state': [42]}
```

```
rf_grid = GridSearchCV(rf,
                      rf_grid_dc,
                      cv=2,
                      scoring=make_scorer(mean_absolute_error))
rf_grid
```

```
GridSearchCV(cv=2,
             estimator=RandomForestRegressor(n_estimators=400, random_state=42),
             param_grid={'bootstrap': [True, False],
                         'n_estimators': [50, 100, 200], 'random_state': [42]},
             scoring=make_scorer(mean_absolute_error))
```

```
rf_grid.fit(x_treino, y_treino)
```

```
GridSearchCV(cv=2,
             estimator=RandomForestRegressor(n_estimators=400, random_state=42),
             param_grid={'bootstrap': [True, False],
                         'n_estimators': [50, 100, 200], 'random_state': [42]},
             scoring=make_scorer(mean_absolute_error))
```

```
rf_grid.best_params_
```

```
{'bootstrap': False, 'n_estimators': 200, 'random_state': 42}
```

```
rf_grid.best_score_
```

```
9.142200399167528
```

Validando a performance em teste

```
mean_absolute_error(y_teste, rf_grid.predict(x_teste))
```

```
8.819379929397304
```

Fazendo o treinamento com tuning de hiperparametros para outro modelo

```
gb = GradientBoostingRegressor(n_estimators=200,
```

```
                              random_state=42)

#dicionario do GB

gb_grid_dc = {
    'max_depth':[1,3,8],
    'n_estimators':[10,20],
    'random_state':[42]
}


gb_grid = GridSearchCV(gb,
                      gb_grid_dc,
                      scoring=make_scorer(mean_absolute_error),
                      n_jobs=4)
gb_grid
```

```
GridSearchCV(estimator=GradientBoostingRegressor(n_estimators=200,
                                                 random_state=42),
             n_jobs=4,
             param_grid={'max_depth': [1, 3, 8], 'n_estimators': [10, 20],
                         'random_state': [42]},
             scoring=make_scorer(mean_absolute_error))
```

```
gb_grid.fit(x_treino, y_treino)
```

```
GridSearchCV(estimator=GradientBoostingRegressor(n_estimators=200,
                                                 random_state=42),
             n_jobs=4,
             param_grid={'max_depth': [1, 3, 8], 'n_estimators': [10, 20],
                         'random_state': [42]},
             scoring=make_scorer(mean_absolute_error))
```

```
gb_grid.best_params_
```

```
{'max_depth': 1, 'n_estimators': 10, 'random_state': 42}
```

Podemos especificar no Tuning qual a métrica que se quer otimizar

```
gb_grid_r2 = GridSearchCV(gb,
                      gb_grid_dc,
                      cv=2,
                          scoring=make_scorer(r2_score))
```

```
gb_grid_r2.fit(x_treino, y_treino)
```

```
GridSearchCV(cv=2,
             estimator=GradientBoostingRegressor(n_estimators=200,
                                                 random_state=42),
             param_grid={'max_depth': [1, 3, 8], 'n_estimators': [10, 20],
                         'random_state': [42]},
             scoring=make_scorer(r2_score))
```

```
gb_grid_r2.best_score_
```

```
0.34321787772907686
```

Métricas

RSME

```
mean_squared_error(y_teste, gb_grid_r2.predict(x_teste), squared=True)
```

```
70.96775109108682
```