Week6_3_Decision_Tree

May 13, 2021

Decision Trees (DT)

- DT model predict who seeks a loan might be defaulter or a non-defaulter using several independent variables checking account balance, credit history, loan amount, and purpose etc.

Importing Python Libraries we need

[1]:
```
import pandas as pd
import numpy as np
from sklearn import metrics
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

import warnings
warnings.filterwarnings('ignore')
```

Load the dataset using URL and display

[2]:
```
url = "credit.csv"
creditData = pd.read_csv(url)

#creditData = pd.read_csv("credit.csv")
creditData.head(10) #several missing values!
```

[2]:
```
  checking_balance  months_loan_duration credit_history                 purpose  \
0           < 0 DM                     6       critical  furniture/appliances
1       1 - 200 DM                    48           good  furniture/appliances
2          unknown                    12       critical               education
3           < 0 DM                    42           good  furniture/appliances
4           < 0 DM                    24           poor                     car
5          unknown                    36           good               education
6          unknown                    24           good  furniture/appliances
7       1 - 200 DM                    36           good                     car
8          unknown                    12           good  furniture/appliances
9       1 - 200 DM                    30       critical                     car
```

```
   amount savings_balance employment_duration  percent_of_income  \
0    1169         unknown           > 7 years                  4
1    5951        < 100 DM         1 - 4 years                  2
2    2096        < 100 DM         4 - 7 years                  2
3    7882        < 100 DM         4 - 7 years                  2
4    4870        < 100 DM         1 - 4 years                  3
5    9055         unknown         1 - 4 years                  2
6    2835   500 - 1000 DM           > 7 years                  3
7    6948        < 100 DM         1 - 4 years                  2
8    3059       > 1000 DM         4 - 7 years                  2
9    5234        < 100 DM          unemployed                  4

   years_at_residence  age other_credit housing  existing_loans_count  \
0                   4   67         none     own                     2
1                   2   22         none     own                     1
2                   3   49         none     own                     1
3                   4   45         none   other                     1
4                   4   53         none   other                     2
5                   4   35         none   other                     1
6                   4   53         none     own                     1
7                   2   35         none    rent                     1
8                   4   61         none     own                     1
9                   2   28         none     own                     2

          job  dependents phone default
0     skilled           1   yes      no
1     skilled           1    no     yes
2   unskilled           2    no      no
3     skilled           2    no      no
4     skilled           2    no     yes
5   unskilled           2   yes      no
6     skilled           1    no      no
7  management           1   yes      no
8   unskilled           1    no      no
9  management           1    no     yes
```

Checking: shape of the data

[3]:
```
creditData.shape
```

[3]: (1000, 17)

- No. of rows (observations): 1000
- No. of columns (features):17 ______ _______

Counting the credit data value

[4]:

```
creditData['default'].value_counts()
```

[4]:

```
no     700
yes    300
Name: default, dtype: int64
```

[5]:

```
creditData.info()  # many columns are of type object i.e. strings. These need␣
↪to be converted to ordinal type
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   checking_balance      1000 non-null   object
 1   months_loan_duration  1000 non-null   int64
 2   credit_history        1000 non-null   object
 3   purpose               1000 non-null   object
 4   amount                1000 non-null   int64
 5   savings_balance       1000 non-null   object
 6   employment_duration   1000 non-null   object
 7   percent_of_income     1000 non-null   int64
 8   years_at_residence    1000 non-null   int64
 9   age                   1000 non-null   int64
 10  other_credit          1000 non-null   object
 11  housing               1000 non-null   object
 12  existing_loans_count  1000 non-null   int64
 13  job                   1000 non-null   object
 14  dependents            1000 non-null   int64
 15  phone                 1000 non-null   object
 16  default               1000 non-null   object
dtypes: int64(7), object(10)
memory usage: 132.9+ KB
```

- Lets convert the columns with an 'object' datatype into categorical variables

[6]:

```
for feature in creditData.columns: # Loop through all columns in the dataframe
    if creditData[feature].dtype == 'object': # Only apply for columns with␣
↪categorical strings
        creditData[feature] = pd.Categorical(creditData[feature])# Replace␣
↪strings with an integer
creditData.head(10)
```

[6]:

```
  checking_balance  months_loan_duration credit_history              purpose  \
0           < 0 DM                     6       critical  furniture/appliances
1       1 - 200 DM                    48           good  furniture/appliances
2          unknown                    12       critical             education
3           < 0 DM                    42           good  furniture/appliances
```

```
4          < 0 DM                    24         poor                  car
5         unknown                    36         good            education
6         unknown                    24         good  furniture/appliances
7      1 - 200 DM                    36         good                  car
8         unknown                    12         good  furniture/appliances
9      1 - 200 DM                    30     critical                  car

   amount savings_balance employment_duration  percent_of_income  \
0    1169         unknown           > 7 years                  4
1    5951        < 100 DM         1 - 4 years                  2
2    2096        < 100 DM         4 - 7 years                  2
3    7882        < 100 DM         4 - 7 years                  2
4    4870        < 100 DM         1 - 4 years                  3
5    9055         unknown         1 - 4 years                  2
6    2835   500 - 1000 DM           > 7 years                  3
7    6948        < 100 DM         1 - 4 years                  2
8    3059       > 1000 DM         4 - 7 years                  2
9    5234        < 100 DM          unemployed                  4

   years_at_residence  age other_credit housing  existing_loans_count  \
0                   4   67         none     own                     2
1                   2   22         none     own                     1
2                   3   49         none     own                     1
3                   4   45         none   other                     1
4                   4   53         none   other                     2
5                   4   35         none   other                     1
6                   4   53         none     own                     1
7                   2   35         none    rent                     1
8                   4   61         none     own                     1
9                   2   28         none     own                     2

          job  dependents phone default
0     skilled           1   yes      no
1     skilled           1    no     yes
2   unskilled           2    no      no
3     skilled           2    no      no
4     skilled           2    no     yes
5   unskilled           2   yes      no
6     skilled           1    no      no
7  management           1   yes      no
8   unskilled           1    no      no
9  management           1    no     yes
```

[7]:

```python
print(creditData.checking_balance.value_counts())
print(creditData.credit_history.value_counts())
print(creditData.purpose.value_counts())
print(creditData.savings_balance.value_counts())
```

```
print(creditData.employment_duration.value_counts())
print(creditData.other_credit.value_counts())
print(creditData.housing.value_counts())
print(creditData.job.value_counts())
print(creditData.phone.value_counts())
```

```
unknown       394
< 0 DM        274
1 - 200 DM    269
> 200 DM       63
Name: checking_balance, dtype: int64
good         530
critical     293
poor          88
very good     49
perfect       40
Name: credit_history, dtype: int64
furniture/appliances    473
car                     337
business                 97
education                59
renovations              22
car0                     12
Name: purpose, dtype: int64
< 100 DM         603
unknown          183
100 - 500 DM     103
500 - 1000 DM     63
> 1000 DM         48
Name: savings_balance, dtype: int64
1 - 4 years    339
> 7 years      253
4 - 7 years    174
< 1 year       172
unemployed      62
Name: employment_duration, dtype: int64
none     814
bank     139
store     47
Name: other_credit, dtype: int64
own      713
rent     179
other    108
Name: housing, dtype: int64
skilled       630
unskilled     200
management    148
```

```
unemployed     22
Name: job, dtype: int64
no      596
yes     404
Name: phone, dtype: int64
```

labelling features

[8]:
```
replaceStruct = {
                "checking_balance":     {"< 0 DM": 1, "1 - 200 DM": 2 ,"> 200␣
 ↪DM": 3 ,"unknown":-1},
                "credit_history": {"critical": 1, "poor":2 , "good": 3, "very␣
 ↪good": 4,"perfect": 5},
                 "savings_balance": {"< 100 DM": 1, "100 - 500 DM":2 , "500 -␣
 ↪1000 DM": 3, "> 1000 DM": 4,"unknown": -1},
                 "employment_duration":     {"unemployed": 1, "< 1 year": 2 ,"1␣
 ↪- 4 years": 3 ,"4 - 7 years": 4 ,"> 7 years": 5},
                "phone":     {"no": 1, "yes": 2 },
                #"job":     {"unemployed": 1, "unskilled": 2, "skilled": 3,␣
 ↪"management": 4 },
                "default":     {"no": 0, "yes": 1 }
                    }
oneHotCols=["purpose","housing","other_credit","job"]
```

[9]:
```
creditData=creditData.replace(replaceStruct)
creditData=pd.get_dummies(creditData, columns=oneHotCols)
creditData.head(10)
```

[9]:
```
   checking_balance  months_loan_duration  credit_history  amount  \
0                 1                     6               1    1169
1                 2                    48               3    5951
2                -1                    12               1    2096
3                 1                    42               3    7882
4                 1                    24               2    4870
5                -1                    36               3    9055
6                -1                    24               3    2835
7                 2                    36               3    6948
8                -1                    12               3    3059
9                 2                    30               1    5234

   savings_balance  employment_duration  percent_of_income  \
0               -1                    5                  4
1                1                    3                  2
2                1                    4                  2
3                1                    4                  2
4                1                    3                  3
5               -1                    3                  2
6                3                    5                  3
```

7	1	3	2
8	4	4	2
9	1	1	4

	years_at_residence	age	existing_loans_count	…	housing_other	\
0	4	67	2	…	0	
1	2	22	1	…	0	
2	3	49	1	…	0	
3	4	45	1	…	1	
4	4	53	2	…	1	
5	4	35	1	…	1	
6	4	53	1	…	0	
7	2	35	1	…	0	
8	4	61	1	…	0	
9	2	28	2	…	0	

	housing_own	housing_rent	other_credit_bank	other_credit_none	\
0	1	0	0	1	
1	1	0	0	1	
2	1	0	0	1	
3	0	0	0	1	
4	0	0	0	1	
5	0	0	0	1	
6	1	0	0	1	
7	0	1	0	1	
8	1	0	0	1	
9	1	0	0	1	

	other_credit_store	job_management	job_skilled	job_unemployed	\
0	0	0	1	0	
1	0	0	1	0	
2	0	0	0	0	
3	0	0	1	0	
4	0	0	1	0	
5	0	0	0	0	
6	0	0	1	0	
7	0	1	0	0	
8	0	0	0	0	
9	0	1	0	0	

	job_unskilled
0	0
1	0
2	1
3	0
4	0
5	1

```
6               0
7               0
8               1
9               0

[10 rows x 29 columns]
```

[10]:
```
creditData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 29 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   checking_balance              1000 non-null   int64
 1   months_loan_duration          1000 non-null   int64
 2   credit_history                1000 non-null   int64
 3   amount                        1000 non-null   int64
 4   savings_balance               1000 non-null   int64
 5   employment_duration           1000 non-null   int64
 6   percent_of_income             1000 non-null   int64
 7   years_at_residence            1000 non-null   int64
 8   age                           1000 non-null   int64
 9   existing_loans_count          1000 non-null   int64
 10  dependents                    1000 non-null   int64
 11  phone                         1000 non-null   int64
 12  default                       1000 non-null   int64
 13  purpose_business              1000 non-null   uint8
 14  purpose_car                   1000 non-null   uint8
 15  purpose_car0                  1000 non-null   uint8
 16  purpose_education             1000 non-null   uint8
 17  purpose_furniture/appliances  1000 non-null   uint8
 18  purpose_renovations           1000 non-null   uint8
 19  housing_other                 1000 non-null   uint8
 20  housing_own                   1000 non-null   uint8
 21  housing_rent                  1000 non-null   uint8
 22  other_credit_bank             1000 non-null   uint8
 23  other_credit_none             1000 non-null   uint8
 24  other_credit_store            1000 non-null   uint8
 25  job_management                1000 non-null   uint8
 26  job_skilled                   1000 non-null   uint8
 27  job_unemployed                1000 non-null   uint8
 28  job_unskilled                 1000 non-null   uint8
dtypes: int64(13), uint8(16)
memory usage: 117.3 KB
```

