Credit Model

The Goal of the project is to build Supervised Machine Learning models to predict the Creditability of people applying for credit cards with a bank. The dataset has details of the exisitng customers of the bank with a credit card along with their payment history which indicates if they have defualted in the past. This data will be used to build train, and test the models and can help the banks make decissions about accepting or rejecting any new incoming applications for credit card.

Part I: Building Machine Learning Models inclusive of all features

Pre Processing

In [134…
```
import pandas as pd
```

In [135…
```
pwd
```

Out[135]:
```
'/Users/pratik'
```

In [136…
```
credit = pd.read_csv('credit.csv')
```

In [137…
```
credit.dtypes
```

Out[137]:
```
Creditability                        int64
Account Balance                      int64
Duration of Credit (month)           int64
Payment Status of Previous Credit    int64
Purpose                              int64
Credit Amount                        int64
Value Savings/Stocks                 int64
Length of current employment         int64
Instalment per cent                  int64
Sex & Marital Status                 int64
Guarantors                           int64
Duration in Current address          int64
Most valuable available asset        int64
Age (years)                          int64
Concurrent Credits                   int64
Type of apartment                    int64
No of Credits at this Bank           int64
Occupation                           int64
No of dependents                     int64
Telephone                            int64
Foreign Worker                       int64
dtype: object
```

In [138…
```
credit.isnull().sum()
```

Out[138]:
```
Creditability                        0
Account Balance                      0
Duration of Credit (month)           0
Payment Status of Previous Credit    0
Purpose                              0
Credit Amount                        0
Value Savings/Stocks                 0
Length of current employment         0
Instalment per cent                  0
Sex & Marital Status                 0
```

```
Guarantors                           0
Duration in Current address          0
Most valuable available asset        0
Age (years)                          0
Concurrent Credits                   0
Type of apartment                    0
No of Credits at this Bank           0
Occupation                           0
No of dependents                     0
Telephone                            0
Foreign Worker                       0
dtype: int64
```

It appears from the above results that there are no no missing values, However, if we encounter any missing valueswe can use multiple imputatiuon methods to replace the missing data with either the mean or the median of the data depending on the distribution of the data. Since the datatypes of all the columns is integer, we can replace the mean values with either the mean or the median which are more relevant in statistical analysis. We may have some criteria to measure the missing values percentage, and if within acceptable range for the study under consideration, the missing values may be replaced.

In [139…
```python
target = credit['Creditability']
```

In [140…
```python
target.value_counts()
```

Out[140]:
```
1    700
0    300
Name: Creditability, dtype: int64
```

In [141…
```python
credit.describe()
```

Out[141]:

	Creditability	Account Balance	Duration of Credit (month)	Payment Status of Previous Credit	Purpose	Credit Amount	Value Savings/Stocks
count	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	1000.00000	1000.000000
mean	0.700000	2.577000	20.903000	2.54500	2.828000	3271.24800	2.105000
std	0.458487	1.257638	12.058814	1.08312	2.744439	2822.75176	1.580023
min	0.000000	1.000000	4.000000	0.00000	0.000000	250.00000	1.000000
25%	0.000000	1.000000	12.000000	2.00000	1.000000	1365.50000	1.000000
50%	1.000000	2.000000	18.000000	2.00000	2.000000	2319.50000	1.000000
75%	1.000000	4.000000	24.000000	4.00000	3.000000	3972.25000	3.000000
max	1.000000	4.000000	72.000000	4.00000	10.000000	18424.00000	5.000000

8 rows × 21 columns

Randomization

In [142…
```python
import random
random.seed(123)
indx = random.sample(range(0, 1000), 1000)
credit_rand = credit.iloc[indx]
target_rand = target.iloc[indx]
```

In [143…
```python
credit_rand.describe()
```

Out[143]:

