ECS784P Data Analytics 220818991

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1 Data Analytics - Coursework 1

1.1 What is the Purpose of Credit Risk Analysis?

Credit risk analysis is a form of analysis performed by a credit analyst on potential borrowers to determine their ability to meet debt obligations. The main goal of credit analysis is to determine the creditworthiness of potential borrowers and their ability to honor their debt obligations. If the borrower presents an acceptable level of default risk, the analyst can recommend the approval of the credit application at the agreed terms. The outcome of the credit risk analysis determines the risk rating that the borrower will be assigned and their ability to access credit.

When calculating the credit risk of a particular borrower, lenders consider various factors commonly referred to as the "5 Cs of Credit." The factors include the borrower's capacity to repay credit, character, capital, conditions, and collateral. The lender uses the factors to evaluate the characteristics of the borrower and conditions of the loan to estimate the probability of default and the subsequent risk of financial loss.

Credit analysts may use various financial analysis techniques, such as ratio analysis and trend analysis to obtain measurable numbers that quantify the credit loss. The techniques measure the risk of credit loss due to changes in the creditworthiness of borrowers.

[ ]:
```
#Import libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# liberary loading
from sklearn.model_selection import train_test_split, KFold, cross_val_score #␣
↪to split the data
# from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪classification_report, fbeta_score #To evaluate our model
from sklearn.metrics import accuracy_score, f1_score, precision_score,␣
↪recall_score, confusion_matrix

from sklearn.model_selection import GridSearchCV

# Algorithmns models to be compared
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from scipy import stats
import warnings
warnings.simplefilter('ignore', category=UserWarning)  # suppresses warning␣
 ↪message from Seaborn

# command below ensures matplotlib output can be included in Notebook

%matplotlib inline
```

2 Data Understanding

[ ]:
```
#Read CSV file and create pandas dataframe
df = pd.read_csv("German Credit Risk Data.csv")
df = df.loc[:, ~df.columns.str.contains('^Unnamed')]

df_copy = df
```

[ ]:
```
df.head(10)
```

[ ]:
```
  Status of existing checking account  Duration in month  \
0                      less than 0 DM                  6
1                 between 0 to 200 DM                 48
2                 no checking account                 12
3                      less than 0 DM                 42
4                      less than 0 DM                 24
5                 no checking account                 36
6                 no checking account                 24
7                 between 0 to 200 DM                 36
8                 no checking account                 12
9                 between 0 to 200 DM                 30

                                     Credit history             Purpose  \
0  critical account/other credits existing (not a…    radio/television
1           existing credits paid back duly till now    radio/television
2  critical account/other credits existing (not a…           education
3           existing credits paid back duly till now  furniture/equipment
4                     delay in paying off in the past            car (new)
5           existing credits paid back duly till now            education
6           existing credits paid back duly till now  furniture/equipment
7           existing credits paid back duly till now           car (used)
8           existing credits paid back duly till now    radio/television
```

```
9  critical account/other credits existing (not a…          car (new)

   Credit amount        Savings account/bonds Present employment since  \
0           1169  unknown/ no savings account        more than 7 years
1           5951              less than 100 DM    between 1 to 4 years
2           2096              less than 100 DM    between 4 to 7 years
3           7882              less than 100 DM    between 4 to 7 years
4           4870              less than 100 DM    between 1 to 4 years
5           9055  unknown/ no savings account    between 1 to 4 years
6           2835        between 500 to 1000 DM       more than 7 years
7           6948              less than 100 DM    between 1 to 4 years
8           3059             more than 1000 DM    between 4 to 7 years
9           5234              less than 100 DM              unemployed

   Installment rate in percentage of disposable income  \
0                                                    4
1                                                    2
2                                                    2
3                                                    2
4                                                    3
5                                                    2
6                                                    3
7                                                    2
8                                                    2
9                                                    4

            Personal status and sex Other debtors / guarantors  …  \
0                     male : single                       none  …
1  female : divorced/separated/married                    none  …
2                     male : single                       none  …
3                     male : single                  gaurantor  …
4                     male : single                       none  …
5                     male : single                       none  …
6                     male : single                       none  …
7                     male : single                       none  …
8           male : divorced/separated                     none  …
9              male : married/widowed                     none  …

                                          Property Age in years  \
0                                      real estate           67
1                                      real estate           22
2                                      real estate           49
3  building society savings agreement/life insurance         45
4                              unknown / no property         53
5                              unknown / no property         35
6  building society savings agreement/life insurance         53
7                   car or other, not in attribute 6         35
```

8	real estate	61
9	car or other, not in attribute 6	28

	Other installment plans	Housing	Number of existing credits at this bank \
0	none	own	2
1	none	own	1
2	none	own	1
3	none	for free	1
4	none	for free	2
5	none	for free	1
6	none	own	1
7	none	rent	1
8	none	own	1
9	none	own	2

	Job \
0	skilled employee / official
1	skilled employee / official
2	unskilled - resident
3	skilled employee / official
4	skilled employee / official
5	unskilled - resident
6	skilled employee / official
7	management/self-employed/highly qualified empl…
8	unskilled - resident
9	management/self-employed/highly qualified empl…

	Number of people being liable to provide maintenance for \
0	1
1	1
2	2
3	2
4	2
5	2
6	1
7	1
8	1
9	1

	Telephone	foreign worker	Risk
0	yes, registered under the customers name	yes	Good
1	none	yes	Bad
2	none	yes	Good
3	none	yes	Good
4	none	yes	Bad
5	yes, registered under the customers name	yes	Good
6	none	yes	Good

```
7  yes, registered under the customers name            yes  Good
8                                      none            yes  Good
9                                      none            yes   Bad

[10 rows x 21 columns]
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   Status of existing checking account                       1000 non-null
object
 1   Duration in month                                         1000 non-null
int64
 2   Credit history                                            1000 non-null
object
 3   Purpose                                                   1000 non-null
object
 4   Credit amount                                             1000 non-null
int64
 5   Savings account/bonds                                     1000 non-null
object
 6   Present employment since                                  1000 non-null
object
 7   Installment rate in percentage of disposable income       1000 non-null
int64
 8   Personal status and sex                                   1000 non-null
object
 9   Other debtors / guarantors                                1000 non-null
object
 10  Present residence since                                   1000 non-null
int64
 11  Property                                                  1000 non-null
object
 12  Age in years                                              1000 non-null
int64
 13  Other installment plans                                   1000 non-null
object
 14  Housing                                                   1000 non-null
object
 15  Number of existing credits at this bank                   1000 non-null
int64
```

```
 16  Job                                                     1000 non-null
object
 17  Number of people being liable to provide maintenance for  1000 non-null
int64
 18  Telephone                                               1000 non-null
object
 19  foreign worker                                          1000 non-null
object
 20  Risk                                                    1000 non-null
object
dtypes: int64(7), object(14)
memory usage: 164.2+ KB
```

[ ]:
```
df.nunique()
```

[ ]:
```
Status of existing checking account                           4
Duration in month                                            33
Credit history                                                5
Purpose                                                       9
Credit amount                                               921
Savings account/bonds                                         5
Present employment since                                      5
Installment rate in percentage of disposable income           4
Personal status and sex                                       4
Other debtors / guarantors                                    3
Present residence since                                       4
Property                                                      4
Age in years                                                 53
Other installment plans                                       3
Housing                                                       3
Number of existing credits at this bank                       4
Job                                                           4
Number of people being liable to provide maintenance for      2
Telephone                                                     2
foreign worker                                                2
Risk                                                          2
dtype: int64
```