0.1 Split Data

[11]:
```
X = creditData.drop("default" , axis=1)
y = creditData.pop("default")
```

[12]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.30,␣
↪random_state=1)
```

0.2 Build Decision Tree Model

We will build our model using the DecisionTreeClassifier function. Using default 'gini' criteria to split. Other option include 'entropy'.

[13]:
```
dTree = DecisionTreeClassifier(criterion = 'gini', random_state=1)
dTree.fit(X_train, y_train)
```

[13]:
```
DecisionTreeClassifier(random_state=1)
```

[14]:
```
dTree = DecisionTreeClassifier(criterion = 'gini', random_state=1)
dTree.fit(X_train, y_train)
```

[14]:
```
DecisionTreeClassifier(random_state=1)
```

0.3 Scoring our Decision Tree

[15]:
```
print("Accuracy on training set : ",dTree.score(X_train, y_train))
print("Accuracy on test set : ",dTree.score(X_test, y_test))
```

```
Accuracy on training set :  1.0
Accuracy on test set :  0.6933333333333334
```

[16]:
```
#Checking number of positives
y.sum(axis = 0)
```

[16]:
```
300
```

- The ratio of positives to negatives is 3:7, so if our model marks each sample as negative, then also we'll get 70% accuracy, hence accuracy is not a good metric to evaluate here.

What does a bank want? * A bank wants to minimize the loss - it can face 2 types of losses here: * Whenever bank lends money to a customer, they don't return that. * A bank doesn't lend money to a customer thinking he will default but in reality he won't - oppurtunity loss.

Which loss is greater ? * Customer not returning the money back.

Since we don't want people to default on the loans we should use Recall as a metric of model evaluation instead of accuracy.

- Recall - It gives the ratio of True positives to Actual positives, so high Recall implies low false negatives, i.e. low chances of predicting a defaulter as non defaulter

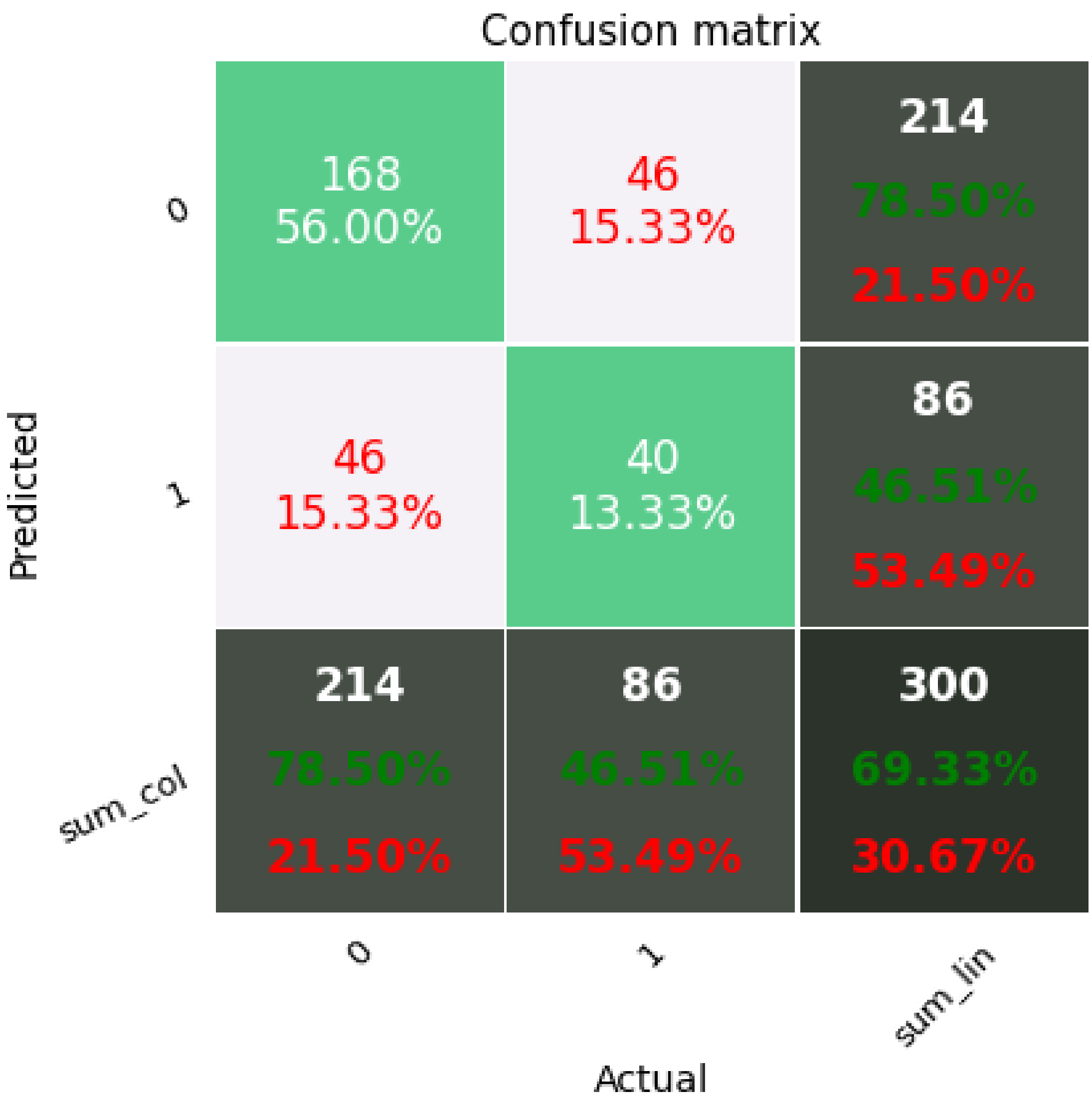
[17]:
```
##  Function to calculate recall score
def get_recall_score(model):

    pred_train = model.predict(X_train)
    pred_test = model.predict(X_test)
    print("Recall on training set : ",metrics.recall_score(y_train,pred_train))
    print("Recall on test set : ",metrics.recall_score(y_test,pred_test))

# Recall on train and test
get_recall_score(dTree)
```

```
Recall on training set :  1.0
Recall on test set :  0.46511627906976744
```

[18]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score

y_pred = dTree.predict(X_test)
# con_res = confusion_matrix(y_test,y_pred, labels=[0, 1])
con_res = metrics.confusion_matrix(y_test,y_pred, labels=[0, 1])

print("Confusion matrix:")
print(confusion_matrix(y_test,y_pred))
print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred)*100))
```

```
Confusion matrix:
[[168  46]
 [ 46  40]]
Accuracy: 69.33%
```

[19]:
```
%run -i '/home/jayanthikishore/Desktop/Analysis/Work/ML_EIT/
 ↪confusion_matrix_different_ways1.py'
df_confmatrx = pd.DataFrame(con_res, range(2),range(2))
df_confmatrx
cmap = 'PuRd'
confusion_matrix_dfrntway(df_confmatrx, cmap=cmap,fz=17)
```



Visualizing the Decision Tree

[20]:
```
feature_names = list(X.columns)
print(feature_names)
```

```
['checking_balance', 'months_loan_duration', 'credit_history', 'amount',
'savings_balance', 'employment_duration', 'percent_of_income',
'years_at_residence', 'age', 'existing_loans_count', 'dependents', 'phone',
'purpose_business', 'purpose_car', 'purpose_car0', 'purpose_education',
'purpose_furniture/appliances', 'purpose_renovations', 'housing_other',
'housing_own', 'housing_rent', 'other_credit_bank', 'other_credit_none',
'other_credit_store', 'job_management', 'job_skilled', 'job_unemployed',
'job_unskilled']
```

[21]:
```
plt.figure(figsize=(20,30))
tree.
↪plot_tree(dTree,feature_names=feature_names,filled=True,fontsize=9,node_ids=True,class_name
plt.show()
```

