

Assignment Week 4

August 26, 2019

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

```
In [2]: from collections import Counter
```

```
In [3]: #Evaluation Metrics
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score
```

```
In [4]: #Read the loans data
loans = pd.read_csv('lending-club-data/lending-club-data.csv')
```

```
/home/shrikrishna/anaconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2785:
interactivity=interactivity, compiler=compiler, result=result)
```

```
In [5]: train_index = pd.read_json('module-5-assignment-2-train-idx.json')
test_index = pd.read_json('module-5-assignment-2-test-idx.json')
```

```
In [6]: train_data = loans.iloc[train_index[0], :]
test_data = loans.iloc[test_index[0], :]
```

```
In [7]: pd.DataFrame(train_index).head()
```

```
Out[7]:
```

	0
0	1
1	6
2	7
3	10
4	12

```
In [8]: train_data.shape
```

```
Out[8]: (37224, 68)
```

```
In [9]: test_data.shape
```

```
Out[9]: (9284, 68)
```

0.0.1 Early stopping methods for decision trees

1. Reached a maximum depth. (set by parameter `max_depth`).
2. Reached a minimum node size. (set by parameter `min_node_size`).
3. Don't split if the gain in error reduction is too small. (set by parameter `min_error_reduction`).

0.1 Features

We will be considering only the following features

```
In [10]: [col for col in train_data.columns if(col.startswith('bad'))]
```

```
Out[10]: ['bad_loans']
```

```
In [11]: #Create a new column named 'safe_loans' using the column 'bad_loans'
def create_safe(data):
    if('bad_loans' in data.columns):
        data['safe_loans'] = data['bad_loans'].apply(lambda x:1 if(x==0) else 0)
```

```
In [12]: list(map(create_safe, [train_data, test_data]))
```

/home/shrikrishna/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:4: SettingWithCopyError: A value is trying to be set on a copy of a slice from a DataFrame.

Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html>
after removing the cwd from sys.path.

```
Out[12]: [None, None]
```

```
In [13]: features = ['grade',           # grade of the loan
                    'term',           # the term of the loan
                    'home_ownership', # home_ownership status: own, mortgage or rent
                    'emp_length',     # number of years of employment
                    ]
target = 'safe_loans'
```

```
In [14]: train_data[features + [target]].dtypes
```

```
Out[14]: grade           object
term           object
home_ownership  object
emp_length     object
safe_loans     int64
dtype: object
```

```
In [15]: test_data[features + [target]].dtypes
```

```
Out[15]: grade           object
         term            object
         home_ownership  object
         emp_length      object
         safe_loans      int64
         dtype: object
```

0.2 Missing Value Analysis

```
In [16]: def find_missing_values(data):
         features = data.columns

         missing_value_count = data.isna().sum()

         missing_value_percentage = data.isna().sum()*100/data.shape[0]

         missing_data = pd.DataFrame({'Features': features,
                                     'Missing Value Count': missing_value_count,
                                     'Missing Value Percentage': missing_value_percentage,
                                     columns = ['Features', 'Missing Value Count',
                                               'Missing Value Percentage']})

         missing_data = missing_data.sort_values(by='Missing Value Percentage',
                                                ascending = False)

         return missing_data
```

```
In [17]: find_missing_values(train_data[features]).head()
```

```
Out[17]:
```

	Features	Missing Value Count	Missing Value Percentage
emp_length	emp_length	1443	3.876531
grade	grade	0	0.000000
term	term	0	0.000000
home_ownership	home_ownership	0	0.000000

```
In [18]: find_missing_values(test_data[features]).head()
```

```
Out[18]:
```

	Features	Missing Value Count	Missing Value Percentage
emp_length	emp_length	349	3.759156
grade	grade	0	0.000000
term	term	0	0.000000
home_ownership	home_ownership	0	0.000000

```
In [19]: set(train_data['emp_length'])
```

```
Out[19]: {'1 year',
          '10+ years',
          '2 years',
          '3 years',
          '4 years',
```

```
'5 years',
'6 years',
'7 years',
'8 years',
'9 years',
'< 1 year',
nan}
```

```
In [20]: #Replace the missing values in the 'emp_length' column with 0
train_data.loc[train_data['emp_length'].isna()==True, 'emp_length'] = '0'
```

/home/shrikrishna/anaconda3/lib/python3.6/site-packages/pandas/core/indexing.py:543: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html>
self.obj[item] = s

```
In [21]: test_data.loc[test_data['emp_length'].isna()==True, 'emp_length'] = '0'
```