[ ]:
```
df.describe()
```

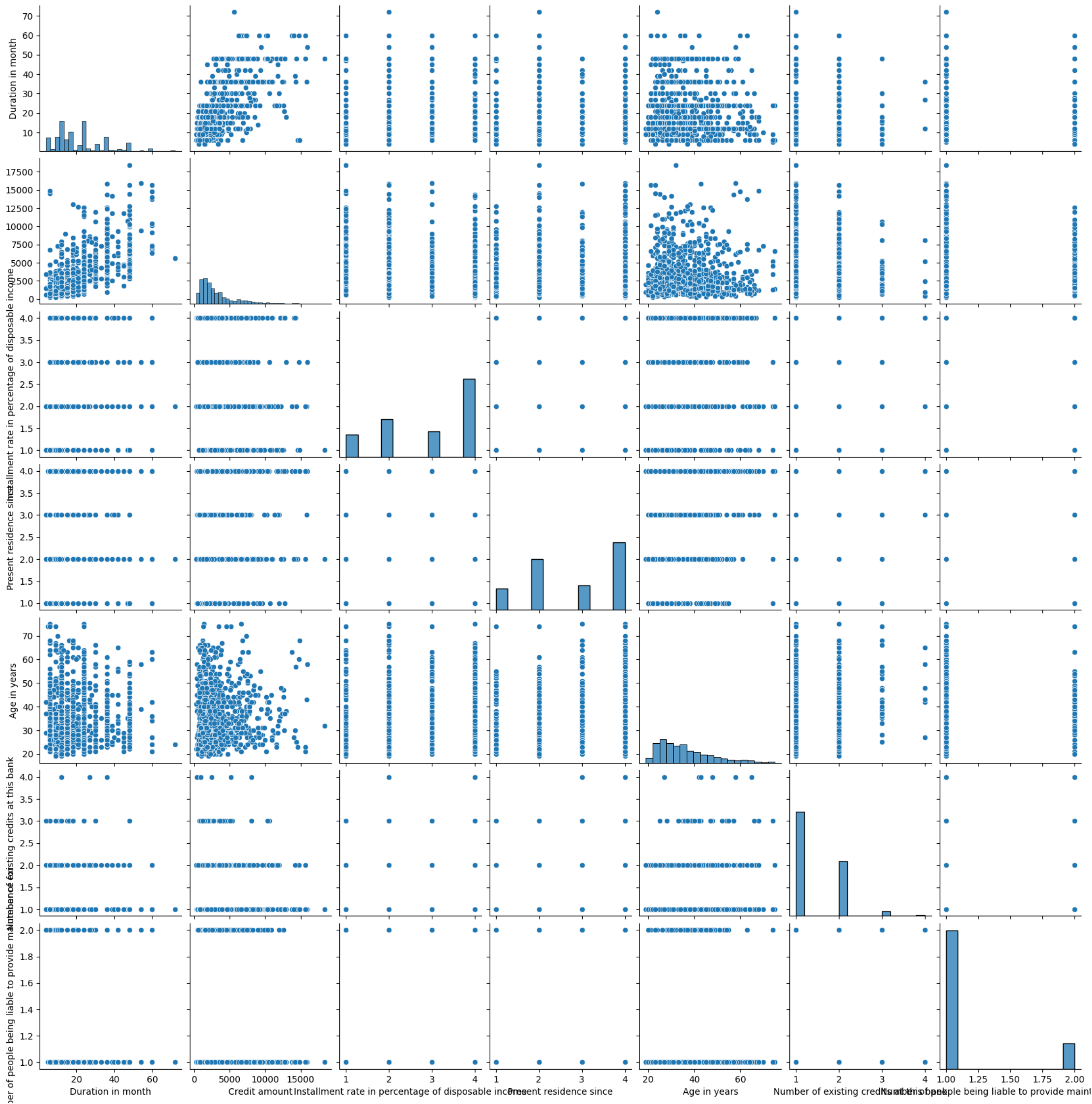
[ ]:
```
       Duration in month  Credit amount  \
count        1000.000000    1000.000000
mean           20.903000    3271.258000
std            12.058814    2822.736876
min             4.000000     250.000000
25%            12.000000    1365.500000
50%            18.000000    2319.500000
```

```
75%           24.000000    3972.250000
max           72.000000   18424.000000

       Installment rate in percentage of disposable income  \
count                                           1000.000000
mean                                               2.973000
std                                                1.118715
min                                                1.000000
25%                                                2.000000
50%                                                3.000000
75%                                                4.000000
max                                                4.000000

       Present residence since  Age in years  \
count              1000.000000   1000.000000
mean                  2.845000     35.546000
std                   1.103718     11.375469
min                   1.000000     19.000000
25%                   2.000000     27.000000
50%                   3.000000     33.000000
75%                   4.000000     42.000000
max                   4.000000     75.000000

       Number of existing credits at this bank  \
count                              1000.000000
mean                                  1.407000
std                                   0.577654
min                                   1.000000
25%                                   1.000000
50%                                   1.000000
75%                                   2.000000
max                                   4.000000

       Number of people being liable to provide maintenance for
count                                           1000.000000
mean                                               1.155000
std                                                0.362086
min                                                1.000000
25%                                                1.000000
50%                                                1.000000
75%                                                1.000000
max                                                2.000000
```

3 Exploratory Data Analysis

[ ]:
```
sns.pairplot(df)
```

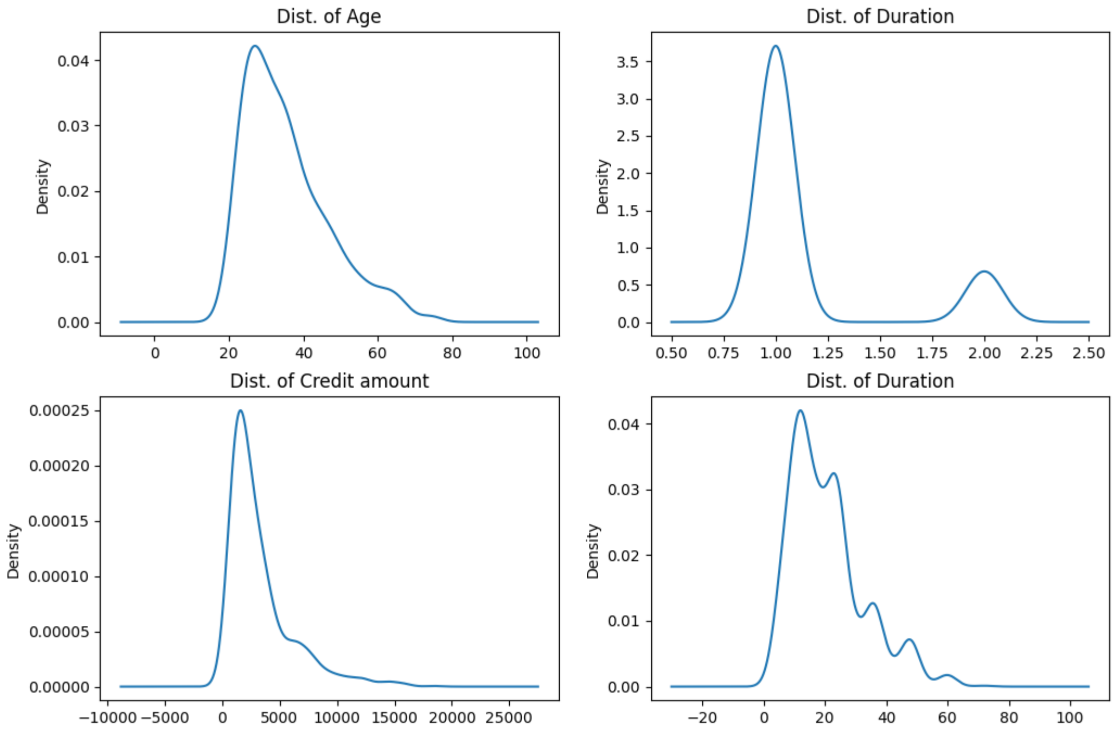
[ ]: <seaborn.axisgrid.PairGrid at 0x19995364790>



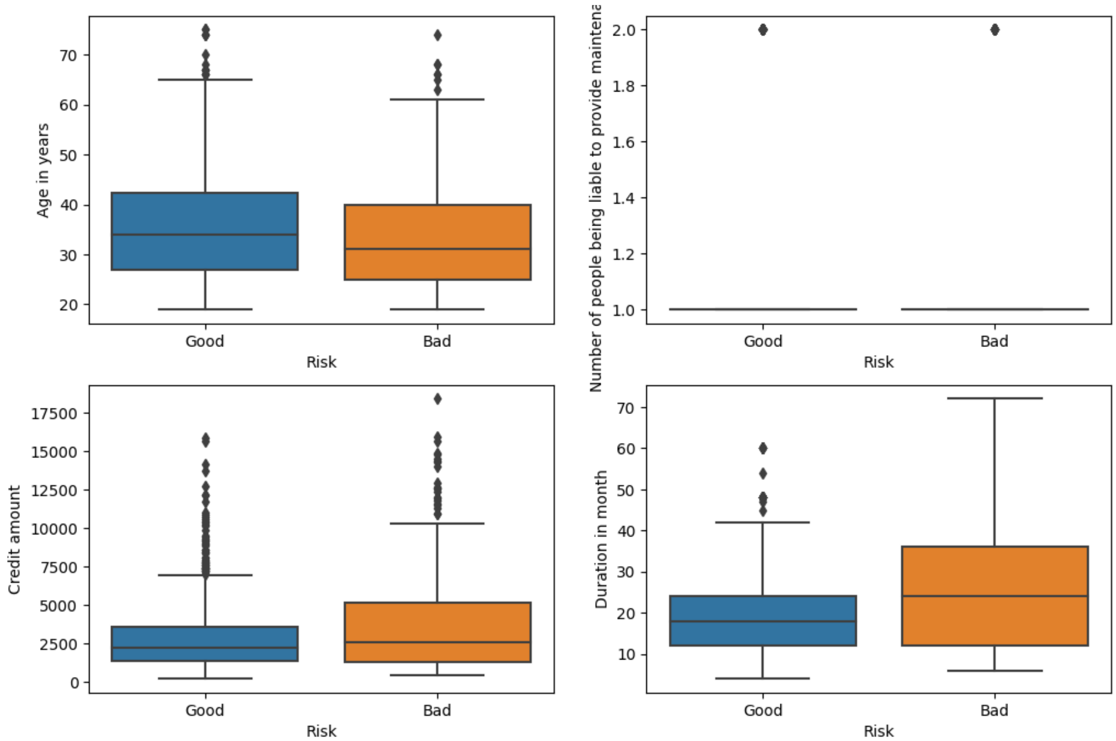
3.1 Analysis of Continuous Variables

[ ]:
```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 8))
df['Age in years'].plot(kind="density",ax=axes[0,0],title="Dist. of Age")
df['Credit amount'].plot(kind="density",ax=axes[1,0],title="Dist. of Credit␣
↪amount")
```

```
df['Duration in month'].plot(kind="density",ax=axes[1,1],title="Dist. of␣
 ↪Duration")
df['Number of people being liable to provide maintenance for'].
 ↪plot(kind="density",ax=axes[0,1],title="Dist. of Duration")
plt.show()
```