Text pattern Tree

[22]:
```
# Text report showing the rules of a decision tree -

print(tree.export_text(dTree,feature_names=feature_names,show_weights=True))
```

```
|--- checking_balance <= 0.00
|   |--- other_credit_none <= 0.50
|   |   |--- purpose_business <= 0.50
|   |   |   |--- age <= 25.50
|   |   |   |   |--- employment_duration <= 3.50
|   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |--- employment_duration >  3.50
|   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |--- age >  25.50
|   |   |   |   |--- age <= 38.50
|   |   |   |   |   |--- age <= 31.50
|   |   |   |   |   |   |--- credit_history <= 4.50
|   |   |   |   |   |   |   |--- weights: [13.00, 0.00] class: 0
|   |   |   |   |   |   |--- credit_history >  4.50
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |--- age >  31.50
|   |   |   |   |   |   |--- purpose_education <= 0.50
|   |   |   |   |   |   |   |--- credit_history <= 1.50
|   |   |   |   |   |   |   |   |--- savings_balance <= 2.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 2.00] class: 1
|   |   |   |   |   |   |   |   |--- savings_balance >  2.50
|   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- credit_history >  1.50
|   |   |   |   |   |   |   |   |--- savings_balance <= 2.50
|   |   |   |   |   |   |   |   |   |--- weights: [6.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- savings_balance >  2.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |--- purpose_education >  0.50
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |--- age >  38.50
|   |   |   |   |   |--- weights: [9.00, 0.00] class: 0
|   |   |--- purpose_business >  0.50
|   |   |   |--- employment_duration <= 4.00
|   |   |   |   |--- years_at_residence <= 1.50
|   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |--- years_at_residence >  1.50
|   |   |   |   |   |--- weights: [0.00, 6.00] class: 1
|   |   |   |--- employment_duration >  4.00
|   |   |   |   |--- weights: [2.00, 0.00] class: 0
```

```
|   |--- other_credit_none >  0.50
|   |   |--- credit_history <= 1.50
|   |   |   |--- amount <= 11867.00
|   |   |   |   |--- weights: [92.00, 0.00] class: 0
|   |   |   |--- amount >  11867.00
|   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |--- credit_history >  1.50
|   |   |   |--- amount <= 4367.50
|   |   |   |   |--- age <= 19.50
|   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |--- age >  19.50
|   |   |   |   |   |--- purpose_renovations <= 0.50
|   |   |   |   |   |   |--- amount <= 475.50
|   |   |   |   |   |   |   |--- housing_rent <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- housing_rent >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |--- amount >  475.50
|   |   |   |   |   |   |   |--- job_unskilled <= 0.50
|   |   |   |   |   |   |   |   |--- months_loan_duration <= 25.50
|   |   |   |   |   |   |   |   |   |--- amount <= 3599.00
|   |   |   |   |   |   |   |   |   |   |--- purpose_business <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [68.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- purpose_business >  0.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |--- amount >  3599.00
|   |   |   |   |   |   |   |   |   |   |--- amount <= 3689.00
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |   |   |--- amount >  3689.00
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [3.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- months_loan_duration >  25.50
|   |   |   |   |   |   |   |   |   |--- housing_rent <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- job_management <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [6.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- job_management >  0.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |   |--- housing_rent >  0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |--- job_unskilled >  0.50
|   |   |   |   |   |   |   |   |--- percent_of_income <= 3.50
|   |   |   |   |   |   |   |   |   |--- weights: [10.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- percent_of_income >  3.50
|   |   |   |   |   |   |   |   |   |--- amount <= 1030.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [3.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |--- amount >  1030.00
|   |   |   |   |   |   |   |   |   |   |--- employment_duration <= 4.00
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |   |   |   |   |   |   |--- employment_duration >  4.00
```

```
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |--- purpose_renovations >  0.50
|   |   |   |   |   |   |--- savings_balance <= 3.50
|   |   |   |   |   |   |   |--- employment_duration <= 2.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |--- employment_duration >  2.50
|   |   |   |   |   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |   |   |   |--- savings_balance >  3.50
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |--- amount >  4367.50
|   |   |   |   |--- amount <= 4640.00
|   |   |   |   |   |--- weights: [0.00, 4.00] class: 1
|   |   |   |   |--- amount >  4640.00
|   |   |   |   |   |--- employment_duration <= 2.50
|   |   |   |   |   |   |--- purpose_car <= 0.50
|   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |   |   |--- purpose_car >  0.50
|   |   |   |   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |   |   |--- employment_duration >  2.50
|   |   |   |   |   |   |--- age <= 58.00
|   |   |   |   |   |   |   |--- weights: [14.00, 0.00] class: 0
|   |   |   |   |   |   |--- age >  58.00
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|--- checking_balance >  0.00
|   |--- months_loan_duration <= 22.50
|   |   |--- credit_history <= 3.50
|   |   |   |--- credit_history <= 2.50
|   |   |   |   |--- percent_of_income <= 2.50
|   |   |   |   |   |--- months_loan_duration <= 20.50
|   |   |   |   |   |   |--- weights: [29.00, 0.00] class: 0
|   |   |   |   |   |--- months_loan_duration >  20.50
|   |   |   |   |   |   |--- purpose_education <= 0.50
|   |   |   |   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |   |   |   |--- purpose_education >  0.50
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |--- percent_of_income >  2.50
|   |   |   |   |   |--- purpose_car <= 0.50
|   |   |   |   |   |   |--- amount <= 3521.00
|   |   |   |   |   |   |   |--- weights: [17.00, 0.00] class: 0
|   |   |   |   |   |   |--- amount >  3521.00
|   |   |   |   |   |   |   |--- employment_duration <= 3.00
|   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- employment_duration >  3.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |--- purpose_car >  0.50
|   |   |   |   |   |   |--- age <= 48.00
|   |   |   |   |   |   |   |--- amount <= 2115.00
|   |   |   |   |   |   |   |   |--- amount <= 1265.50
```

```
|   |   |   |   |   |   |   |   |   |--- amount <= 650.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |--- amount >  650.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 5.00] class: 1
|   |   |   |   |   |   |   |   |--- amount >  1265.50
|   |   |   |   |   |   |   |   |   |--- weights: [4.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- amount >  2115.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |   |   |--- age >  48.00
|   |   |   |   |   |   |   |--- weights: [5.00, 0.00] class: 0
|   |   |   |--- credit_history >  2.50
|   |   |   |   |--- amount <= 7491.50
|   |   |   |   |   |--- amount <= 1373.00
|   |   |   |   |   |   |--- phone <= 1.50
|   |   |   |   |   |   |   |--- purpose_furniture/appliances <= 0.50
|   |   |   |   |   |   |   |   |--- savings_balance <= 1.50
|   |   |   |   |   |   |   |   |   |--- age <= 53.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 15.00] class: 1
|   |   |   |   |   |   |   |   |   |--- age >  53.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- savings_balance >  1.50
|   |   |   |   |   |   |   |   |   |--- employment_duration <= 4.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [4.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |--- employment_duration >  4.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |--- purpose_furniture/appliances >  0.50
|   |   |   |   |   |   |   |   |--- age <= 22.50
|   |   |   |   |   |   |   |   |   |--- savings_balance <= 3.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 4.00] class: 1
|   |   |   |   |   |   |   |   |   |--- savings_balance >  3.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- age >  22.50
|   |   |   |   |   |   |   |   |   |--- amount <= 708.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [7.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |--- amount >  708.50
|   |   |   |   |   |   |   |   |   |   |--- employment_duration <= 3.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |   |   |   |--- employment_duration >  3.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |--- phone >  1.50
|   |   |   |   |   |   |   |--- months_loan_duration <= 15.00
|   |   |   |   |   |   |   |   |--- weights: [9.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- months_loan_duration >  15.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |--- amount >  1373.00
|   |   |   |   |   |   |--- existing_loans_count <= 1.50
|   |   |   |   |   |   |   |--- age <= 27.50
|   |   |   |   |   |   |   |   |--- amount <= 2770.50
```

```
|   |   |   |   |   |   |   |   |   |--- percent_of_income <= 1.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |   |   |   |   |   |--- percent_of_income >  1.50
|   |   |   |   |   |   |   |   |   |   |--- amount <= 2425.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |   |--- amount >  2425.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 2.00] class: 1
|   |   |   |   |   |   |   |   |--- amount >  2770.50
|   |   |   |   |   |   |   |   |   |--- weights: [6.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- age >  27.50
|   |   |   |   |   |   |   |   |--- years_at_residence <= 2.50
|   |   |   |   |   |   |   |   |   |--- dependents <= 1.50
|   |   |   |   |   |   |   |   |   |   |--- months_loan_duration <= 14.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [13.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- months_loan_duration >  14.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |--- dependents >  1.50
|   |   |   |   |   |   |   |   |   |   |--- amount <= 3406.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 2.00] class: 1
|   |   |   |   |   |   |   |   |   |   |--- amount >  3406.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- years_at_residence >  2.50
|   |   |   |   |   |   |   |   |   |--- weights: [24.00, 0.00] class: 0
|   |   |   |   |   |   |--- existing_loans_count >  1.50
|   |   |   |   |   |   |   |--- percent_of_income <= 3.00
|   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- percent_of_income >  3.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |--- amount >  7491.50
|   |   |   |   |   |--- weights: [0.00, 4.00] class: 1
|   |   |--- credit_history >  3.50
|   |   |   |--- amount <= 517.50
|   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |--- amount >  517.50
|   |   |   |   |--- years_at_residence <= 3.50
|   |   |   |   |   |--- purpose_education <= 0.50
|   |   |   |   |   |   |--- weights: [0.00, 14.00] class: 1
|   |   |   |   |   |--- purpose_education >  0.50
|   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |--- years_at_residence >  3.50
|   |   |   |   |   |--- checking_balance <= 1.50
|   |   |   |   |   |   |--- phone <= 1.50
|   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |   |   |--- phone >  1.50
|   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |--- checking_balance >  1.50
|   |   |   |   |   |   |--- weights: [3.00, 0.00] class: 0
|   |--- months_loan_duration >  22.50
```

```
|   |   |--- savings_balance <= 0.00
|   |   |   |--- checking_balance <= 1.50
|   |   |   |   |--- dependents <= 1.50
|   |   |   |   |   |--- percent_of_income <= 2.50
|   |   |   |   |   |   |--- age <= 23.00
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |--- age >  23.00
|   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |--- percent_of_income >  2.50
|   |   |   |   |   |   |--- weights: [0.00, 6.00] class: 1
|   |   |   |   |--- dependents >  1.50
|   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |--- checking_balance >  1.50
|   |   |   |   |--- amount <= 1529.50
|   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |--- amount >  1529.50
|   |   |   |   |   |--- amount <= 12296.50
|   |   |   |   |   |   |--- weights: [18.00, 0.00] class: 0
|   |   |   |   |   |--- amount >  12296.50
|   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |--- savings_balance >  0.00
|   |   |   |--- months_loan_duration <= 47.50
|   |   |   |   |--- amount <= 11025.00
|   |   |   |   |   |--- amount <= 2249.00
|   |   |   |   |   |   |--- savings_balance <= 2.50
|   |   |   |   |   |   |   |--- employment_duration <= 4.50
|   |   |   |   |   |   |   |   |--- years_at_residence <= 1.50
|   |   |   |   |   |   |   |   |   |--- age <= 23.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |   |--- age >  23.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- years_at_residence >  1.50
|   |   |   |   |   |   |   |   |   |--- savings_balance <= 1.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 16.00] class: 1
|   |   |   |   |   |   |   |   |   |--- savings_balance >  1.50
|   |   |   |   |   |   |   |   |   |   |--- employment_duration <= 3.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |   |   |   |   |   |   |--- employment_duration >  3.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- employment_duration >  4.50
|   |   |   |   |   |   |   |   |--- months_loan_duration <= 27.00
|   |   |   |   |   |   |   |   |   |--- purpose_business <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [4.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |--- purpose_business >  0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |--- months_loan_duration >  27.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |   |   |--- savings_balance >  2.50
```

```
|   |   |   |   |   |   |   |--- weights: [3.00, 0.00] class: 0
|   |   |   |   |   |--- amount >  2249.00
|   |   |   |   |   |   |--- checking_balance <= 2.50
|   |   |   |   |   |   |   |--- percent_of_income <= 2.50
|   |   |   |   |   |   |   |   |--- dependents <= 1.50
|   |   |   |   |   |   |   |   |   |--- years_at_residence <= 3.50
|   |   |   |   |   |   |   |   |   |   |--- credit_history <= 1.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |   |   |--- credit_history >  1.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |   |   |--- years_at_residence >  3.50
|   |   |   |   |   |   |   |   |   |   |--- months_loan_duration <= 25.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [3.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- months_loan_duration >  25.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |--- dependents >  1.50
|   |   |   |   |   |   |   |   |   |--- weights: [6.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- percent_of_income >  2.50
|   |   |   |   |   |   |   |   |--- age <= 55.00
|   |   |   |   |   |   |   |   |   |--- housing_rent <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- amount <= 4832.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 6
|   |   |   |   |   |   |   |   |   |   |--- amount >  4832.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 6.00] class: 1
|   |   |   |   |   |   |   |   |   |--- housing_rent >  0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 8.00] class: 1
|   |   |   |   |   |   |   |   |--- age >  55.00
|   |   |   |   |   |   |   |   |   |--- weights: [4.00, 0.00] class: 0
|   |   |   |   |   |   |--- checking_balance >  2.50
|   |   |   |   |   |   |   |--- amount <= 4341.50
|   |   |   |   |   |   |   |   |--- amount <= 4061.50
|   |   |   |   |   |   |   |   |   |--- weights: [4.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- amount >  4061.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |--- amount >  4341.50
|   |   |   |   |   |   |   |   |--- weights: [5.00, 0.00] class: 0
|   |   |   |   |--- amount >  11025.00
|   |   |   |   |   |--- weights: [0.00, 7.00] class: 1
|   |   |   |--- months_loan_duration >  47.50
|   |   |   |   |--- years_at_residence <= 1.50
|   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |--- years_at_residence >  1.50
|   |   |   |   |   |--- employment_duration <= 1.50
|   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |--- employment_duration >  1.50
|   |   |   |   |   |   |--- amount <= 3748.50
|   |   |   |   |   |   |   |--- purpose_business <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 2.00] class: 1
```

```
|   |   |   |   |   |   |   |--- purpose_business >  0.50
|   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |--- amount >  3748.50
|   |   |   |   |   |   |   |--- weights: [0.00, 21.00] class: 1
```

[23]:

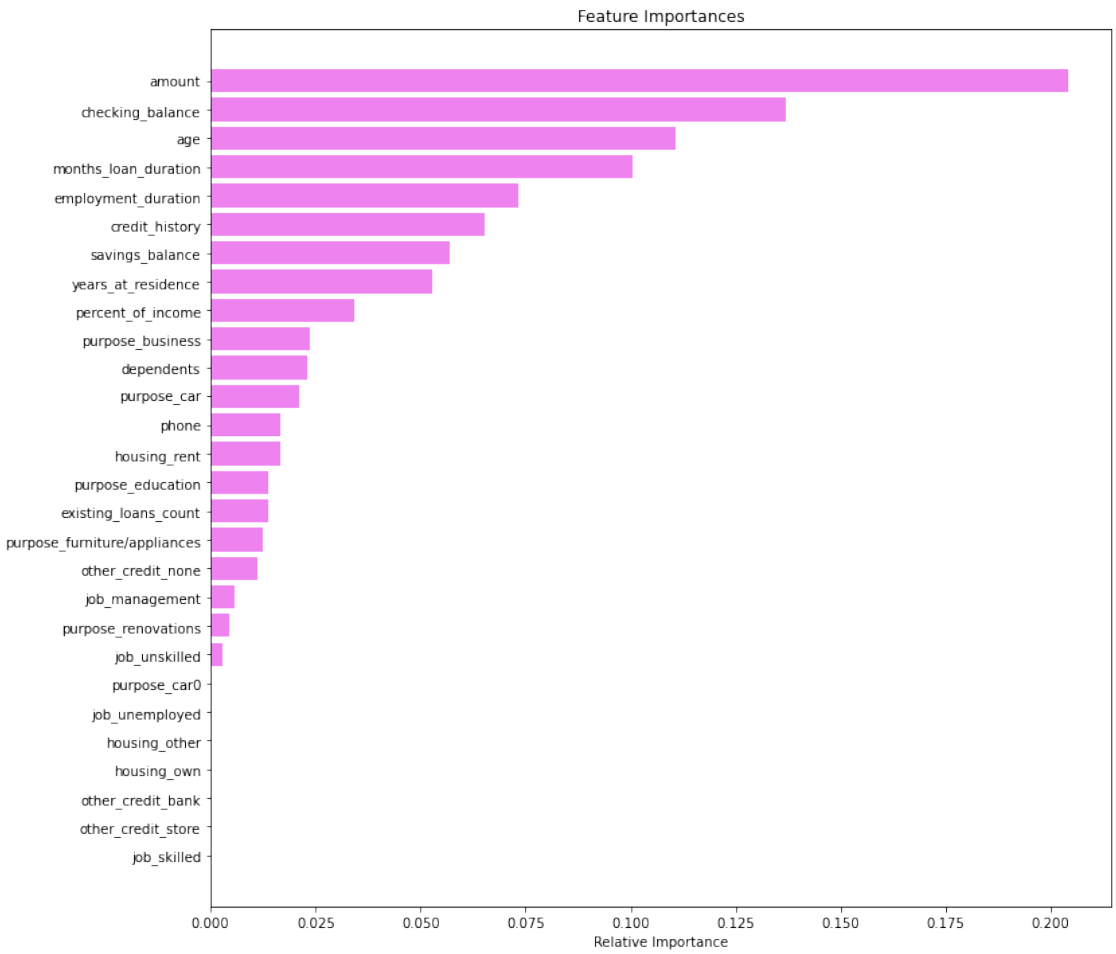
```
# importance of features in the tree building ( The importance of a feature is␣
↪computed as the
#(normalized) total reduction of the criterion brought by that feature. It is␣
↪also known as the Gini importance )

print (pd.DataFrame(dTree.feature_importances_, columns = ["Imp"], index =␣
↪X_train.columns).sort_values(by = 'Imp', ascending = False))
```

```
                                   Imp
amount                        0.204163
checking_balance              0.136840
age                           0.110746
months_loan_duration          0.100323
employment_duration           0.073225
credit_history                0.065357
savings_balance               0.057059
years_at_residence            0.052719
percent_of_income             0.034128
purpose_business              0.023784
dependents                    0.023062
purpose_car                   0.021217
phone                         0.016737
housing_rent                  0.016646
purpose_education             0.013767
existing_loans_count          0.013575
purpose_furniture/appliances  0.012421
other_credit_none             0.011156
job_management                0.005769
purpose_renovations           0.004489
job_unskilled                 0.002818
other_credit_bank             0.000000
housing_own                   0.000000
other_credit_store            0.000000
housing_other                 0.000000
job_skilled                   0.000000
job_unemployed                0.000000
purpose_car0                  0.000000
```

[24]:

```
importances = dTree.feature_importances_
indices = np.argsort(importances)
```

```
plt.figure(figsize=(12,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='violet',␣
 ↪align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



- According to the decision tree model, Amount is the most important variable for predicting the customer default.
- The Tree above is very complex, such a tree often overfits

Reducing over fitting

- In general, the deeper you allow your tree to grow, the more complex your model will become because you will have more splits and it captures more information about the data and this is one of the root causes of overfitting
- Let's try Limiting the max_depth of tree to 3

[25]:
```
dTree1 = DecisionTreeClassifier(criterion = 'gini',max_depth=3,random_state=1)
dTree1.fit(X_train, y_train)
```

[25]:
```
DecisionTreeClassifier(max_depth=3, random_state=1)
```

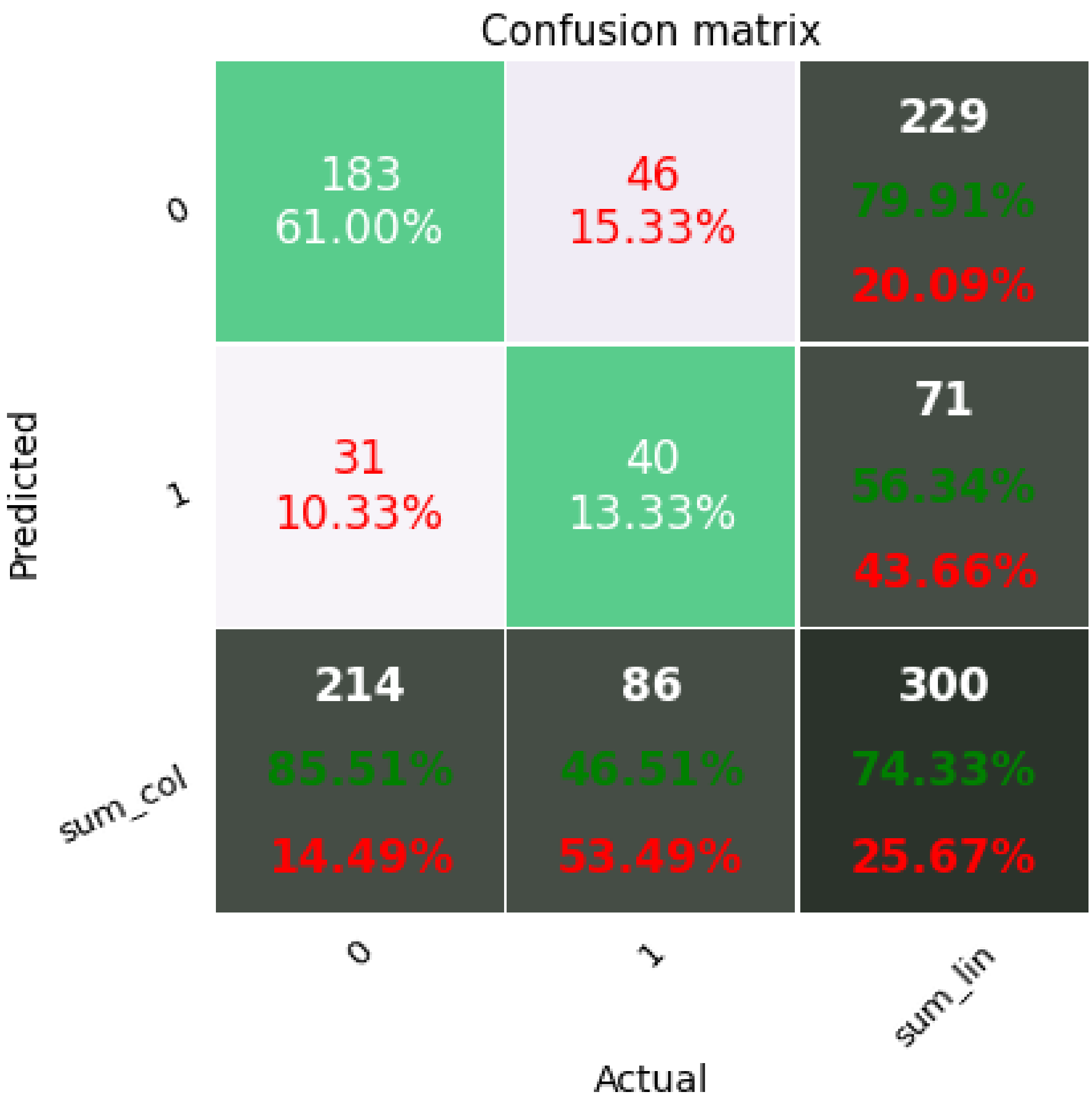
Confusing Matrix: Decision Tree with depth is restricted to 3

[26]:
```
y_pred = dTree1.predict(X_test)
# con_res = confusion_matrix(y_test,y_pred, labels=[0, 1])
con_res = metrics.confusion_matrix(y_test,y_pred, labels=[0, 1])

print("Confusion matrix:")
print(confusion_matrix(y_test,y_pred))
print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred)*100))
```

```
Confusion matrix:
[[183  31]
 [ 46  40]]
Accuracy: 74.33%
```

[27]:
```
%run -i '/home/jayanthikishore/Desktop/Analysis/Work/ML_EIT/
 ↪confusion_matrix_different_ways1.py'
df_confmatrx = pd.DataFrame(con_res, range(2),range(2))
df_confmatrx
cmap = 'PuRd'
confusion_matrix_dfrntway(df_confmatrx, cmap=cmap,fz=17)
```

```
<Figure size 432x288 with 0 Axes>
```



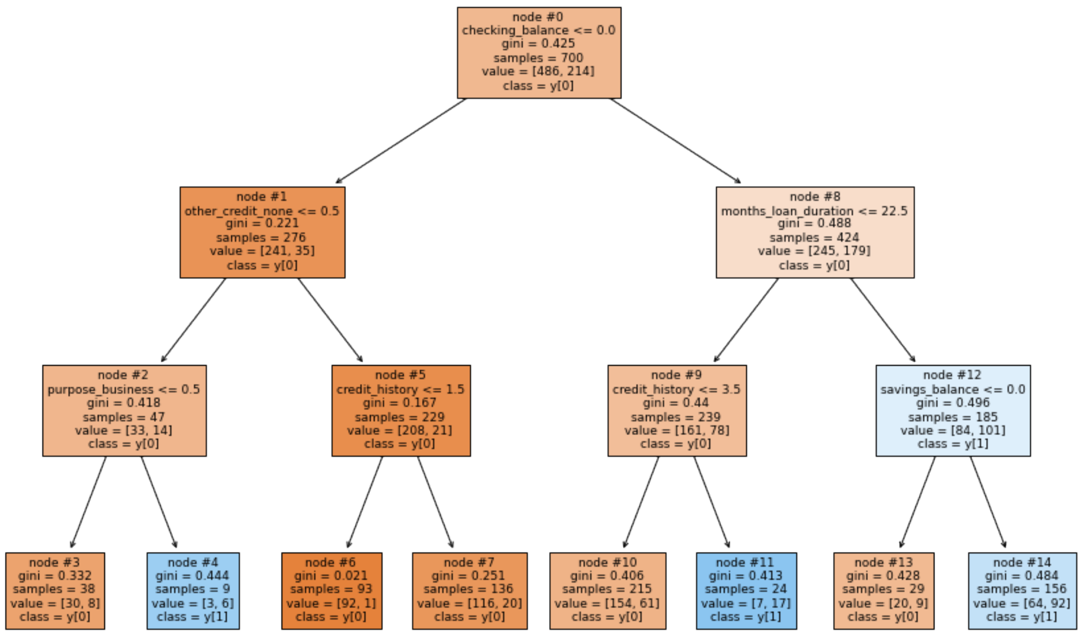
[28]:
```
# Accuracy on train and test
print("Accuracy on training set : ",dTree1.score(X_train, y_train))
print("Accuracy on test set : ",dTree1.score(X_test, y_test))
# Recall on train and test
get_recall_score(dTree1)
```