	Creditability	Account Balance	Duration of Credit (month)	Payment Status of Previous Credit	Purpose	Credit Amount	Value Savings/Stocks
count	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	1000.00000	1000.000000
mean	0.700000	2.577000	20.903000	2.54500	2.828000	3271.24800	2.105000
std	0.458487	1.257638	12.058814	1.08312	2.744439	2822.75176	1.580023
min	0.000000	1.000000	4.000000	0.00000	0.000000	250.00000	1.000000
25%	0.000000	1.000000	12.000000	2.00000	1.000000	1365.50000	1.000000
50%	1.000000	2.000000	18.000000	2.00000	2.000000	2319.50000	1.000000
75%	1.000000	4.000000	24.000000	4.00000	3.000000	3972.25000	3.000000
max	1.000000	4.000000	72.000000	4.00000	10.000000	18424.00000	5.000000

8 rows × 21 columns

On comparison after randomization it can be seen that the summary of the variables with reference to the mean,standard Deviation, Median, Minimum and Maximum values for each column before and after randomization is the same.

Decision Tree Model

In [144…

```
from sklearn.model_selection import train_test_split
y = target
x = credit.drop(['Creditability'], axis = 1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_state
```

In [145…

```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
model = tree.DecisionTreeClassifier()
model = model.fit(x_train, y_train)
```

In [146…

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
y_predict = model.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[ 45  39]
 [ 57 159]]
```

In [147…

```
print(accuracy_score(y_test, y_predict)*100)
```

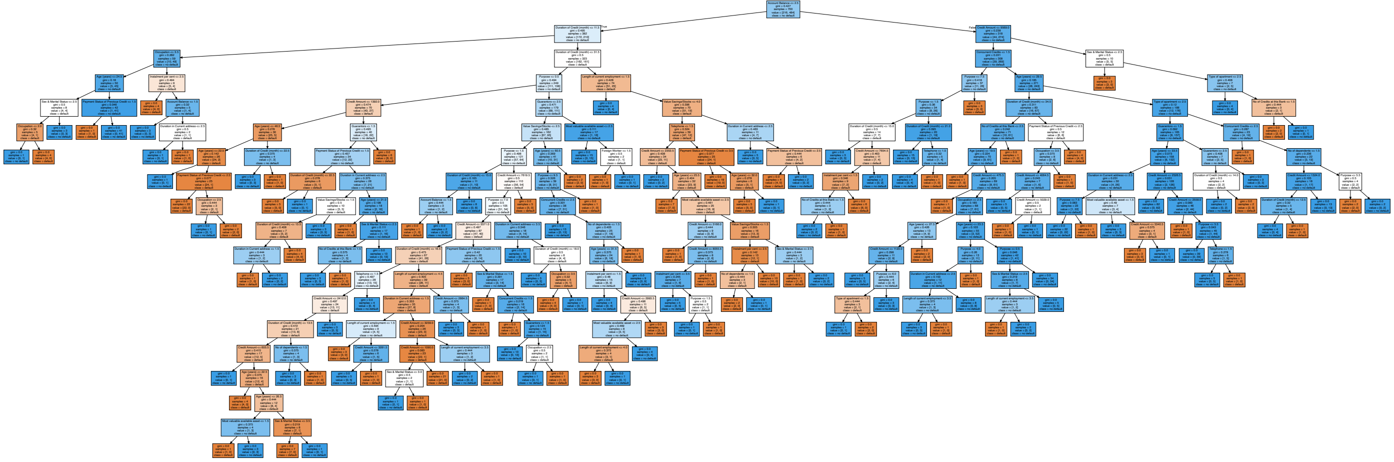
```
68.0
```

The accuracy for the model usign Decision Tree Classifier is 67.66%

In [148…

```
#To visualize the model, we can use
#conda install python-graphviz used in anaconda command prompt to install graphviz

from IPython.display import SVG
from graphviz import Source
from IPython.display import display
graph = Source(tree.export_graphviz(model, out_file = None,
                                    feature_names = x.columns,
                                    class_names = ['default', 'no default'], filled = Tr
display(SVG(graph.pipe(format = 'svg')))
```



Random Forest

In [149…

```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier()
clf.fit(x_train, y_train)
```

Out[149]:

```
RandomForestClassifier()
```

In [150…

```
y_predict = clf.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[ 38  46]
 [ 30 186]]
```

In [151…