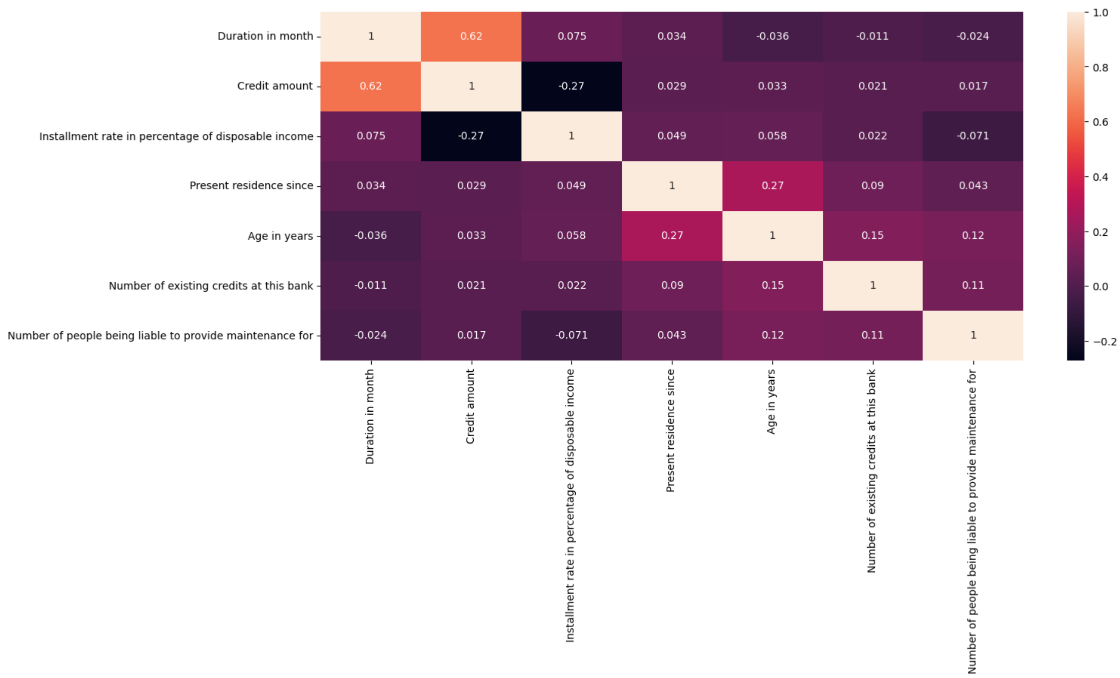


[ ]:
```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 8))
sns.boxplot(x="Risk",y="Age in years",data=df,ax=axes[0,0])
sns.boxplot(x="Risk",y="Credit amount",data=df,ax=axes[1,0])
sns.boxplot(x="Risk",y="Duration in month",data=df,ax=axes[1,1])
sns.boxplot(x="Risk",y="Number of people being liable to provide maintenance␣
 ↪for",data=df_copy,ax=axes[0,1])
plt.show()
```



[ ]:
```python
corr=df.corr() # gives us the correlation values
plt.figure(figsize=(15,6))
sns.heatmap(corr, annot = True)  # let's visualise the correlation matrix
plt.show()
```

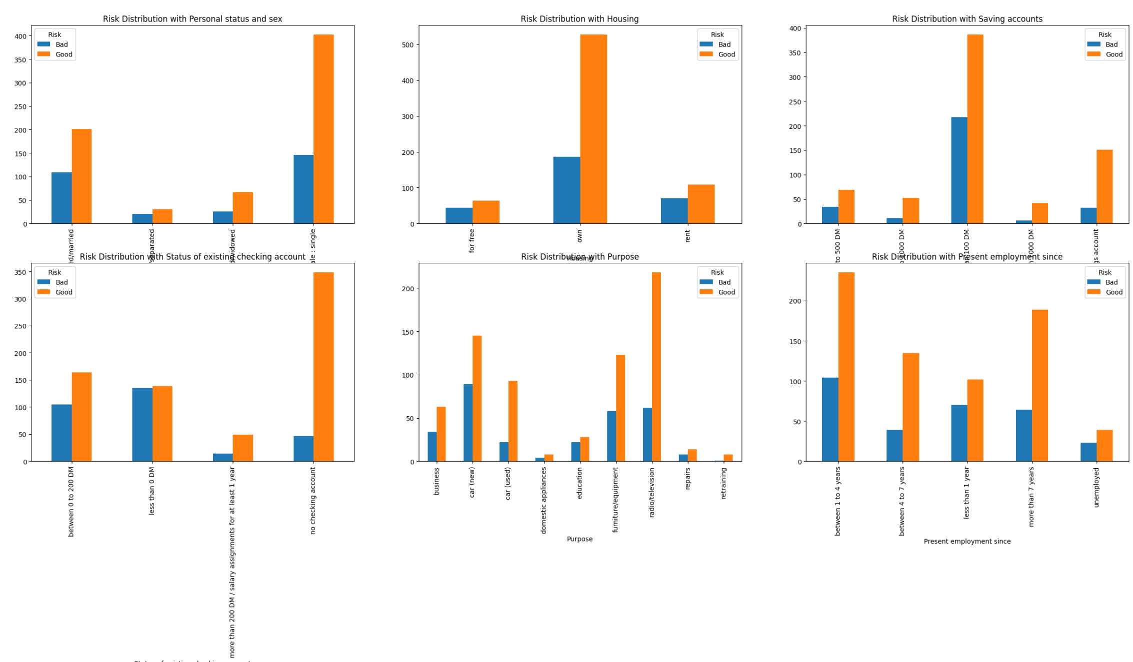
```
C:\Users\naman\AppData\Local\Temp\ipykernel_29860\4011089631.py:1:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  corr=df.corr() # gives us the correlation values
```

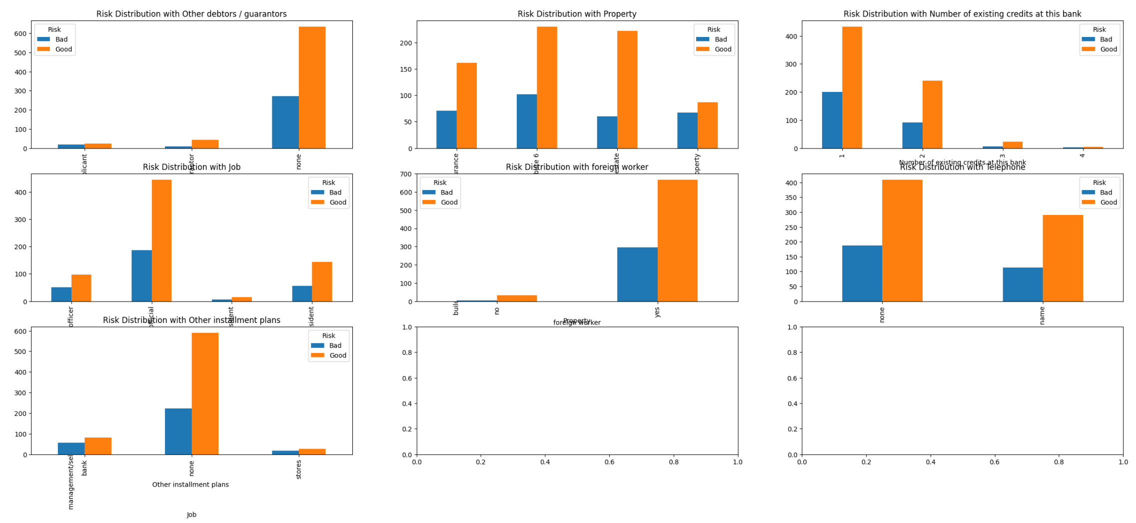


3.2 Analysis of Categorical variables

[ ]:
```python
#Plot cross tabulation of features with Risk
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(30, 12))
sex = pd.crosstab(df['Personal status and sex'],df['Risk'])
sex.plot(kind='bar',title="Risk Distribution with Personal status and sex",ax=axes[0,0])
housing = pd.crosstab(df['Housing'],df['Risk'])
housing.plot(kind='bar',title="Risk Distribution with Housing",ax=axes[0,1])
saving_acc = pd.crosstab(df['Savings account/bonds'],df['Risk'])
saving_acc.plot(kind='bar',title="Risk Distribution with Saving accounts",ax=axes[0,2])
checking_acc = pd.crosstab(df['Status of existing checking account'],df['Risk'])
checking_acc.plot(kind='bar',title="Risk Distribution with Status of existing checking account",ax=axes[1,0])
purpose = pd.crosstab(df['Purpose'],df['Risk'])
purpose.plot(kind='bar',title="Risk Distribution with Purpose",ax=axes[1,1])
pes = pd.crosstab(df['Present employment since'],df['Risk'])
pes.plot(kind='bar',title="Risk Distribution with Present employment since",ax=axes[1,2])
plt.show()

fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(30, 12))
odg = pd.crosstab(df['Other debtors / guarantors'],df['Risk'])
```

```
odg.plot(kind='bar',title="Risk Distribution with Other debtors / guarantors",ax=axes[0,0])
prop = pd.crosstab(df['Property'],df['Risk'])
prop.plot(kind='bar',title="Risk Distribution with Property",ax=axes[0,1])
existing_crd = pd.crosstab(df['Number of existing credits at this bank'],df['Risk'])
existing_crd.plot(kind='bar',title="Risk Distribution with Number of existing credits at this bank",ax=axes[0,2])
job = pd.crosstab(df['Job'],df['Risk'])
job.plot(kind='bar',title="Risk Distribution with Job",ax=axes[1,0])
foreign_worker = pd.crosstab(df['foreign worker'],df['Risk'])
foreign_worker.plot(kind='bar',title="Risk Distribution with foreign worker",ax=axes[1,1])
tel = pd.crosstab(df['Telephone'],df['Risk'])
tel.plot(kind='bar',title="Risk Distribution with Telephone",ax=axes[1,2])
oip = pd.crosstab(df['Other installment plans '],df['Risk'])
oip.plot(kind='bar',title="Risk Distribution with Other installment plans",ax=axes[2,0])
plt.show()
```