```
Accuracy on training set :  0.7528571428571429
Accuracy on test set :  0.7433333333333333
Recall on training set :  0.5373831775700935
Recall on test set :  0.46511627906976744
```

- Recall on training set has reduced from 1 to 0.53 but this is an improvement because now the model is not overfitting and we have a generalized model.

Visualizing the Decision Tree with depth is restricted to 3

[29]:
```
plt.figure(figsize=(15,10))

tree.
 ↪plot_tree(dTree1,feature_names=feature_names,filled=True,fontsize=9,node_ids=True,class_nam
plt.show()
```



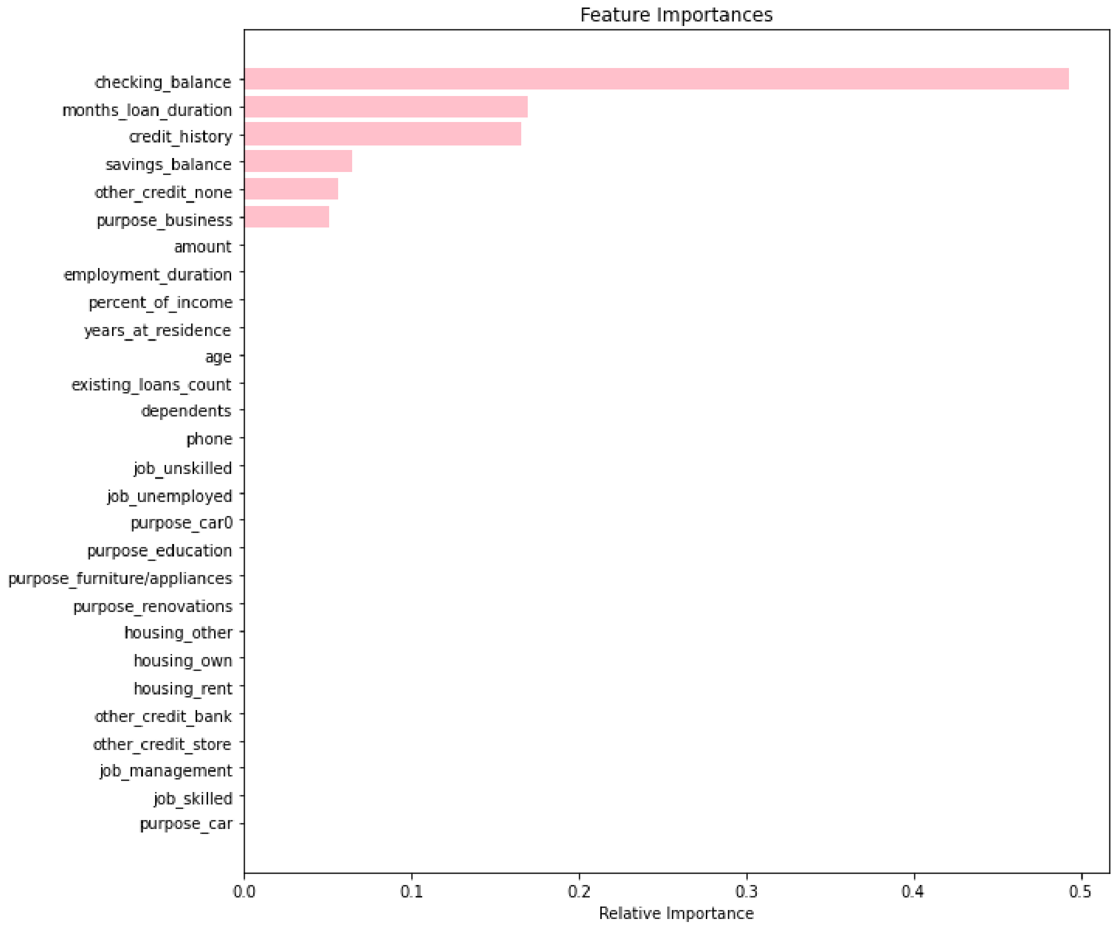
[30]:
```
# importance of features in the tree building ( The importance of a feature is␣
 ↪computed as the
#(normalized) total reduction of the criterion brought by that feature. It is␣
 ↪also known as the Gini importance )

print (pd.DataFrame(dTree1.feature_importances_, columns = ["Imp"], index =␣
 ↪X_train.columns).sort_values(by = 'Imp', ascending = False))
```

```
                                 Imp
checking_balance            0.492510
months_loan_duration        0.169806
credit_history              0.166109
savings_balance             0.064467
other_credit_none           0.055977
purpose_business            0.051129
purpose_furniture/appliances  0.000000
```

```
job_unemployed              0.000000
job_skilled                 0.000000
job_management              0.000000
other_credit_store          0.000000
other_credit_bank           0.000000
housing_rent                0.000000
housing_own                 0.000000
housing_other               0.000000
purpose_renovations         0.000000
purpose_car0                0.000000
purpose_education           0.000000
purpose_car                 0.000000
phone                       0.000000
dependents                  0.000000
existing_loans_count        0.000000
age                         0.000000
years_at_residence          0.000000
percent_of_income           0.000000
employment_duration         0.000000
amount                      0.000000
job_unskilled               0.000000
```

[31]:

```
importances = dTree1.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(10,10))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='pink',␣
 ↪align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



- You can see in important features of previous model, amount was on top, but here importance of amount variable is zero this is the shortcoming of pre pruning, we just limit it even before knowing the importance of features and split.
- That's why we will go for pre pruning using grid search, maybe setting max_depth to 3 is not good enough
- It is bad to have a very low depth because your model will underfit
- Let's see how to find the best values

Using GridSearch for Hyperparameter tuning of our tree model

- Grid search is a tuning technique that attempts to compute the optimum values of hyperparameters.

[32]:
```
from sklearn.model_selection import GridSearchCV
```

[33]:
```
# Choose the type of classifier.
estimator = DecisionTreeClassifier(random_state=1)
```

```
# Grid of parameters to choose from
## add from article
parameters = {'max_depth': np.arange(1,10),
              'min_samples_leaf': [1, 2, 5, 7, 10,15,20],
              'max_leaf_nodes' : [2, 3, 5, 10],
              'min_impurity_decrease': [0.001,0.01,0.1]
             }

# Type of scoring used to compare parameter combinations
acc_scorer = metrics.make_scorer(metrics.recall_score)

# Run the grid search
grid_obj = GridSearchCV(estimator, parameters, scoring=acc_scorer,cv=5)
grid_obj = grid_obj.fit(X_train, y_train)

# Set the clf to the best combination of parameters
estimator = grid_obj.best_estimator_

# Fit the best algorithm to the data.
estimator.fit(X_train, y_train)
```

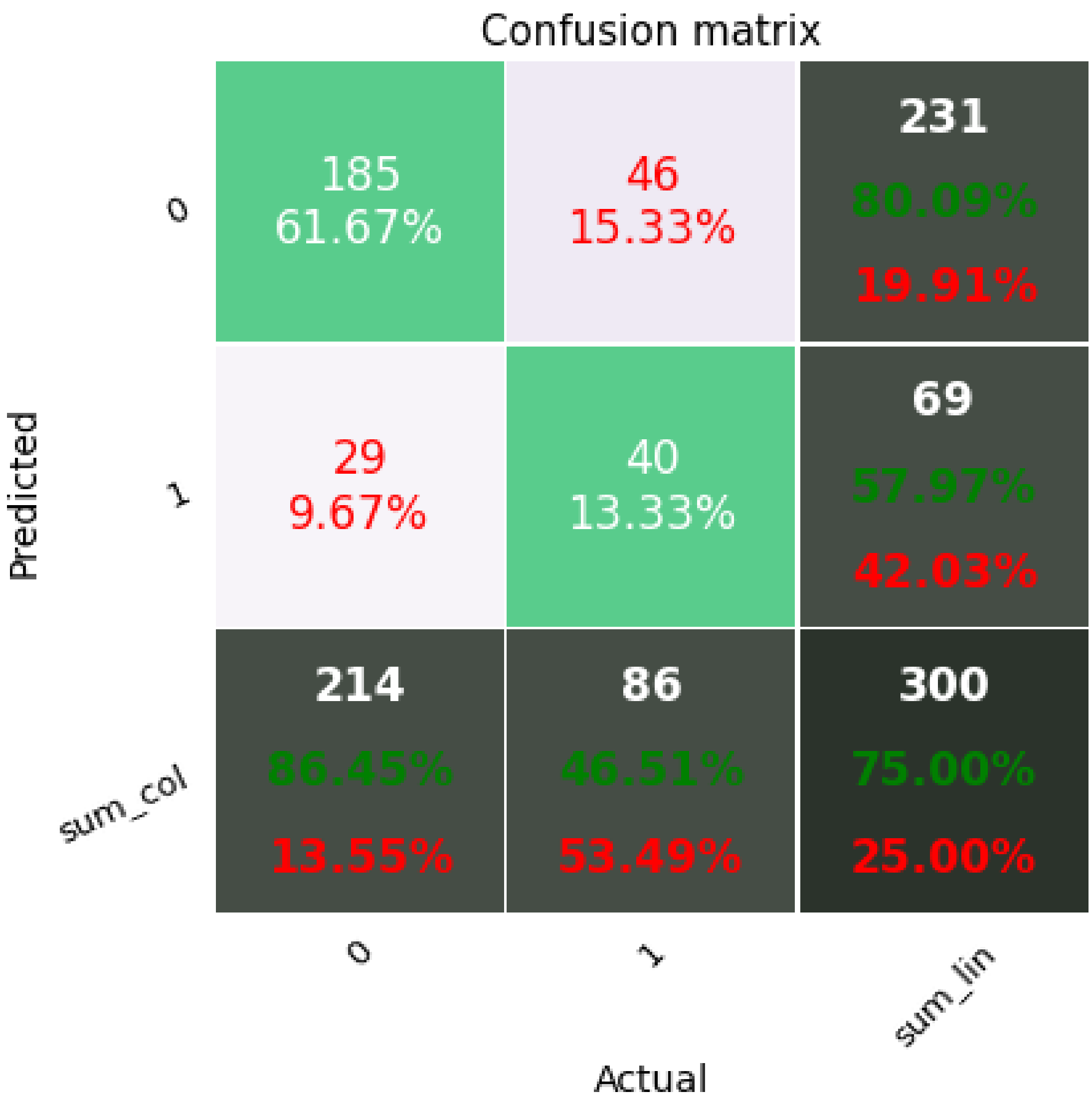
[33]:
```
DecisionTreeClassifier(max_depth=4, max_leaf_nodes=10,
                       min_impurity_decrease=0.001, min_samples_leaf=20,
                       random_state=1)
```

[38]:
```
y_pred = estimator.predict(X_test)
# con_res = confusion_matrix(y_test,y_pred, labels=[0, 1])
con_res = metrics.confusion_matrix(y_test,y_pred, labels=[0, 1])

print("Confusion matrix:")
print(confusion_matrix(y_test,y_pred))
print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred)*100))
```

```
Confusion matrix:
[[185  29]
 [ 46  40]]
Accuracy: 75.00%
```

[39]:
```
%run -i '/home/jayanthikishore/Desktop/Analysis/Work/ML_EIT/
 ↪confusion_matrix_different_ways1.py'
df_confmatrx = pd.DataFrame(con_res, range(2),range(2))
df_confmatrx
cmap = 'PuRd'
confusion_matrix_dfrntway(df_confmatrx, cmap=cmap,fz=17)
```

```
<Figure size 432x288 with 0 Axes>
```