```
print(accuracy_score(y_test, y_predict)*100)
```

```
74.66666666666667
```

The accuracy increased to 74% when we used Random Forest Algorithn

Gaussian Naive Bayes Model

Splitting into Training and Test Data Sets

In [152…

```
from sklearn.model_selection import train_test_split
y = target
x = credit.drop(['Creditability'], axis = 1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state
```

The data after randomization is split into 75% Training Data and 25% Test Data Set, with a random seed of 123.

Percentage of Targets for Training and Test Data Sets

In [153…

```
y_train.value_counts() / y_train.shape
```

Out[153]:

```
1    0.713333
0    0.286667
Name: Creditability, dtype: float64
```

In [154…

```
y_test.value_counts() / y_test.shape
```

Out[154]:

```
1    0.66
0    0.34
Name: Creditability, dtype: float64
```

It appears that for the trainiing data set, the percentage of targets(Creditability) with Crediatability score 1 was 71 % and that with score 0 was 29%.For the Test Data Set, the percentage of targets with Creditability score 1 was 66% and with Creditability score 0 was 34%

Model Training

In [155…
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb = gnb.fit(x_train, y_train)
```

Model Evaluation

In [156…
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
y_predict = gnb.predict(x_test)
```

In [157…
```
print(confusion_matrix(y_test, y_predict))
print(accuracy_score(y_test, y_predict)*100)
```

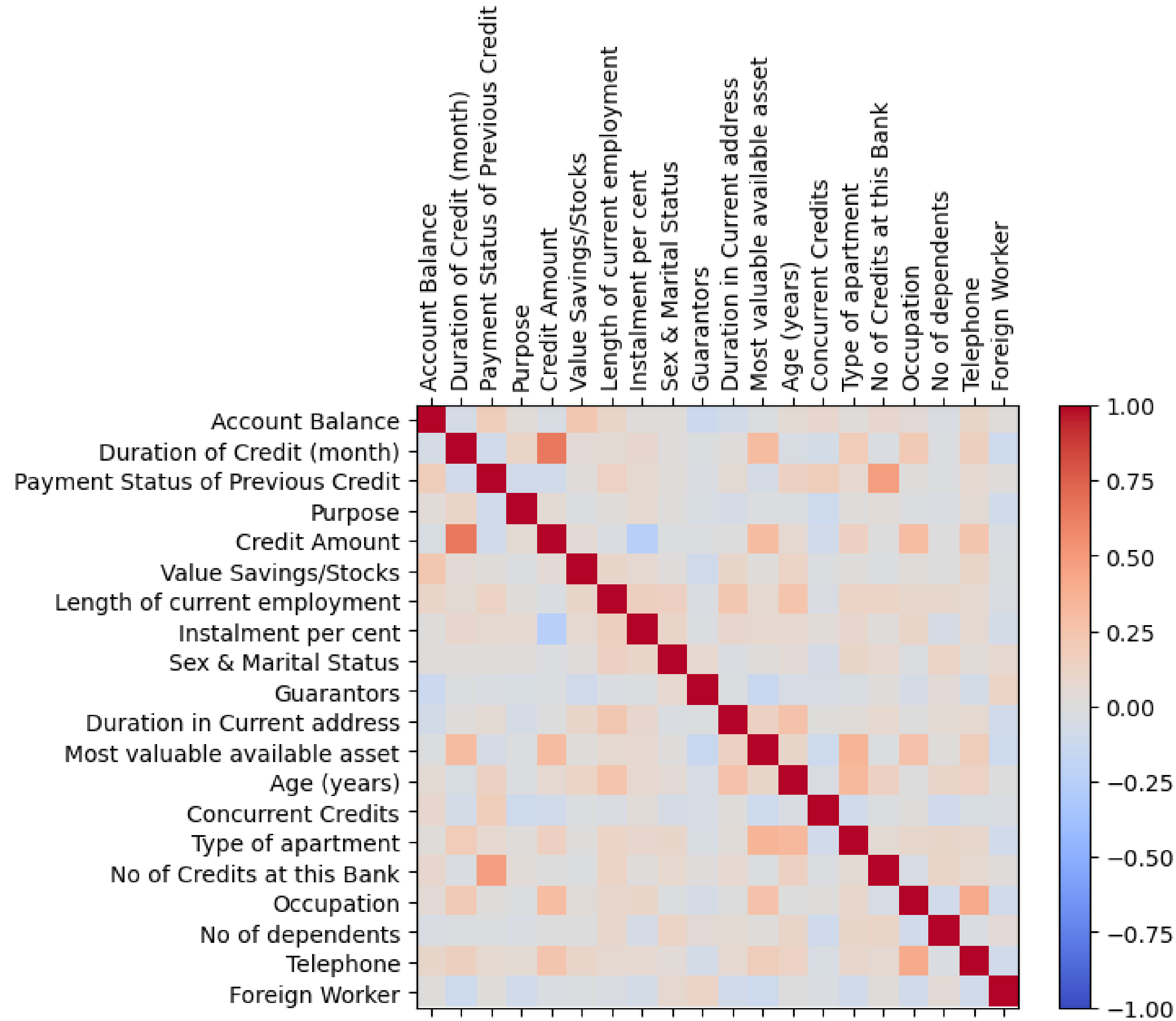
```
[[ 60  25]
 [ 34 131]]
76.4
```

The Evaluation shows 60 True Positives and 113 True Negatives out of all predictions with an accuracy of 76%. The accuracy for Gaussian Naive Bayes was the highest compared to the Decision Tree and Random Forest models.

Part II: Improving Performance by dropping highly correlated features

Feature Correlation

In [158…
```
import matplotlib.pyplot as plt
import numpy as np
corr = x_train.corr()
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(corr,cmap='coolwarm', vmin=-1, vmax=1)
fig.colorbar(cax)
ticks = np.arange(0,len(x_train.columns),1)
ax.set_xticks(ticks)
plt.xticks(rotation=90)
ax.set_yticks(ticks)
ax.set_xticklabels(x_train.columns)
ax.set_yticklabels(x_train.columns)
plt.show()
```



Removing the highgly Correlated Variables

Create Correlation Matrix

In [71]:
```
corr_matrix = x.corr().abs()
```

Select Upper triangle of correlation matrix

In [72]:
```
import numpy as np
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape) , k=1).astype(np.bool))
```