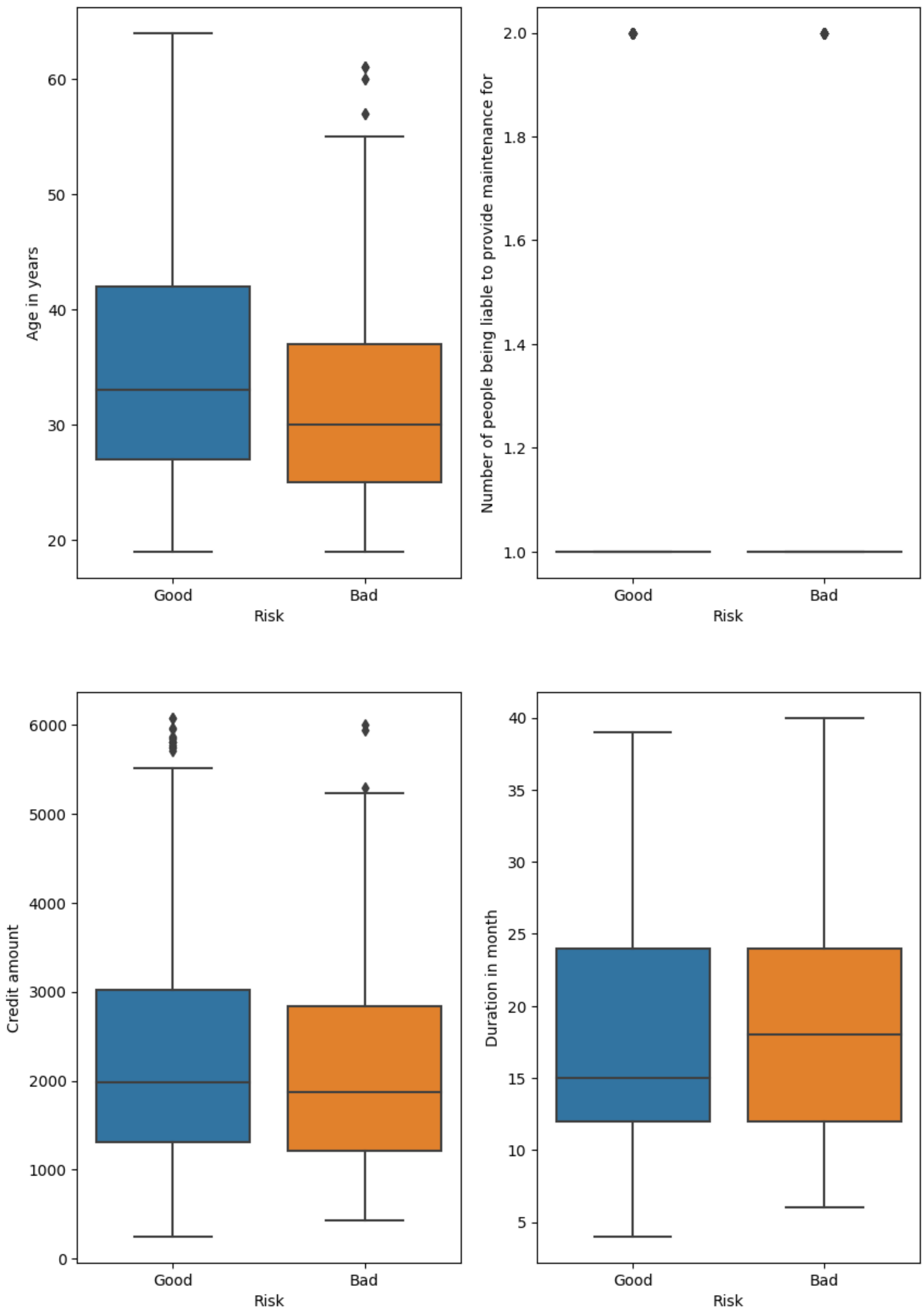


4 Data Preprocessing

Treatment for Outliers

[ ]:
```
Q1=df_copy['Age in years'].quantile(0.25)
Q3=df_copy['Age in years'].quantile(0.75)
IQR=Q3-Q1
Lower_Whisker = Q1-1.5*IQR
Upper_Whisker = Q3+1.5*IQR
df_copy = df_copy[df_copy['Age in years']< Upper_Whisker]
df_copy = df_copy[df_copy['Age in years']> Lower_Whisker]

threshold = 4
for i in range(threshold):
    Q1=df_copy['Credit amount'].quantile(0.25)
    Q3=df_copy['Credit amount'].quantile(0.75)
    IQR=Q3-Q1
    Lower_Whisker = Q1-1.5*IQR
    Upper_Whisker = Q3+1.5*IQR
    df_copy = df_copy[df_copy['Credit amount']< Upper_Whisker]
    df_copy = df_copy[df_copy['Credit amount']> Lower_Whisker]

Q1=df_copy['Duration in month'].quantile(0.25)
Q3=df_copy['Duration in month'].quantile(0.75)
IQR=Q3-Q1
Lower_Whisker = Q1-1.5*IQR
Upper_Whisker = Q3+1.5*IQR
df_copy = df_copy[df_copy['Duration in month']< Upper_Whisker]
df_copy = df_copy[df_copy['Duration in month']> Lower_Whisker]
```

[ ]:
```python
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10, 15))
sns.boxplot(x="Risk",y="Age in years",data=df_copy,ax=axes[0,0])
sns.boxplot(x="Risk",y="Credit amount",data=df_copy,ax=axes[1,0])
sns.boxplot(x="Risk",y="Duration in month",data=df_copy,ax=axes[1,1])
sns.boxplot(x="Risk",y="Number of people being liable to provide maintenance␣
 ↪for",data=df_copy,ax=axes[0,1])
plt.show()
```



Age in years
60
50
40
30
20
Good
Bad
Risk
Number of people being liable to provide maintenance for
2.0
1.8
1.6
1.4
1.2
1.0
Good
Bad
Risk
Credit amount
6000
5000
4000
3000
2000
1000
0
Good
Bad
Risk
Duration in month
40
35
30
25
20
15
10
5
Good
Bad
Risk

[ ]:
```
df_copy.isnull().value_counts()
```

[ ]:
```
Status of existing checking account  Duration in month  Credit history  Purpose
Credit amount  Savings account/bonds  Present employment since  Installment rate
in percentage of disposable income  Personal status and sex  Other debtors /
guarantors  Present residence since  Property  Age in years  Other installment
plans   Housing  Number of existing credits at this bank  Job   Number of
people being liable to provide maintenance for  Telephone  foreign worker  Risk
False                                False              False           False
False          False                  False                         False
False                   False                            False
False     False          False                     False    False
False  False                                                   False
False           False    807
dtype: int64
```

[ ]:
```
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 807 entries, 2 to 997
Data columns (total 21 columns):
 #   Column                                                  Non-Null Count
Dtype
---  ------                                                  --------------
-----
 0   Status of existing checking account                     807 non-null
object
 1   Duration in month                                       807 non-null
int64
 2   Credit history                                          807 non-null
object
 3   Purpose                                                 807 non-null
object
 4   Credit amount                                           807 non-null
int64
 5   Savings account/bonds                                   807 non-null
object
 6   Present employment since                                807 non-null
object
 7   Installment rate in percentage of disposable income     807 non-null
int64
 8   Personal status and sex                                 807 non-null
object
 9   Other debtors / guarantors                              807 non-null
object
 10  Present residence since                                 807 non-null
int64
```

```
 11   Property                                              807 non-null
object
 12   Age in years                                          807 non-null
int64
 13   Other installment plans                               807 non-null
object
 14   Housing                                               807 non-null
object
 15   Number of existing credits at this bank               807 non-null
int64
 16   Job                                                   807 non-null
object
 17   Number of people being liable to provide maintenance for  807 non-null
int64
 18   Telephone                                             807 non-null
object
 19   foreign worker                                        807 non-null
object
 20   Risk                                                  807 non-null
object
dtypes: int64(7), object(14)
memory usage: 138.7+ KB
```