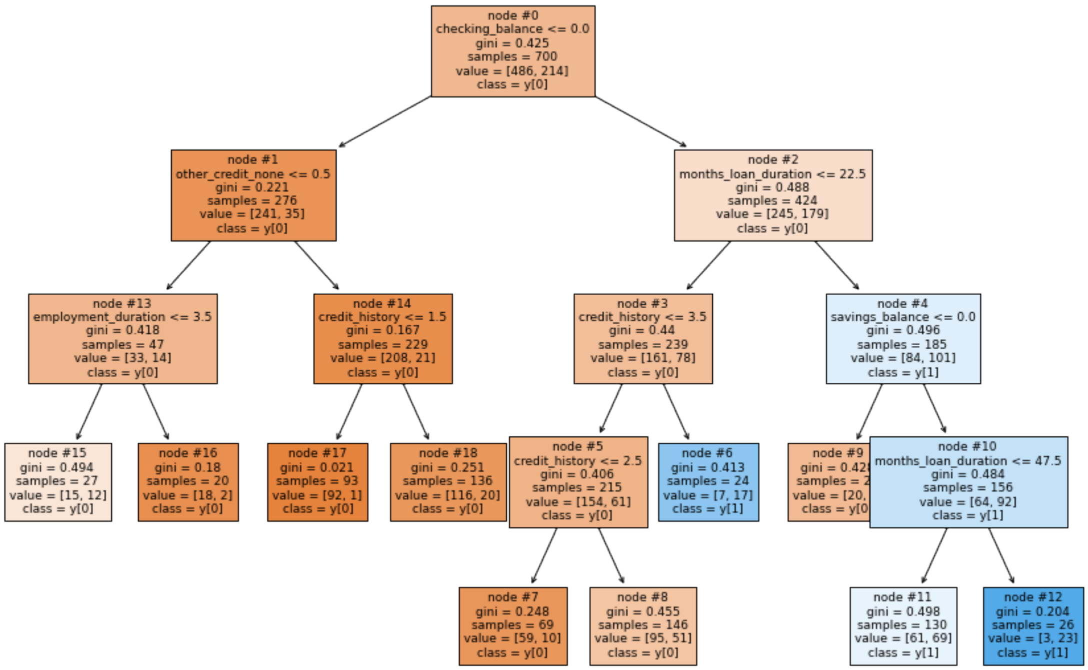
[40]:
```
# Accuracy on train and test
print("Accuracy on training set : ",estimator.score(X_train, y_train))
print("Accuracy on test set : ",estimator.score(X_test, y_test))
# Recall on train and test
get_recall_score(estimator)
```

```
Accuracy on training set :  0.7485714285714286
Accuracy on test set :  0.75
Recall on training set :  0.5093457943925234
Recall on test set :  0.46511627906976744
```

- Recall has improved for both train and test set after hyperparameter tuning.

Visualizing the Hyper parameter tuned Decision Tree

[41]:
```
plt.figure(figsize=(15,10))

tree.
↪plot_tree(estimator,feature_names=feature_names,filled=True,fontsize=9,node_ids=True,class_
plt.show()
```



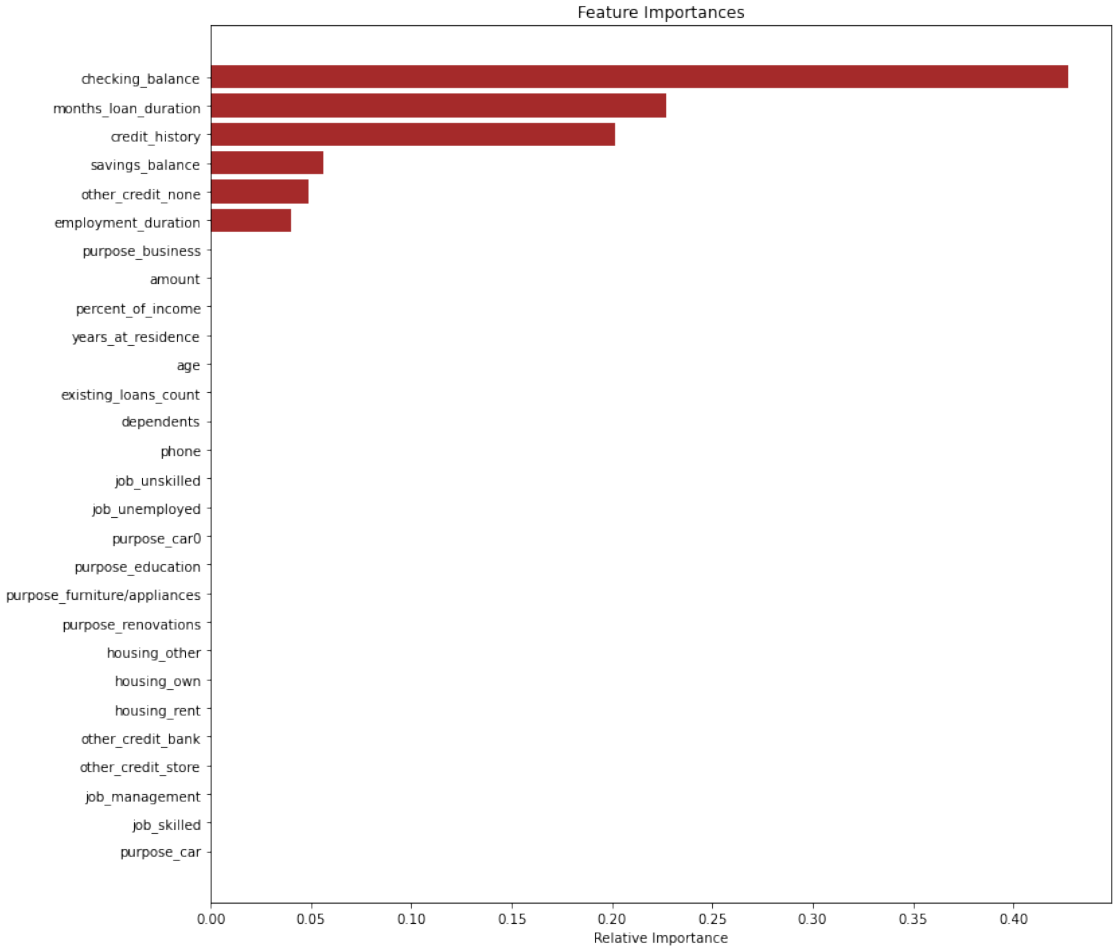
[42]:
```
# importance of features in the tree building ( The importance of a feature is␣
↪computed as the
#(normalized) total reduction of the 'criterion' brought by that feature. It is␣
↪also known as the Gini importance )

print (pd.DataFrame(estimator.feature_importances_, columns = ["Imp"], index =␣
↪X_train.columns).sort_values(by = 'Imp', ascending = False))

#Here we will see that importance of features has increased
```

```
                                  Imp
checking_balance             0.427296
months_loan_duration         0.226805
credit_history               0.201464
savings_balance              0.055931
other_credit_none            0.048565
employment_duration          0.039938
purpose_furniture/appliances 0.000000
```

```
job_unemployed                0.000000
job_skilled                   0.000000
job_management                0.000000
other_credit_store            0.000000
other_credit_bank             0.000000
housing_rent                  0.000000
housing_own                   0.000000
housing_other                 0.000000
purpose_renovations           0.000000
purpose_car0                  0.000000
purpose_education             0.000000
purpose_car                   0.000000
purpose_business              0.000000
phone                         0.000000
dependents                    0.000000
existing_loans_count          0.000000
age                           0.000000
years_at_residence            0.000000
percent_of_income             0.000000
amount                        0.000000
job_unskilled                 0.000000
```

[43]:

```
importances = estimator.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(12,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='brown',␣
 ↪align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



Cost Complexity Pruning

- The `DecisionTreeClassifier` provides parameters such as `min_samples_leaf` and `max_depth` to prevent a tree from overfiting.
- Cost complexity pruning provides another option to control the size of a tree. *In `DecisionTreeClassifier`, this pruning technique is parameterized by the cost complexity parameter, `ccp_alpha`.
- Greater values of `ccp_alpha` increase the number of nodes pruned.
- Here we only show the effect of `ccp_alpha` on regularizing the trees and how to choose a `ccp_alpha` based on validation scores.

0.4 Total impurity of leaves vs effective alphas of pruned tree

Minimal cost complexity pruning recursively finds the node with the "weakest link". The weakest link is characterized by an effective alpha, where the nodes with the smallest effective alpha are pruned first. To get an idea of what values of `ccp_alpha` could be appropriate, scikit-learn provides `DecisionTreeClassifier.cost_complexity_pruning_path` that returns the effective alphas and the corresponding total leaf impurities at each step of the pruning process. As alpha increases, more of the tree is pruned, which increases the total impurity of its leaves.

https://online.stat.psu.edu/stat508/lesson/11/11.8/11.8.2

[44]:
```
clf = DecisionTreeClassifier(random_state=1)
path = clf.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas, impurities = path.ccp_alphas, path.impurities
```

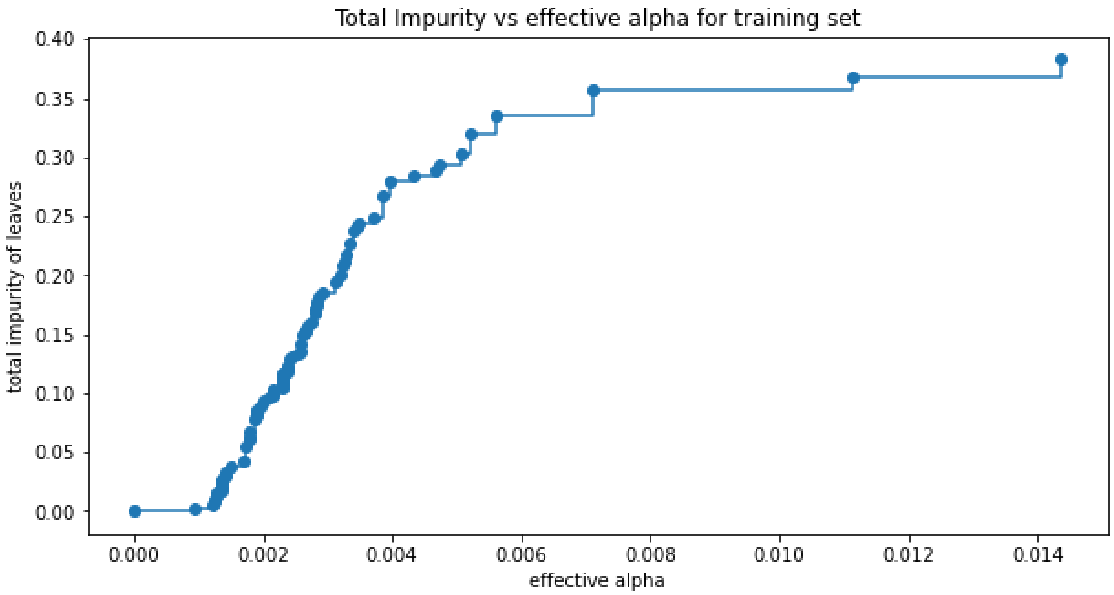
[45]:
```
pd.DataFrame(path)
```

[45]:

	ccp_alphas	impurities
0	0.000000	0.000000
1	0.000940	0.002819
2	0.001224	0.005268
3	0.001250	0.007768
4	0.001250	0.010268
..	…	…
73	0.005618	0.335998
74	0.007117	0.357350
75	0.011122	0.368471
76	0.014366	0.382838
77	0.041668	0.424506

[78 rows x 2 columns]

[46]:
```
fig, ax = plt.subplots(figsize=(10,5))
ax.plot(ccp_alphas[:-1], impurities[:-1], marker='o', drawstyle="steps-post")
ax.set_xlabel("effective alpha")
ax.set_ylabel("total impurity of leaves")
ax.set_title("Total Impurity vs effective alpha for training set")
plt.show()
```

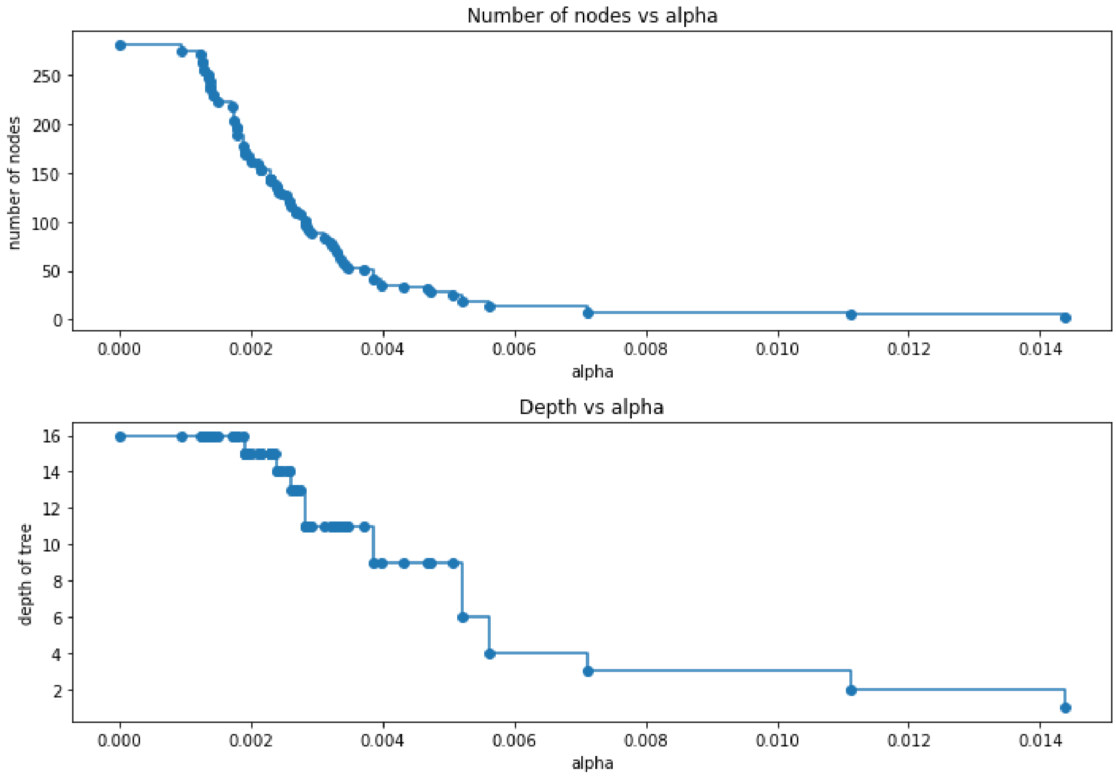


- Next, we train a decision tree using the effective alphas. The last value in `ccp_alphas` is the alpha value that prunes the whole tree, leaving the tree, `clfs[-1]`, with one node.

[47]:
```
clfs = []
for ccp_alpha in ccp_alphas:
    clf = DecisionTreeClassifier(random_state=1, ccp_alpha=ccp_alpha)
    clf.fit(X_train, y_train)
    clfs.append(clf)
print("Number of nodes in the last tree is: {} with ccp_alpha: {}".format(
      clfs[-1].tree_.node_count, ccp_alphas[-1]))
```

