# Chapter 7

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### 0.1 Hands-On Data Preprocessing in Python

Learn how to effectively prepare data for successful data analytics

AUTHOR: Dr. Roy Jafari

## 1 Chapter 7: Classification

```
[1]: import pandas as pd import matplotlib.pyplot as plt import numpy as np
```

- 1.1 Classification models
- 1.1.1 Example of designing a classification model
- 1.1.2 Classification Algorithms
- 1.2 K-Nearest Neighbors (KNN)
- 1.2.1 Example of using KNN for classification

```
[2]: applicant_df = pd.read_csv('CustomerLoan.csv')
applicant_df.drop(columns = ['Name'],inplace=True)
applicant_df
```

```
[2]:
                   score default
          income
           78479
     0
                     800
                                NO
     1
           95483
                     801
                                NO
     2
          101641
                     815
                                NO
     3
          104234
                     790
                                NO
     4
          108726
                     795
                                NO
     5
          112845
                     750
                                NO
     6
          114114
                     799
                                NO
     7
          114799
                     801
                                NO
     8
          119147
                     805
                                NO
     9
          119976
                     790
                                NO
     10
           84519
                              Yes
                     740
           86504
     11
                     753
                              Yes
     12
           89292
                     750
                              Yes
```

```
97262
                   777
                           Yes
     14
     15 102658
                   680
                           Yes
     16 103760
                  740
                           Yes
     17 104451
                  730
                           Yes
     18 107388
                  789
                           Yes
     19 107400
                   690
                           Yes
     20
          98487
                   785
                           NaN
[3]: newApplicant = applicant_df.iloc[20]
     newApplicant
[3]: income
                98487
     score
                  785
     default
                  {\tt NaN}
     Name: 20, dtype: object
[4]: applicant_df = pd.read_csv('CustomerLoan.csv')
     applicant_df.drop(index = [20],inplace=True)
     fig, ax = plt.subplots()
     subset = applicant_df.loc[applicant_df['default']=='Yes']
     ax.scatter(subset.income, subset.score, marker='o', label='Default-YES', __

color='C1')

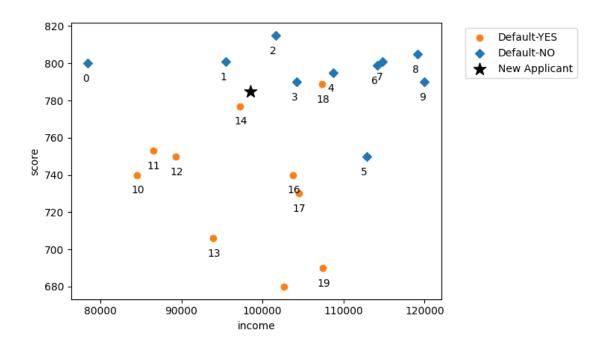
     subset = applicant_df.loc[applicant_df['default']=='NO']
     ax.scatter(subset.income, subset.score, marker='D', label='Default-NO', u
      ⇔color='CO')
     ax.scatter(newApplicant.income, newApplicant.score, marker='*', label='New_
      →Applicant', color='black', s=150)
     plt.xlabel('income') # set x-axis label
     plt.ylabel('score') # set y-axis label
     for _, row in applicant_df.iterrows():
         ax.annotate(row.Name, (row.income -700, row.score-10))
     handles, labels = ax.get_legend_handles_labels()
     ax.legend(handles, labels, bbox_to_anchor=(1.05, 1))
     plt.show()
```

13

93941

706

Yes



```
[5]: applicant_df = pd.read_csv('CustomerLoan.csv')
applicant_df['income_Normalized'] = (applicant_df.income - applicant_df.income.

→min())/(applicant_df.income.max() - applicant_df.income.min())
applicant_df['score_Normalized'] = (applicant_df.score - applicant_df.score.

→min())/(applicant_df.score.max() - applicant_df.score.min())

[6]: applicant_df.drop(columns = ['Name'])
```

```
[6]:
                                   income Normalized
          income
                  score default
                                                        score Normalized
     0
           78479
                     800
                               NO
                                             0.00000
                                                                 0.888889
           95483
     1
                     801
                               NO
                                             0.409765
                                                                 0.896296
         101641
                     815
                               NO
     2
                                             0.558161
                                                                 1.000000
     3
         104234
                     790
                               NO
                                             0.620647
                                                                 0.814815
     4
         108726
                     795
                               NO
                                             0.728896
                                                                 0.851852
     5
         112845
                               NO
                     750
                                             0.828156
                                                                 0.518519
     6
         114114
                     799
                               NO
                                             0.858737
                                                                 0.881481
     7
         114799
                               NO
                     801
                                             0.875244
                                                                 0.896296
     8
         119147
                     805
                               NO
                                             0.980023
                                                                 0.925926
         119976
                     790
                               NO
                                             1.000000
                                                                 0.814815
     9
     10
          84519
                     740
                              Yes
                                             0.145553
                                                                 0.44444
     11
          86504
                     753
                              Yes
                                             0.193387
                                                                 0.540741
                                                                 0.518519
     12
           89292
                              Yes
                     750
                                             0.260573
     13
           93941
                     706
                              Yes
                                             0.372605
                                                                 0.192593
     14
          97262
                     777
                              Yes
                                             0.452635
                                                                 0.718519
     15
         102658
                     680
                              Yes
                                             0.582669
                                                                 0.000000
     16
         103760
                     740
                              Yes
                                             0.609225
                                                                 0.44444
```

```
17 104451
              730
                       Yes
                                      0.625877
                                                         0.370370
18 107388
              789
                       Yes
                                      0.696653
                                                         0.807407
19 107400
              690
                       Yes
                                      0.696942
                                                         0.074074
    98487
                                                         0.777778
20
              785
                       {\tt NaN}
                                      0.482155
```

['ON']

### 1.3 Decision Trees

### 1.3.1 Example of using Decision Trees for classification

```
print(predict_y)
```

['Yes']