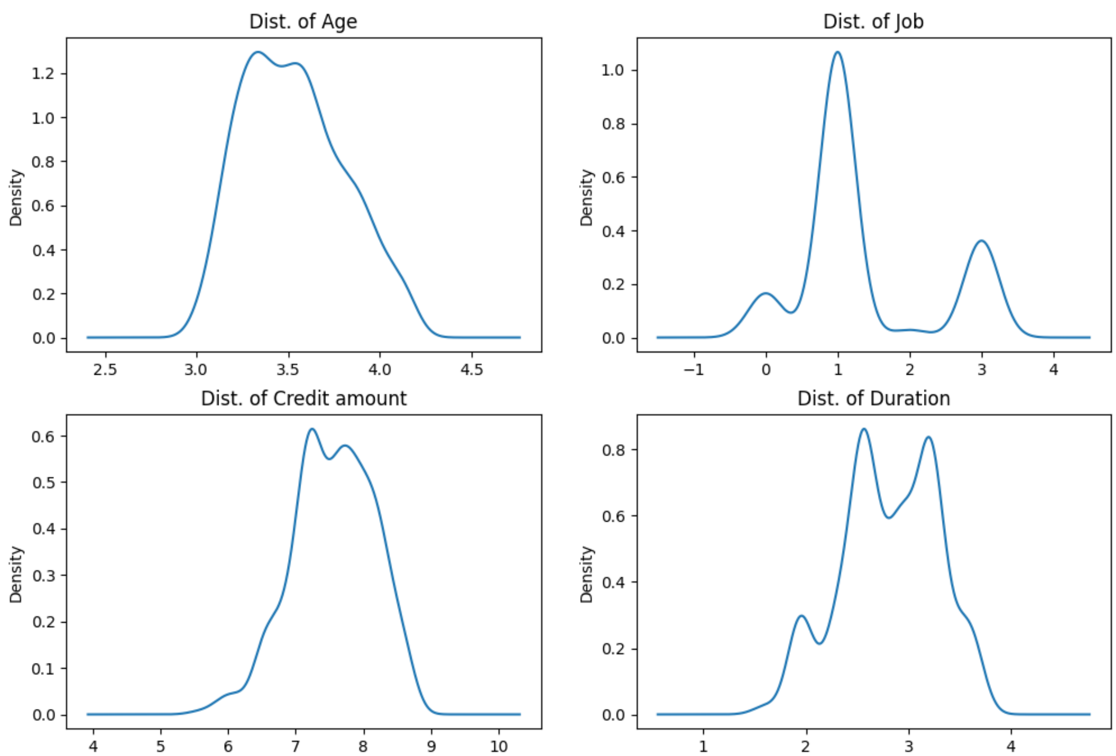
Categorical values converted to numerical values

[ ]:
```
df_copy['Present employment since'] = df_copy['Present employment since'].
 ↪astype('category').cat.codes
df_copy['Purpose'] = df_copy['Purpose'].astype('category').cat.codes
df_copy['Credit history'] = df_copy['Purpose'].astype('category').cat.codes
df_copy['Status of existing checking account'] = df_copy['Status of existing␣
 ↪checking account'].astype('category').cat.codes
df_copy['Savings account/bonds'] = df_copy['Savings account/bonds'].
 ↪astype('category').cat.codes
df_copy['Housing'] = df_copy['Housing'].astype('category').cat.codes
df_copy['Personal status and sex'] = df_copy['Personal status and sex'].
 ↪astype('category').cat.codes
df_copy['Other debtors / guarantors'] = df_copy['Other debtors / guarantors'].
 ↪astype('category').cat.codes
df_copy['Property'] = df_copy['Property'].astype('category').cat.codes
df_copy['Other installment plans '] = df_copy['Other installment plans '].
 ↪astype('category').cat.codes
df_copy['Job'] = df_copy['Job'].astype('category').cat.codes
df_copy['Telephone'] = df_copy['Telephone'].astype('category').cat.codes
df_copy['foreign worker'] = df_copy['foreign worker'].astype('category').cat.
 ↪codes
df_copy['Risk'] = df_copy['Risk'].astype('category').cat.codes
```

Log tranformation

```
[ ]: df_copy['Age in years']=np.log(df_copy['Age in years']+1)
     df_copy['Credit amount']=np.log(df_copy['Credit amount']+1)
     df_copy['Duration in month']=np.log(df_copy['Duration in month']+1)
```

```
[ ]: fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 8))
     df_copy['Age in years'].plot(kind="density",ax=axes[0,0],title="Dist. of Age")
     df_copy['Job'].plot(kind="density",ax=axes[0,1],title="Dist. of Job")
     df_copy['Credit amount'].plot(kind="density",ax=axes[1,0],title="Dist. of␣
      ↪Credit amount")
     df_copy['Duration in month'].plot(kind="density",ax=axes[1,1],title="Dist. of␣
      ↪Duration")
     plt.show()
```




```
[ ]: df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 807 entries, 2 to 997
Data columns (total 21 columns):
 #   Column                                                       Non-Null Count
Dtype
---  ------                                                       --------------
-----
```

```
 0   Status of existing checking account                           807 non-null
int8
 1   Duration in month                                             807 non-null
float64
 2   Credit history                                                807 non-null
int8
 3   Purpose                                                       807 non-null
int8
 4   Credit amount                                                 807 non-null
float64
 5   Savings account/bonds                                         807 non-null
int8
 6   Present employment since                                      807 non-null
int8
 7   Installment rate in percentage of disposable income           807 non-null
int64
 8   Personal status and sex                                       807 non-null
int8
 9   Other debtors / guarantors                                    807 non-null
int8
 10  Present residence since                                       807 non-null
int64
 11  Property                                                      807 non-null
int8
 12  Age in years                                                  807 non-null
float64
 13  Other installment plans                                       807 non-null
int8
 14  Housing                                                       807 non-null
int8
 15  Number of existing credits at this bank                       807 non-null
int64
 16  Job                                                           807 non-null
int8
 17  Number of people being liable to provide maintenance for  807 non-null
int64
 18  Telephone                                                     807 non-null
int8
 19  foreign worker                                                807 non-null
int8
 20  Risk                                                          807 non-null
int8
dtypes: float64(3), int64(4), int8(14)
memory usage: 61.5 KB
```

5 Feature Engineering

[ ]:
```
df_train = df_copy
df_train.head()
```

[ ]:
```
   Status of existing checking account  Duration in month  Credit history  \
2                                    3           2.564949               4
4                                    1           3.218876               1
6                                    3           3.218876               5
8                                    3           2.564949               6
9                                    0           3.433987               1

   Purpose  Credit amount  Savings account/bonds  Present employment since  \
2        4       7.648263                      2                         1
4        1       8.491055                      2                         0
6        5       7.950150                      1                         3
8        6       8.026170                      3                         1
9        1       8.563122                      2                         4

   Installment rate in percentage of disposable income  \
2                                                  2
4                                                  3
6                                                  3
8                                                  2
9                                                  4

   Personal status and sex  Other debtors / guarantors  …  Property  \
2                        3                           2  …         2
4                        3                           2  …         3
6                        3                           2  …         0
8                        1                           2  …         2
9                        2                           2  …         1

   Age in years  Other installment plans   Housing  \
2      3.912023                        1         1
4      3.988984                        1         0
6      3.988984                        1         1
8      4.127134                        1         1
9      3.367296                        1         1

   Number of existing credits at this bank  Job  \
2                                        1    3
4                                        2    1
6                                        1    1
8                                        1    3
9                                        2    0
```

```
   Number of people being liable to provide maintenance for  Telephone  \
2                                                         2          0
4                                                         2          0
6                                                         1          0
8                                                         1          0
9                                                         1          0

   foreign worker  Risk
2               1     1
4               1     0
6               1     1
8               1     1
9               1     0

[5 rows x 21 columns]
```