```
Number of nodes in the last tree is: 1 with ccp_alpha: 0.041668413944741134
```

[48]:
```
clfs = clfs[:-1]
ccp_alphas = ccp_alphas[:-1]

node_counts = [clf.tree_.node_count for clf in clfs]
depth = [clf.tree_.max_depth for clf in clfs]
fig, ax = plt.subplots(2, 1,figsize=(10,7))
ax[0].plot(ccp_alphas, node_counts, marker='o', drawstyle="steps-post")
ax[0].set_xlabel("alpha")
ax[0].set_ylabel("number of nodes")
ax[0].set_title("Number of nodes vs alpha")
ax[1].plot(ccp_alphas, depth, marker='o', drawstyle="steps-post")
ax[1].set_xlabel("alpha")
ax[1].set_ylabel("depth of tree")
ax[1].set_title("Depth vs alpha")
fig.tight_layout()
```

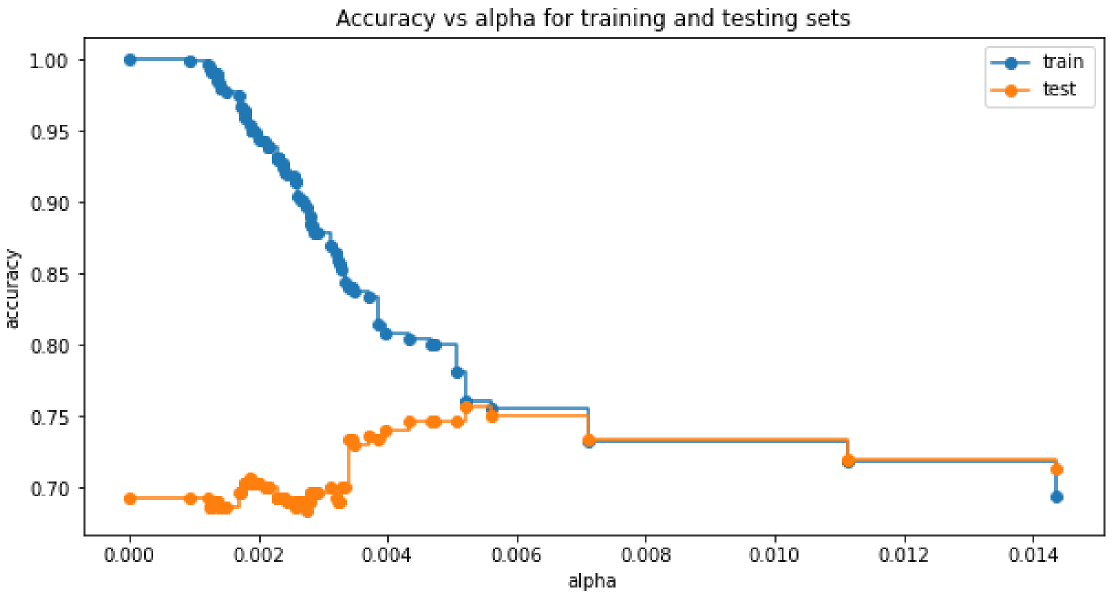


0.5 Accuracy vs alpha for training and testing sets

When `ccp_alpha` is set to zero and keeping the other default parameters of `DecisionTreeClassifier`, the tree overfits, leading to a 100% training accuracy and 69% testing accuracy. As alpha increases, more of the tree is pruned, thus creating a decision tree that generalizes better.

[50]:
```
train_scores = [clf.score(X_train, y_train) for clf in clfs]
test_scores = [clf.score(X_test, y_test) for clf in clfs]
```

[51]:
```
fig, ax = plt.subplots(figsize=(10,5))
ax.set_xlabel("alpha")
ax.set_ylabel("accuracy")
ax.set_title("Accuracy vs alpha for training and testing sets")
ax.plot(ccp_alphas, train_scores, marker='o', label="train",
        drawstyle="steps-post")
ax.plot(ccp_alphas, test_scores, marker='o', label="test",
        drawstyle="steps-post")
ax.legend()
plt.show()
```



[52]:
```
index_best_model = np.argmax(test_scores)
best_model = clfs[index_best_model]
print(best_model)
print('Training accuracy of best model: ',best_model.score(X_train, y_train))
print('Test accuracy of best model: ',best_model.score(X_test, y_test))
```

```
DecisionTreeClassifier(ccp_alpha=0.005203486535576088, random_state=1)
Training accuracy of best model:  0.7614285714285715
Test accuracy of best model:  0.7566666666666667
```

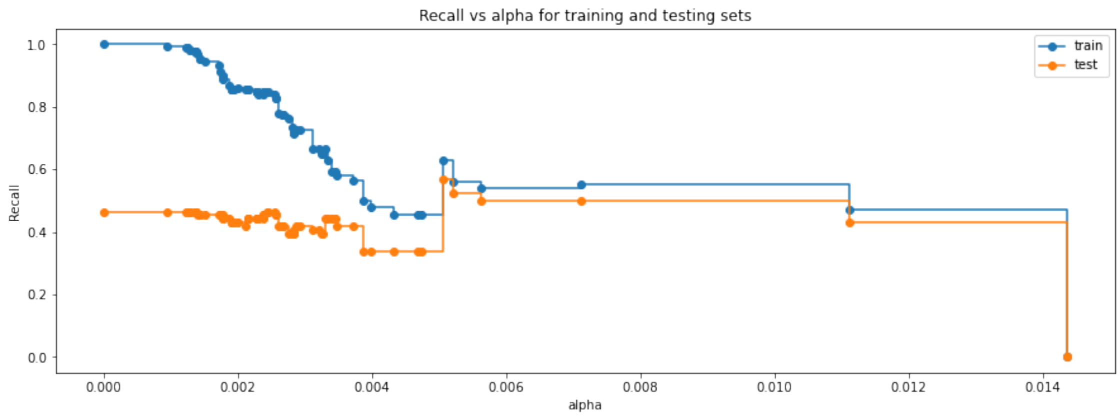
Since accuracy isn't the right metric for our data we would want high recall

[53]:
```
recall_train=[]
for clf in clfs:
    pred_train3=clf.predict(X_train)
    values_train=metrics.recall_score(y_train,pred_train3)
    recall_train.append(values_train)
```

[54]:
```
recall_test=[]
for clf in clfs:
    pred_test3=clf.predict(X_test)
    values_test=metrics.recall_score(y_test,pred_test3)
    recall_test.append(values_test)
```

[55]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax.set_xlabel("alpha")
ax.set_ylabel("Recall")
```

```
ax.set_title("Recall vs alpha for training and testing sets")
ax.plot(ccp_alphas, recall_train, marker='o', label="train",
        drawstyle="steps-post")
ax.plot(ccp_alphas, recall_test, marker='o', label="test",
        drawstyle="steps-post")
ax.legend()
plt.show()
```



[56]:
```
# creating the model where we get highest train and test recall
index_best_model = np.argmax(recall_test)
best_model = clfs[index_best_model]
print(best_model)
```

```
DecisionTreeClassifier(ccp_alpha=0.0050611694980498625, random_state=1)
```

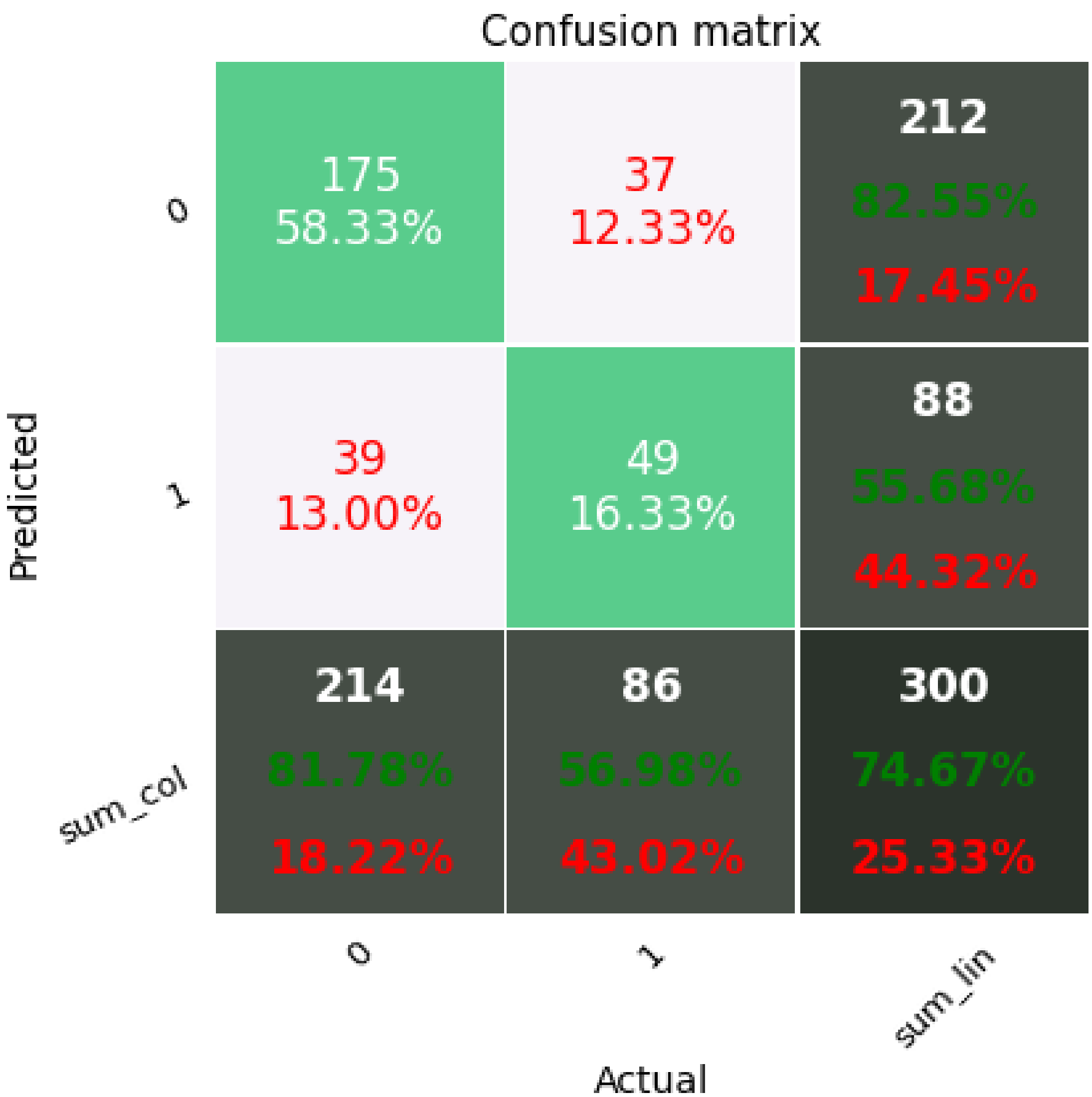
[57]:
```
y_pred = best_model.predict(X_test)
# con_res = confusion_matrix(y_test,y_pred, labels=[0, 1])
con_res = metrics.confusion_matrix(y_test,y_pred, labels=[0, 1])

print("Confusion matrix:")
print(confusion_matrix(y_test,y_pred))
print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred)*100))
```

```
Confusion matrix:
[[175  39]
 [ 37  49]]
Accuracy: 74.67%
```

