Real-World Case Study: Predicting Student Grant Recommendations

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Recuperação de Dados

```
In [1]: import pandas as pd
# turn of warning messages
pd.options.mode.chained_assignment = None # default='warn'

# get data
df = pd.read_csv('student_records.csv')
df

Out[1]: Name OverallGrade Obedient ResearchScore ProjectScore Recommend

O Henry A Y 90 85 Yes
```

:		Name	OverallGrade	Obedient	ResearchScore	ProjectScore	Recommend
	0	Henry	А	Υ	90	85	Yes
	1	John	С	N	85	51	Yes
	2	David	F	N	10	17	No
	3	Holmes	В	Υ	75	71	No
	4	Marvin	Е	Ν	20	30	No
	5	Simon	А	Υ	92	79	Yes
	6	Robert	В	Υ	60	59	No
	7	Trent	С	Υ	75	33	No

Preparação dos dados

```
In [2]: #get features and corresponding outcomes
    feature_names = ['OverallGrade', 'Obedient', 'ResearchScore', 'ProjectScore']
    training_features = df[feature_names]
    outcome_name = ['Recommend']
    outcome_labels = df[outcome_name]
In [3]: # view features
```

Out[3]: OverallGrade Obedient ResearchScore ProjectScore

		OveraliGrade	Opedient	KesearcnScore	ProjectScore
	0	А	Υ	90	85
	1	С	N	85	51
	2	F	Ν	10	17
	3	В	Υ	75	71
	4	Е	Ν	20	30
	5	А	Υ	92	79
	6	В	Υ	60	59
	7	С	Υ	75	33

```
In [4]: # view outcome labels
  outcome_labels
```

```
Out[4]: Recommend

0 Yes

1 Yes

2 No

3 No

4 No

5 Yes

6 No

7 No
```

```
In [5]: # List down features based on type
numeric_feature_names = ['ResearchScore', 'ProjectScore']
```

```
categoricial_feature_names = ['OverallGrade', 'Obedient']
```

Modelando

```
In [6]: from sklearn.preprocessing import StandardScaler
          ss = StandardScaler()
          # fit scaler on numeric features
          ss.fit(training_features[numeric_feature_names])
          # scale numeric features now
          training_features[numeric_feature_names] = ss.transform(training_features[numeric_feature_names])
          # view updated featureset
          training_features
 Out[6]:
             OverallGrade Obedient ResearchScore ProjectScore
          0
                      Α
                                Υ
                                        0.899583
                                                    1.376650
                      C
                                Ν
                                        0.730648
                                                   -0.091777
          2
                       F
                                Ν
                                       -1.803390
                                                   -1.560203
          3
                       В
                                        0.392776
                                                    0.772004
                       Ε
          4
                                Ν
                                       -1.465519
                                                   -0.998746
                                        0.967158
                                                    1.117516
          6
                      В
                                Υ
                                       -0.114032
                                                    0.253735
                                                    -0.869179
                                        0.392776
 In [7]: training_features = pd.get_dummies(training_features, columns=categoricial_feature_names)
          # view newly engineering features
          training_features
 Out[7]:
             ResearchScore ProjectScore OverallGrade_A OverallGrade_B OverallGrade_C OverallGrade_E OverallGrade_F Obedient_N Obedient_Y
          0
                  0.899583
                              1.376650
                                                                 0
                                                                                0
                                                                                              0
                                                                                                             0
                                                                                                                        0
                                                                                                                                    1
                             -0.091777
                                                                                              0
          1
                  0.730648
                                                   0
                                                                 0
                                                                                                             0
                                                                                                                                   0
          2
                                                   0
                                                                                0
                                                                                              0
                 -1.803390
                             -1.560203
                                                                 0
                                                                                                             1
                                                                                                                        1
                                                                                                                                    0
                                                                                                             0
                                                                                                                        0
          3
                  0.392776
                              0.772004
                                                   0
                                                                                0
                                                                                              0
          4
                                                   0
                                                                 0
                                                                                0
                                                                                                             0
                                                                                                                        1
                                                                                                                                    0
                 -1.465519
                             -0.998746
                                                                                              1
                  0.967158
                              1.117516
                                                                                              0
                                                                                                             0
                                                                                                                        0
          6
                                                   0
                                                                                0
                                                                                              0
                                                                                                            0
                                                                                                                        0
                 -0.114032
                              0.253735
                                                                 1
          7
                  0.392776
                                                                                                                        0
                             -0.869179
                                                                                                             0
 In [8]: # get list of new categorical features
          categorical_engineered_features = list(set(training_features.columns) - set(numeric_feature_names))
 In [9]: from sklearn.linear_model import LogisticRegression
          import numpy as np
          # fit the model
          lr = LogisticRegression()
          model = lr.fit(training_features,
          np.array(outcome_labels['Recommend']))
          # view model parameters
          model
          ▼ LogisticRegression
          LogisticRegression()
          LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True, intercept_scaling=1,
                              max_iter=100, multi_class='ovr', n_jobs=1, penalty='12',
                              random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                              warm_start=False)
Out[10]:
                                       LogisticRegression
```