[ ]:
```
df_train.columns
```

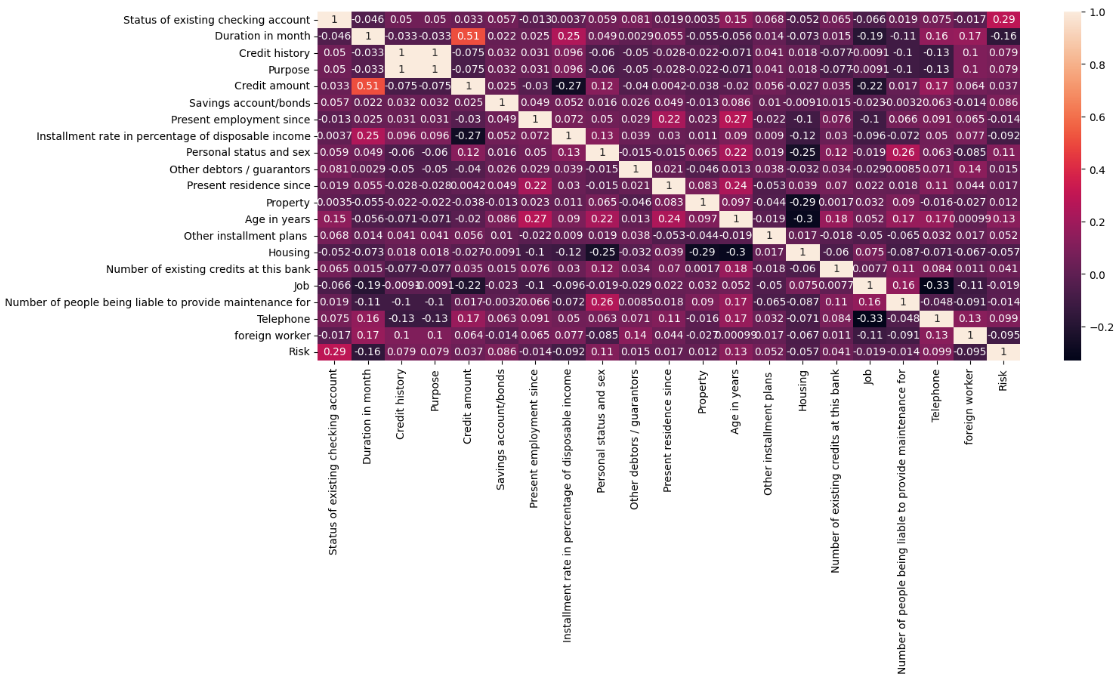
[ ]:
```
Index(['Status of existing checking account', 'Duration in month',
       'Credit history', 'Purpose', 'Credit amount', 'Savings account/bonds',
       'Present employment since',
       'Installment rate in percentage of disposable income',
       'Personal status and sex', 'Other debtors / guarantors',
       'Present residence since', 'Property', 'Age in years',
       'Other installment plans ', 'Housing',
       'Number of existing credits at this bank', 'Job',
       'Number of people being liable to provide maintenance for', 'Telephone',
       'foreign worker', 'Risk'],
      dtype='object')
```

[ ]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 807 entries, 2 to 997
Data columns (total 21 columns):
 #   Column                                                    Non-Null Count
Dtype
---  ------                                                    --------------
-----
 0   Status of existing checking account                       807 non-null
int8
 1   Duration in month                                         807 non-null
float64
 2   Credit history                                            807 non-null
int8
 3   Purpose                                                   807 non-null
int8
```

```
 4   Credit amount                                          807 non-null
float64
 5   Savings account/bonds                                  807 non-null
int8
 6   Present employment since                               807 non-null
int8
 7   Installment rate in percentage of disposable income    807 non-null
int64
 8   Personal status and sex                                807 non-null
int8
 9   Other debtors / guarantors                             807 non-null
int8
 10  Present residence since                                807 non-null
int64
 11  Property                                               807 non-null
int8
 12  Age in years                                           807 non-null
float64
 13  Other installment plans                                807 non-null
int8
 14  Housing                                                807 non-null
int8
 15  Number of existing credits at this bank                807 non-null
int64
 16  Job                                                    807 non-null
int8
 17  Number of people being liable to provide maintenance for  807 non-null
int64
 18  Telephone                                              807 non-null
int8
 19  foreign worker                                         807 non-null
int8
 20  Risk                                                   807 non-null
int8
dtypes: float64(3), int64(4), int8(14)
memory usage: 61.5 KB
```

[ ]:
```
corr=df_train.corr() # gives us the correlation values
plt.figure(figsize=(15,6))
sns.heatmap(corr, annot = True,)  # let's visualise the correlation matrix
plt.show()
```



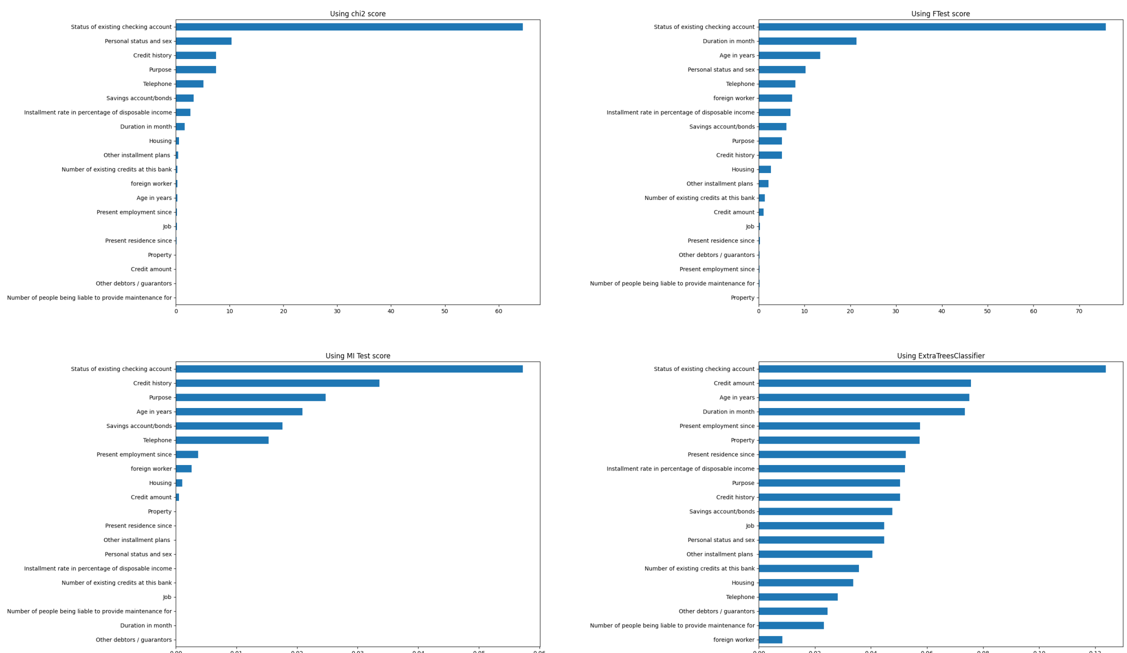

```
[ ]: X = df_train.drop(['Risk'],axis=1)
     y = df_train['Risk']
```

Feature scoring methods

```
[ ]: from sklearn.feature_selection import SelectKBest, chi2, mutual_info_classif,␣
      ↪f_classif

     # let's call the k-best method with Chi-squared score and pass X and y as inputs

     chi2 = SelectKBest(score_func = chi2, k = 'all').fit(X,y)

     # create Series with variable name as index, and scores as values, and sort␣
      ↪lowest to highest ready for plotting

     chi2_sorted = pd.Series(data=chi2.scores_, index=X.columns).sort_values()

     # Repeat but with other scoring functions

     ftest = SelectKBest(score_func = f_classif, k = 'all').fit(X,y)
     ftest_sorted = pd.Series(data=ftest.scores_, index=X.columns).sort_values()

     mitest = SelectKBest(score_func = mutual_info_classif, k = 'all').fit(X,y)
     mitest_sorted = pd.Series(data=mitest.scores_, index=X.columns).sort_values()
```

```
[ ]: from sklearn.ensemble import ExtraTreesClassifier # this is a method alternative to k-best

xtrees = ExtraTreesClassifier().fit(X, y)
xtrees_sorted = pd.Series(data=xtrees.feature_importances_, index=X.columns).sort_values()

from sklearn.feature_selection import mutual_info_classif

muinfo = mutual_info_classif(X,y)
muinfo_sorted = pd.Series(data=muinfo, index=X.columns).sort_values()
```

```
[ ]: fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(30, 20))
plt.subplots_adjust(wspace=0.6)
chi2_sorted.plot(kind='barh', ax=axes[0, 0], title='Using chi2 score')
ftest_sorted.plot(kind='barh', ax=axes[0, 1], title='Using FTest score')
xtrees_sorted.plot(kind='barh', ax=axes[1, 1], title='Using ExtraTreesClassifier')
mitest_sorted.plot(kind='barh', ax=axes[1, 0], title='Using MI Test score')
plt.show()
```



6 Model Construction and Evaluation

```
[ ]: X = X.drop(['Status of existing checking account'],axis=1)
```

```
[ ]: Result = {}
```

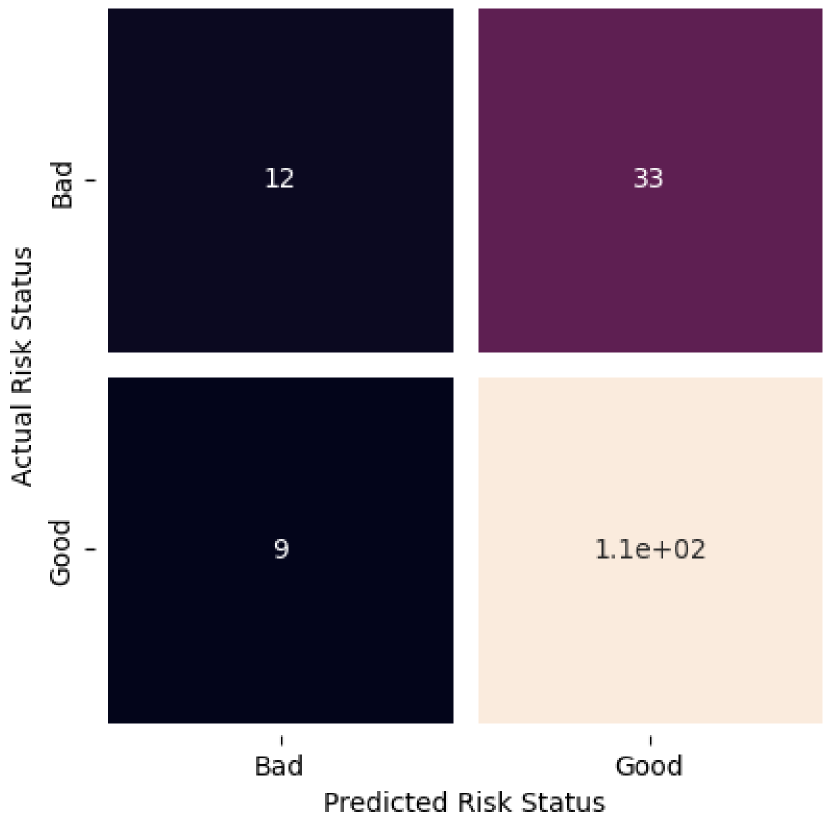
```
[ ]: def train_and_evaluate(model, X, y, name=""):
         """
             Train and evaluate a classification model on training data
             and produce accuracy metrics for a separate test set.
         """

         print('\nResults from algorithm {}:'.format(model))