[58]:
```
%run -i '/home/jayanthikishore/Desktop/Analysis/Work/ML_EIT/
 ↪confusion_matrix_different_ways1.py'
df_confmatrx = pd.DataFrame(con_res, range(2),range(2))
df_confmatrx
```

```
cmap = 'PuRd'
confusion_matrix_dfrntway(df_confmatrx, cmap=cmap,fz=17)
```

```
<Figure size 432x288 with 0 Axes>
```



[61]:
```
# Accuracy on train and test
print("Accuracy on training set : ",best_model.score(X_train, y_train))
print("Accuracy on test set : ",best_model.score(X_test, y_test))
# Recall on train and test
get_recall_score(estimator)
```

```
Accuracy on training set :  0.7814285714285715
Accuracy on test set :  0.7466666666666667
```

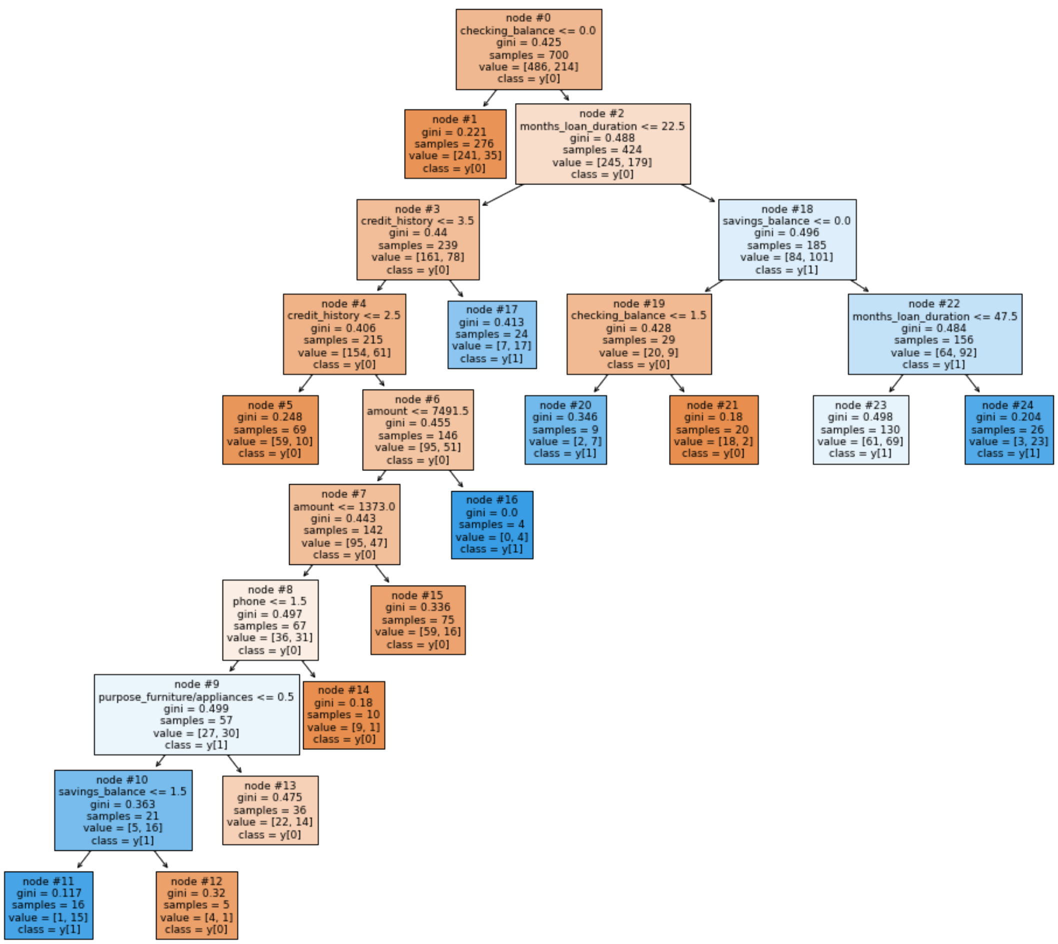
```
Recall on training set :  0.5093457943925234
Recall on test set :  0.46511627906976744
```

[62]:
```
# Recall on train and test
get_recall_score(best_model)
```

```
Recall on training set :  0.6308411214953271
Recall on test set :  0.5697674418604651
```

0.6 Visualizing the Decision Tree

[63]:
```
plt.figure(figsize=(17,15))

tree.
↪plot_tree(best_model,feature_names=feature_names,filled=True,fontsize=9,node_ids=True,class
plt.show()
```

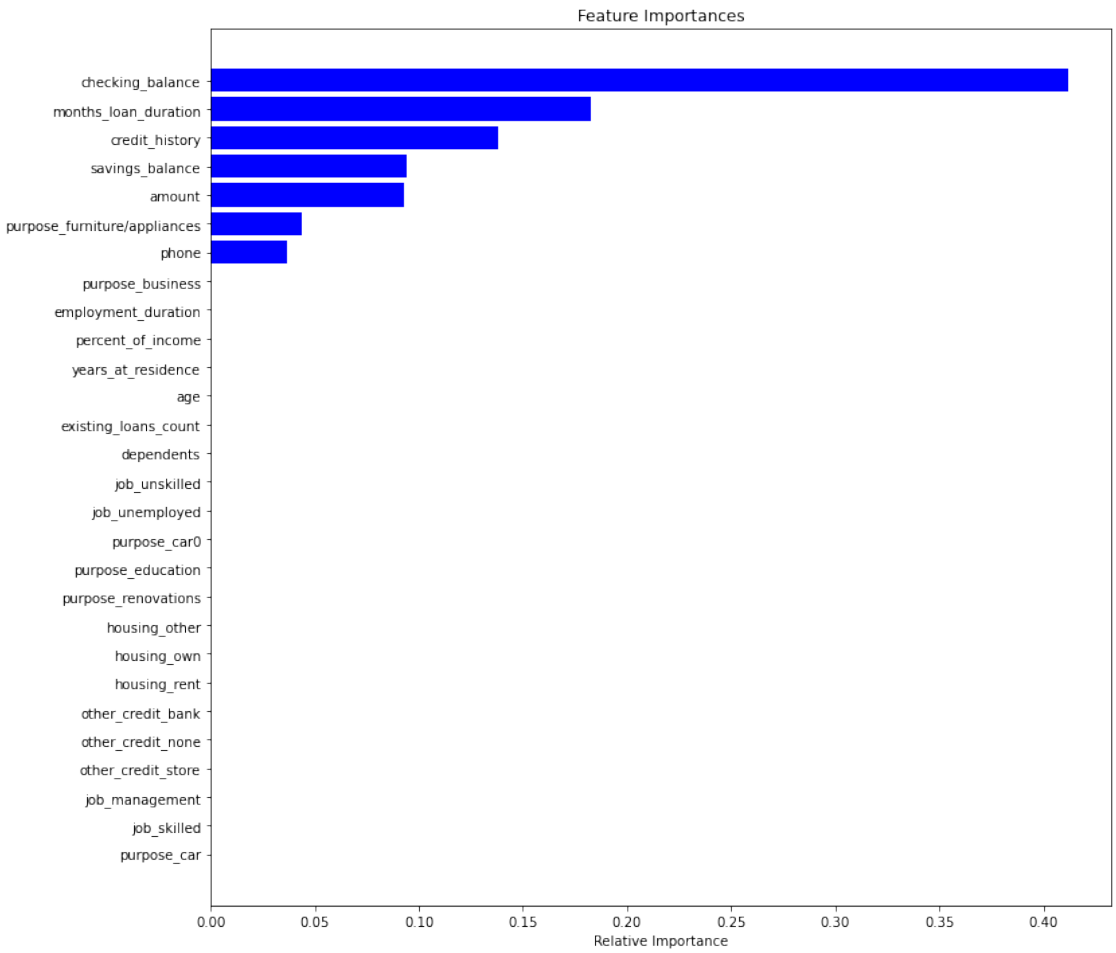


[64]:
```
# importance of features in the tree building ( The importance of a feature is␣
↪computed as the
#(normalized) total reduction of the 'criterion' brought by that feature. It is␣
↪also known as the Gini importance )

print (pd.DataFrame(best_model.feature_importances_, columns = ["Imp"], index =␣
↪X_train.columns).sort_values(by = 'Imp', ascending = False))
```

```
                                  Imp
checking_balance             0.411788
months_loan_duration         0.182828
credit_history               0.138164
savings_balance              0.094024
amount                       0.093092
purpose_furniture/appliances 0.043586
phone                        0.036518
job_skilled                  0.000000
job_management               0.000000
purpose_renovations          0.000000
other_credit_none            0.000000
other_credit_bank            0.000000
housing_rent                 0.000000
housing_own                  0.000000
job_unemployed               0.000000
housing_other                0.000000
other_credit_store           0.000000
purpose_car0                 0.000000
purpose_education            0.000000
purpose_car                  0.000000
purpose_business             0.000000
dependents                   0.000000
existing_loans_count         0.000000
age                          0.000000
years_at_residence           0.000000
percent_of_income            0.000000
employment_duration          0.000000
job_unskilled                0.000000
```

[65]:
```
importances = best_model.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(12,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='blue',␣
↪align='center')
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
```

```
plt.show()
```



0.7 Comparing all the decision tree models

[66]:
```
comparison_frame = pd.DataFrame({'Model':['Initial decision tree␣
↪model','Decision tree with restricted maximum depth','Decision treee with␣
↪hyperparameter tuning',
                                          'Decision tree with post-pruning'],␣
↪'Train_Recall':[1,0.53,0.56,0.63], 'Test_Recall':[0.46,0.46,0.52,0.56]})
comparison_frame
```

[66]:

	Model	Train_Recall	Test_Recall
0	Initial decision tree model	1.00	0.46
1	Decision tree with restricted maximum depth	0.53	0.46
2	Decision treee with hyperparameter tuning	0.56	0.52
3	Decision tree with post-pruning	0.63	0.56

```
[ ]:
```