```
/var/folders/fp/szpx3gxd4ln849f9dbx_lqw00000gn/T/ipykernel_1760/2665990962.py:2: Depreca
tionWarning: `np.bool` is a deprecated alias for the builtin `bool`. To silence this war
ning, use `bool` by itself. Doing this will not modify any behavior and is safe. If you
specifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/relea
se/1.20.0-notes.html#deprecations
  upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape) , k=1).astype(np.bool))
```

In [73]:
```
upper
```

Out[73]:

	Account Balance	Duration of Credit (month)	Payment Status of	Purpose	Credit Amount	Value Savings/Stocks	Length of current employment	Instalment per cent

			Previous Credit					
Account Balance	NaN	0.072013	0.192191	0.028783	0.042695	0.222867	0.106339	0.00528
Duration of Credit (month)	NaN	NaN	0.077186	0.147492	0.624988	0.047661	0.057381	0.07474
Payment Status of Previous Credit	NaN	NaN	NaN	0.090336	0.059915	0.039058	0.138225	0.04437
Purpose	NaN	NaN	NaN	NaN	0.068480	0.018684	0.016013	0.04836
Credit Amount	NaN	NaN	NaN	NaN	NaN	0.064632	0.008376	0.27132
Value Savings/Stocks	NaN	NaN	NaN	NaN	NaN	NaN	0.120950	0.02199
Length of current employment	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.126161
Instalment per cent	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Sex & Marital Status	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Guarantors	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Duration in Current address	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Most valuable available asset	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Age (years)	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Concurrent Credits	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Type of apartment	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
No of Credits at this Bank	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Occupation	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
No of dependents	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Telephone	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Foreign Worker	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Find index of feature columns with correlation greater than 0.95

In [74]:

```
to_drop = [column for column in upper.columns if any(upper[column] > 0.6)]
xnew = x.drop(to_drop, axis = 1)
```

In [75]:

```
xnew
```

Out[75]:

	Account Balance	Duration of Credit (month)	Payment Status of Previous Credit	Purpose	Value Savings/Stocks	Length of current employment	Instalment per cent	Sex & Marital Status	Guarantors

0	1	18	4	2	1	2	4	2	1
1	1	9	4	0	1	3	2	3	1
2	2	12	2	9	2	4	2	2	1
3	1	12	4	0	1	3	3	3	1
4	1	12	4	0	1	3	4	3	1
...	...	...	...	...	...	...	...	...	...
995	1	24	2	3	1	3	2	3	1
996	1	24	2	0	1	5	4	3	2
997	4	21	4	0	5	5	4	3	1
998	2	12	2	3	5	1	2	3	1
999	1	30	2	2	5	5	4	3	1

1000 rows × 19 columns

New Accuracy with new Xnew(after dropping highly correlated variables)

Using Xnew(after dropping highly correlated var) for randomising, Splitting, Training model and evaluating

In [76]:
```
to_drop
```

Out[76]:
```
['Credit Amount']
```

Dropping "Credit Amount", which has high correlation with one of the Independent Variables

In [77]:
```
credit_new = credit.drop(columns="Credit Amount")
```

In [78]:
```
credit_new.dtypes
```

Out[78]:
```
Creditability                         int64
Account Balance                       int64
Duration of Credit (month)            int64
Payment Status of Previous Credit     int64
Purpose                               int64
Value Savings/Stocks                  int64
Length of current employment          int64
Instalment per cent                   int64
Sex & Marital Status                  int64
Guarantors                            int64
Duration in Current address           int64
Most valuable available asset         int64
Age (years)                           int64
Concurrent Credits                    int64
Type of apartment                     int64
No of Credits at this Bank            int64
Occupation                            int64
No of dependents                      int64
Telephone                             int64
Foreign Worker                        int64
dtype: object
```

In [79]:
```
target_new = credit_new['Creditability']
```

In [80]:
```
credit_new.describe()
```

Out[80]:

	Creditability	Account Balance	Duration of Credit (month)	Payment Status of Previous Credit	Purpose	Value Savings/Stocks	Length of current employment	
count	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	1000.000000	1000.000000	1(
mean	0.700000	2.577000	20.903000	2.54500	2.828000	2.105000	3.384000	
std	0.458487	1.257638	12.058814	1.08312	2.744439	1.580023	1.208306	
min	0.000000	1.000000	4.000000	0.00000	0.000000	1.000000	1.000000	
25%	0.000000	1.000000	12.000000	2.00000	1.000000	1.000000	3.000000	
50%	1.000000	2.000000	18.000000	2.00000	2.000000	1.000000	3.000000	
75%	1.000000	4.000000	24.000000	4.00000	3.000000	3.000000	5.000000	
max	1.000000	4.000000	72.000000	4.00000	10.000000	5.000000	5.000000	

Randomization

In [81]:
```
import random
random.seed(123)
indx = random.sample(range(0, 1000), 1000)
credit_new_rand = credit_new.iloc[indx]
target_new_rand = target_new.iloc[indx]
```

In [82]:
```
credit_new_rand.describe()
```

Out[82]:

	Creditability	Account Balance	Duration of Credit (month)	Payment Status of Previous Credit	Purpose	Value Savings/Stocks	Length of current employment	
count	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	1000.000000	1000.000000	1(
mean	0.700000	2.577000	20.903000	2.54500	2.828000	2.105000	3.384000	
std	0.458487	1.257638	12.058814	1.08312	2.744439	1.580023	1.208306	