         # Split data into train and test - we will use test for the final accuracy␣
      ↪metrics
         # and not use it to train the model. This is good practice, particularly␣
      ↪when you are
         # using cross-validation to select model parameters ... that way, the␣
      ↪characteristics
         # of the test data don't leak into the model training

         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
      ↪random_state=42)

         # Cross-validation accuracy gives an indication of variation in accuracy␣
      ↪and a better
         # estimate for overall accuracy than just a single estimate. The mean␣
      ↪cross-validation
         # accuracy is therefore a better guide when selecting model parameters or␣
      ↪comparing models

         scores = cross_val_score(model, X_train, y_train, cv=10, scoring='accuracy')
         print('Mean cross-validation accuracy is {:.3f} with SD {:.3f}'
               .format(np.mean(scores), np.std(scores)))

         # Fit model using all of the reserved training data ... look at training␣
      ↪accuracy
         # which we generally expect to be better than test accuracy

         learnt_model = model.fit(X_train, y_train)
         print('\nAccuracy on training data is {:.3f}\n'.format(model.score(X_train,␣
      ↪y_train)))

         # User predict() to predict target values from test feature variables, and␣
      ↪then
```

```
    # use functions to compute evaluation metrics relevant to binary outcome␣
↪variable

    y_pred = model.predict(X_test)
    print('Test data metrics: accuracy={:.3f}, f1={:.3f}, precision={:.3f},␣
↪recall={:.3f}'
          .format(accuracy_score(y_true=y_test, y_pred=y_pred),
                  f1_score(y_true=y_test, y_pred=y_pred),
                  precision_score(y_true=y_test, y_pred=y_pred),
                  recall_score(y_true=y_test, y_pred=y_pred)))

    # Draw out a confusion matrix
    cm = confusion_matrix(y_true=y_test, y_pred=y_pred)
    plt.figure(figsize=(5,5))
    ax = sns.heatmap(cm,annot=True, xticklabels=['Bad', 'Good'], cbar=False,
                     yticklabels=['Bad', 'Good'], square=True,
                     linewidths=8.0) # plots the confusion matrix
    ax.set_xlabel('Predicted Risk Status')
    ax.set_ylabel('Actual Risk Status')
    plt.show()

    Result[name] = {"Train" : model.score(X_train, y_train) ,"Test" :␣
↪accuracy_score(y_true=y_test, y_pred=y_pred)}

    return learnt_model
```

Logitsic Regression

[ ]:
```
lr_model = LogisticRegression()
_ = train_and_evaluate(lr_model, X, y, "LogisticRegression")
```

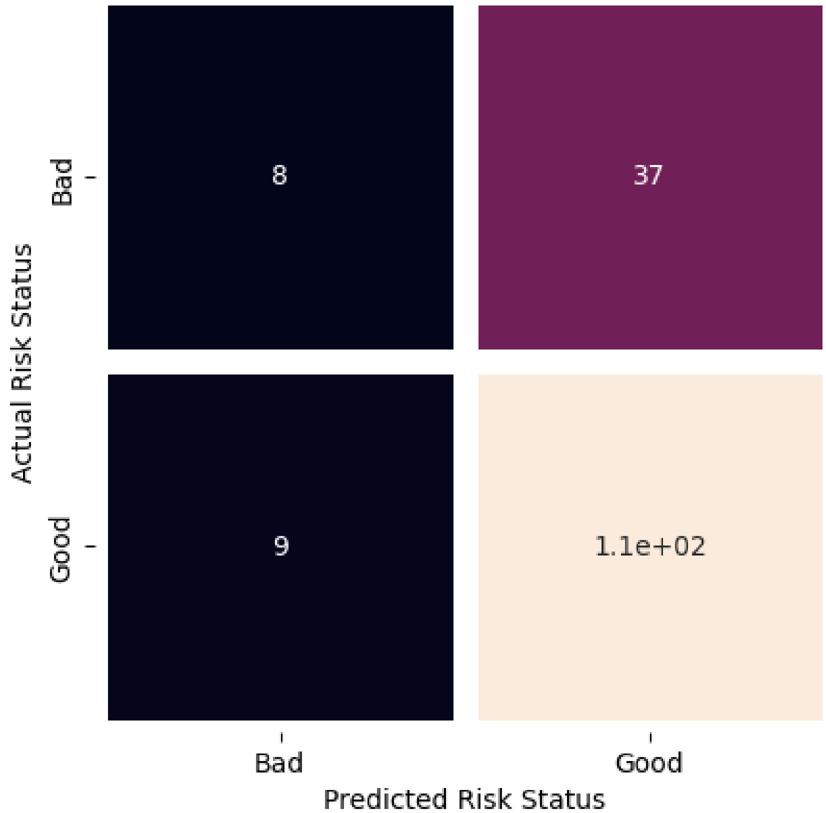
```
Results from algorithm LogisticRegression():
Mean cross-validation accuracy is 0.747 with SD 0.034

Accuracy on training data is 0.764

Test data metrics: accuracy=0.741, f1=0.837, precision=0.766, recall=0.923
```



K-Nearest Neighbour Classification

```
[ ]: knn_model = KNeighborsClassifier()
_ = train_and_evaluate(knn_model, X, y,"KNeighborsClassifier")
```

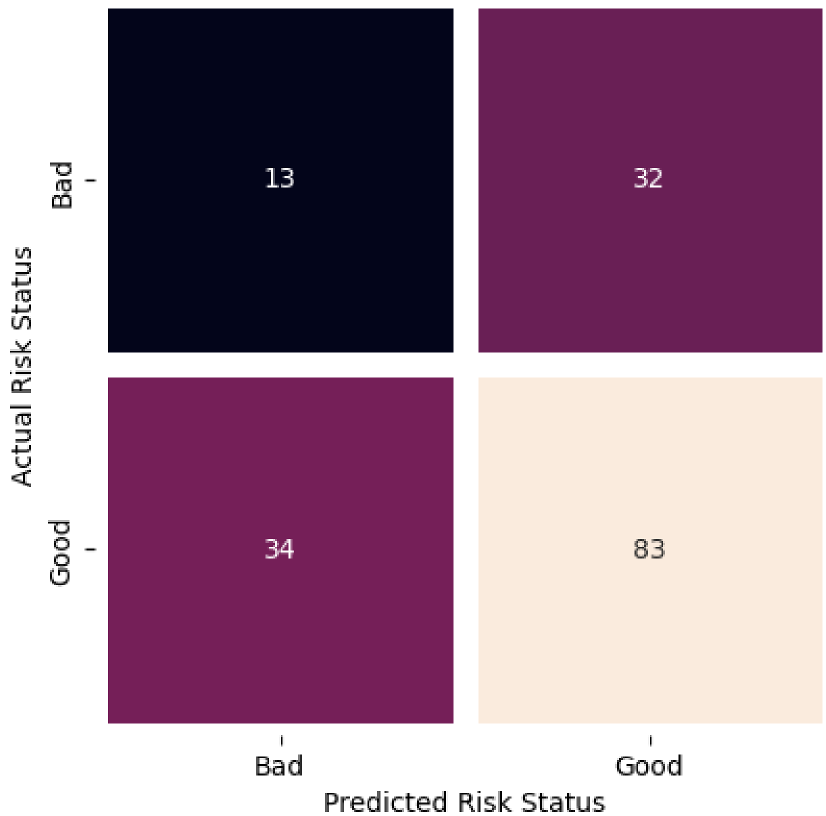
```
Results from algorithm KNeighborsClassifier():
Mean cross-validation accuracy is 0.709 with SD 0.048