Avaliação do modelo

LogisticRegression(multi_class='ovr', n_jobs=1, solver='liblinear')

```
In [11]: # simple evaluation on training data
pred_labels = model.predict(training_features)
```

```
actual_labels = np.array(outcome_labels['Recommend'])
# evaluate model performance
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
print('Accuracy:', float(accuracy_score(actual_labels, pred_labels))*100, '%')
print('Classification Stats:')
print(classification_report(actual_labels, pred_labels))
Accuracy: 100.0 %
Classification Stats:
                           recall f1-score
             precision
                                              support
         No
                   1.00
                             1.00
                                       1.00
                                                    5
                   1.00
                             1.00
                                       1.00
                                                    3
        Yes
   accuracy
                                       1.00
                                                    8
                   1.00
                             1.00
                                       1.00
                                                    8
  macro avg
weighted avg
                   1.00
                             1.00
                                       1.00
                                                    8
```

Implantação do modelo

```
In [12]: #from sklearn.externals import joblib
         # a partir da versão 0.23 do scikit-learn, o módulo joblib foi removido de sklearn.externals.
         # É necessário instalar e importar o joblib diretamente.
          !pip install joblib
         import joblib
         import os
          # save models to be deployed on your server
         if not os.path.exists('Model'):
           os.mkdir('Model')
         if not os.path.exists('Scaler'):
           os.mkdir('Scaler')
         joblib.dump(model, r'Model/model.pickle')
         joblib.dump(ss, r'Scaler/scaler.pickle')
         Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
         Requirement already satisfied: joblib in /usr/local/lib/python3.9/dist-packages (1.1.1)
         ['Scaler/scaler.pickle']
Out[12]:
```

```
Predição em ação
In [13]: # Load model and scaler objects
         model = joblib.load(r'Model/model.pickle')
         scaler = joblib.load(r'Scaler/scaler.pickle')
In [14]: ## data retrieval
         new_data = pd.DataFrame([{'Name': 'Nathan', 'OverallGrade': 'F',
           'Obedient': 'N', 'ResearchScore': 30, 'ProjectScore': 20},
          {'Name': 'Thomas', 'OverallGrade': 'A',
            'Obedient': 'Y', 'ResearchScore': 78, 'ProjectScore': 80}])
         new_data = new_data[['Name', 'OverallGrade', 'Obedient', 'ResearchScore', 'ProjectScore']]
         new_data
             Name OverallGrade Obedient ResearchScore ProjectScore
Out[14]:
         0 Nathan
                                                   30
                                                              20
                                      Ν
         1 Thomas
                                                   78
                                                              80
In [15]:
         ## data preparation
         prediction_features = new_data[feature_names]
         # scaling
         prediction_features[numeric_feature_names] = scaler.transform(prediction_features[numeric_feature_names])
         # engineering categorical variables
         prediction features = pd.get dummies(prediction features,
         columns=categoricial_feature_names)
         # view feature set
         prediction_features
Out[15]:
            ResearchScore ProjectScore OverallGrade_A OverallGrade_F Obedient_N Obedient_Y
                -1.127647
                            -1.430636
```

```
# add missing categorical feature columns
current_categorical_engineered_features = set(prediction_features.columns) - set(numeric_feature_names)
missing_features = set(categorical_engineered_features) - current_categorical_engineered_features
```

0.494137

1.160705

1

```
for feature in missing_features:
    # add zeros since feature is absent in these data samples
    prediction_features[feature] = [0] * len(prediction_features)

# Esta linha garante que a ordem das colunas em prediction_features seja exatamente a mesma que a ordem das colunas em training_j
prediction_features = prediction_features[training_features.columns]

# view final feature set
prediction_features
```

 Out[16]:
 ResearchScore
 ProjectScore
 OverallGrade_A
 OverallGrade_B
 OverallGrade_C
 OverallGrade_E
 OverallGrade_F
 Obedient_N
 Obedient_Y

 0
 -1.127647
 -1.430636
 0
 0
 0
 0
 1
 1
 0

 1
 0.494137
 1.160705
 1
 0
 0
 0
 0
 0
 0
 1

```
In [17]: ## predict using model
predictions = model.predict(prediction_features)

## display results
new_data['Recommend'] = predictions
new_data
```

Out[17]:		Name	OverallGrade	Obedient	ResearchScore	ProjectScore	Recommend
	0	Nathan	F	N	30	20	No
	1	Thomas	А	Υ	78	80	Yes