min	0.000000	1.000000	4.000000	0.00000	0.000000	1.000000	1.000000	
25%	0.000000	1.000000	12.000000	2.00000	1.000000	1.000000	3.000000	
50%	1.000000	2.000000	18.000000	2.00000	2.000000	1.000000	3.000000	
75%	1.000000	4.000000	24.000000	4.00000	3.000000	3.000000	5.000000	
max	1.000000	4.000000	72.000000	4.00000	10.000000	5.000000	5.000000	

As seen above, Randomized credit_new data has similar statistical parameters as before randomizing

Train Test Split

In [83]:
```
y = target_new
x = xnew
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, random_state
```

Percentage of Targets for Training and Test

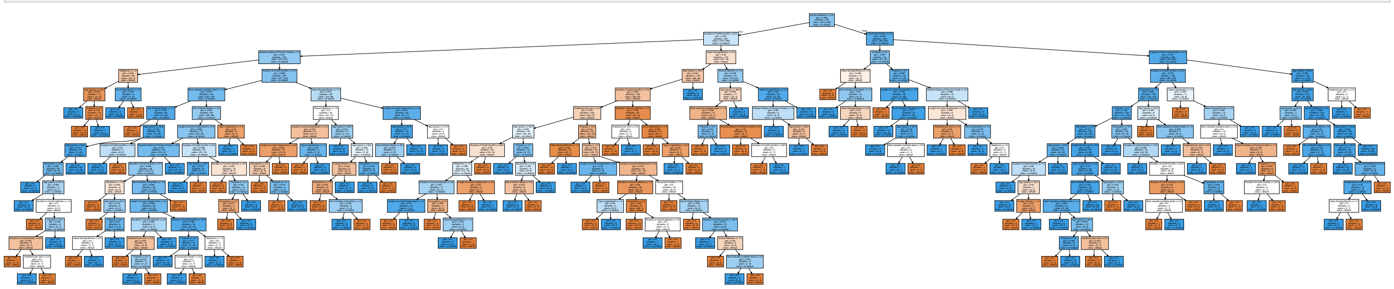
In [84]:
```
y_train.value_counts() / y_train.shape
```
Out[84]:
```
1    0.713333
0    0.286667
Name: Creditability, dtype: float64
```
In [85]:
```
y_test.value_counts() / y_test.shape
```
Out[85]:
```
1    0.66
0    0.34
Name: Creditability, dtype: float64
```

It appears that for the trainiing data set, the percentage of targets(Creditability) with Crediatability score 1 was 71 % and that with score 0 was 29%. For the Test Data Set, the percentage of targets with Creditability score 1 was 66% and with Creditability score 0 was 34%.

Decision Tree Model

In [89]:
```
# Design Decision Tree
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
```
In [90]:
```
model = tree.DecisionTreeClassifier()
model = model.fit(x_train, y_train)
```

To visualize the model we can use "conda install python-graphviz", in anaconda command prompt to install graphviz

In [91]:
```
from IPython.display import SVG
from graphviz import Source
from IPython.display import display
graph = Source(tree.export_graphviz(model, out_file = None,
                                    feature_names = x.columns,
                                    class_names = ['default', 'no default'], filled = Tr
display(SVG(graph.pipe(format = 'svg')))
```


In [92]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
y_predict = model.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```
```
[[ 49  36]
 [ 33 132]]
```
In [93]:
```
print(accuracy_score(y_test, y_predict)*100)
```
```
72.39999999999999
```

Random Forest

In [94]:
```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier()
```

```
clf.fit(x_train, y_train)
```

Out[94]:
```
RandomForestClassifier()
```

In [95]:
```
y_predict = clf.predict(x_test)
print(confusion_matrix(y_test, y_predict))
```

```
[[ 35  50]
 [ 15 150]]
```

In [96]:
```
print(accuracy_score(y_test, y_predict)*100)
```

```
74.0
```

Gausian Naive Bayes

Model Training

In [99]:
```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb = gnb.fit(x_train, y_train)
```

Model Evaluation

In [101…
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
y_predict = gnb.predict(x_test)
```

In [102…
```
print(confusion_matrix(y_test, y_predict))
print(accuracy_score(y_test, y_predict))
```

```
[[ 65  20]
 [ 37 128]]
0.772
```

On dropping the correlated features, the accuracy of Decision Tree model increased from 68% to 72%, and that for Gaussian Naive Bayes model increased from 76% to 77%. The Gaussian Naive Bayes models gave the highest accuracy amongst all models considered in both parts, before and after dropping the highly correlated variables.