Accuracy on training data is 0.802

Test data metrics: accuracy=0.716, f1=0.824, precision=0.745, recall=0.923
```



Decision Tree Classification

[ ]:
```
dtc_model = DecisionTreeClassifier()
learnt_model = train_and_evaluate(dtc_model, X, y,"DecisionTreeClassifier")
```

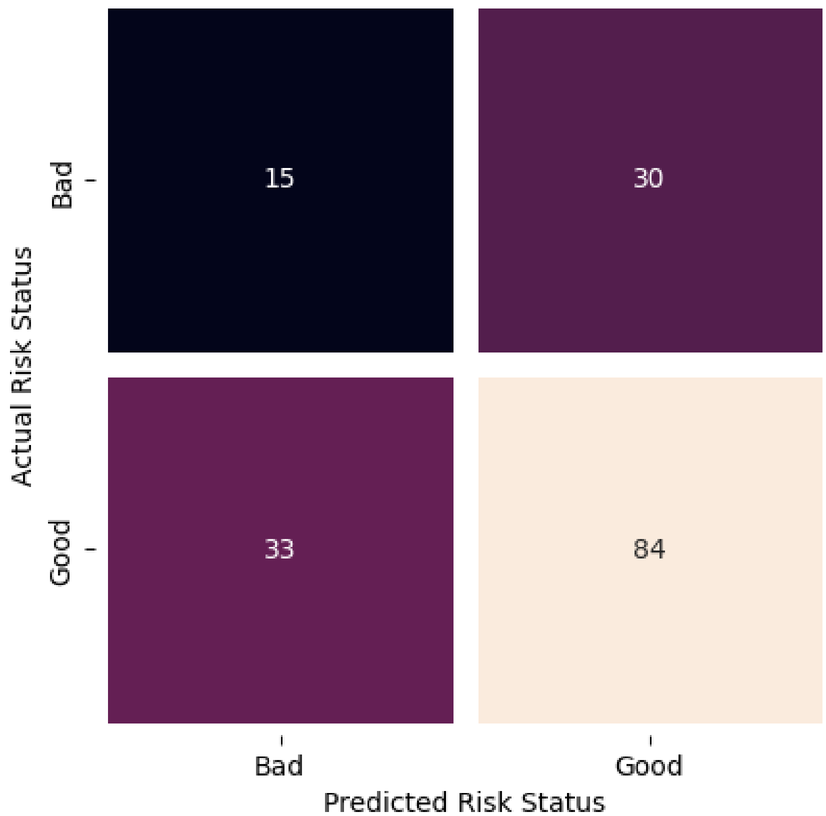
```
Results from algorithm DecisionTreeClassifier():
Mean cross-validation accuracy is 0.647 with SD 0.047

Accuracy on training data is 1.000

Test data metrics: accuracy=0.593, f1=0.716, precision=0.722, recall=0.709
```



Random Forest Classification

```
[ ]: rf_model =RandomForestClassifier()
_ = train_and_evaluate(dtc_model, X, y,"RandomForestClassifier")
```

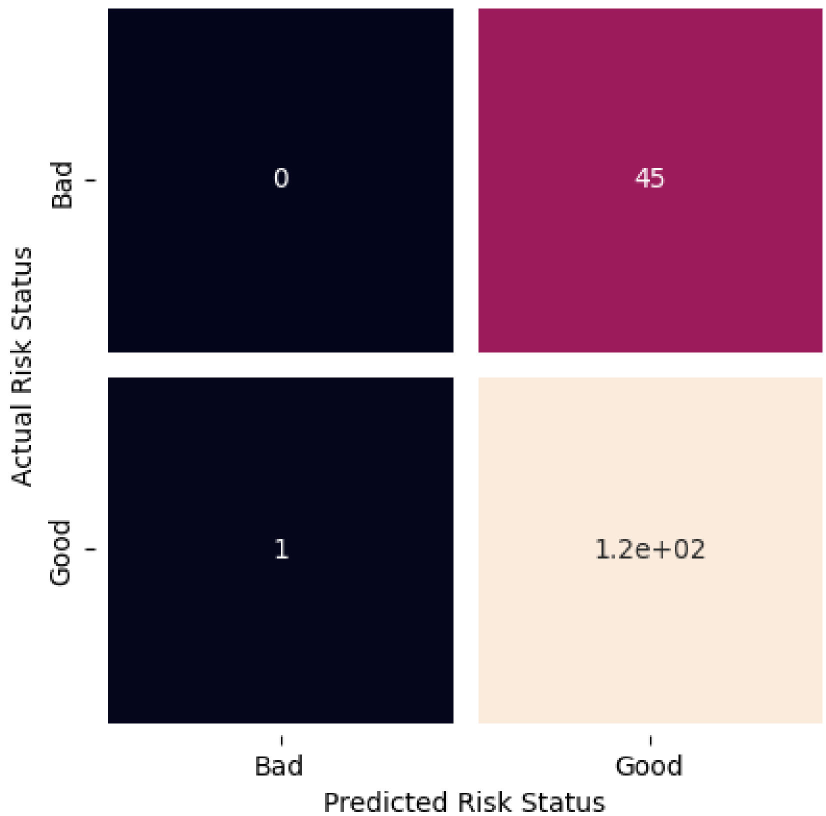
```
Results from algorithm DecisionTreeClassifier():
Mean cross-validation accuracy is 0.644 with SD 0.058

Accuracy on training data is 1.000

Test data metrics: accuracy=0.611, f1=0.727, precision=0.737, recall=0.718
```



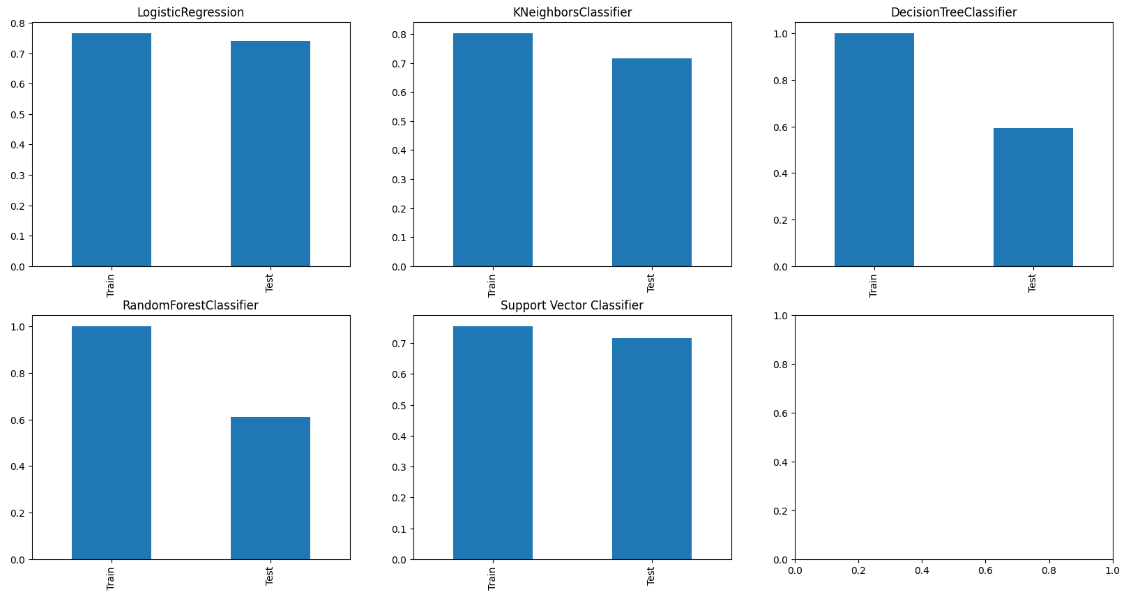
Support Vector Classification

[ ]:
```
svc_model = SVC(gamma='auto')
_ = train_and_evaluate(svc_model, X, y,"Support Vector Classifier")
```

```
Results from algorithm SVC(gamma='auto'):
Mean cross-validation accuracy is 0.744 with SD 0.011

Accuracy on training data is 0.753

Test data metrics: accuracy=0.716, f1=0.835, precision=0.720, recall=0.991
```



[ ]:
```
result_pd = pd.DataFrame(Result)
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(20, 10))
result_pd['LogisticRegression'].
  ↪plot(kind='bar',ax=axes[0,0],title="LogisticRegression")
result_pd['KNeighborsClassifier'].
  ↪plot(kind='bar',ax=axes[0,1],title="KNeighborsClassifier")
result_pd['DecisionTreeClassifier'].
  ↪plot(kind='bar',ax=axes[0,2],title="DecisionTreeClassifier")
result_pd['RandomForestClassifier'].
  ↪plot(kind='bar',ax=axes[1,0],title="RandomForestClassifier")
result_pd['Support Vector Classifier'].
  ↪plot(kind='bar',ax=axes[1,1],title="Support Vector Classifier")
plt.show()
```



7 Feature Reduction using PCA

Used to corroborate feature selection in Feature Engineering

[ ]:
```
df_pca = df_train.copy()
```

[ ]:
```
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
cols = df_pca.columns
le = LabelEncoder()                           # initialise the necessary function␣
↪taken from the LabelEncoder library
for col in cols:                              # iterate over all variables in cols
    df_pca[col] = le.fit_transform(df_pca[col])    # convert categorical values␣
↪into integer values

X = df_pca.drop(['Risk'],axis=1)
y = df_pca['Risk']

scaler = MinMaxScaler()
scaler.fit(X)
X = scaler.transform(X)
```

[ ]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=20).fit(X)
plt.plot(range(1,21), np.cumsum(pca.explained_variance_ratio_)) #plt.plot(np.
↪cumsum(pca.explained_variance_ratio_))
plt.xticks(range(1,21))
plt.xlabel('number of components')
```

```
plt.ylabel('cumulative explained variance')
plt.show()
```