/home/shrikrishna/anaconda3/lib/python3.6/site-packages/pandas/core/indexing.py:543: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html>
self.obj[item] = s

```
In [22]: find_missing_values(train_data[features]).head()
```

```
Out[22]:
```

	Features	Missing Value Count	Missing Value Percentage
grade	grade	0	0.0
term	term	0	0.0
home_ownership	home_ownership	0	0.0
emp_length	emp_length	0	0.0

```
In [23]: find_missing_values(test_data[features]).head()
```

```
Out[23]:
```

	Features	Missing Value Count	Missing Value Percentage
grade	grade	0	0.0
term	term	0	0.0
home_ownership	home_ownership	0	0.0
emp_length	emp_length	0	0.0

```
In [24]: set(train_data['emp_length'])
```

```
Out[24]: {'0',
'1 year',
```

```

'10+ years',
'2 years',
'3 years',
'4 years',
'5 years',
'6 years',
'7 years',
'8 years',
'9 years',
'< 1 year'}

```

```
In [25]: set(test_data['emp_length'])
```

```

Out[25]: {'0',
'1 year',
'10+ years',
'2 years',
'3 years',
'4 years',
'5 years',
'6 years',
'7 years',
'8 years',
'9 years',
'< 1 year'}

```

0.3 Transform categorical data into binary features

```
In [26]: train_data[features].head()
```

```

Out[26]:   grade      term home_ownership emp_length
1         C   60 months             RENT    < 1 year
6         F   60 months              OWN     4 years
7         B   60 months             RENT    < 1 year
10        C   36 months             RENT    < 1 year
12        B   36 months             RENT     3 years

```

```
In [27]: test_data[features].head()
```

```

Out[27]:   grade      term home_ownership emp_length
24        D   60 months             RENT     2 years
41        A   36 months          MORTGAGE  10+ years
60        F   60 months             RENT     4 years
93        D   60 months             RENT  10+ years
132       B   36 months             RENT     2 years

```

```

In [28]: OHE_features = []
def to_categorical(data, features = features):
    global OHE_features

```

```

#Convert the categorical features to One-Hot-Encoded features
df = pd.get_dummies(data[features])
OHE_features = df.columns.tolist()

#Append the new encoded data frame to the original data frame
data = pd.concat([data, df], axis=1)

#Drop the original categorical variables
if(set(features).intersection() == set(features)):
    data = data.drop(features, axis=1)

return (data)

```

In [29]: `#train_data.columns.tolist()`

In [30]: `train_data, test_data = list(map(to_categorical, [train_data, test_data]))`

In [31]: `#Check whether the old features are present in the data`
`set(train_data.columns).intersection(features) == set() and \`
`set(test_data.columns).intersection(features) == set()`

Out[31]: True

In [32]: `#Check whether the old features are present in the data`
`set(train_data.columns).intersection(features) != set() or \`
`set(test_data.columns).intersection(features) != set()`

Out[32]: False

In [33]: `train_data.head()`

Out[33]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	int_rate	\
1	1077430	1314167	2500	2500	2500	15.27	
6	1071795	1306957	5600	5600	5600	21.28	
7	1071570	1306721	5375	5375	5350	12.69	
10	1064687	1298717	9000	9000	9000	13.49	
12	1069057	1303503	10000	10000	10000	10.65	

	installment	sub_grade	emp_title	annual_inc	\
1	59.83	C4	Ryder	30000.0	
6	152.39	F2	NaN	40000.0	
7	121.45	B5	Starbucks	15000.0	
10	305.38	C1	Va. Dept of Conservation/Recreation	30000.0	
12	325.74	B2	SFMTA	100000.0	

	...	emp_length_10+ years	emp_length_2 years	\
1	...	0	0	
6	...	0	0	
7	...	0	0	

10	...	0	0
12	...	0	0

	emp_length_3 years	emp_length_4 years	emp_length_5 years	\
1	0	0	0	
6	0	1	0	
7	0	0	0	
10	0	0	0	
12	1	0	0	

	emp_length_6 years	emp_length_7 years	emp_length_8 years	\
1	0	0	0	
6	0	0	0	
7	0	0	0	
10	0	0	0	
12	0	0	0	

	emp_length_9 years	emp_length_< 1 year
1	0	1
6	0	0
7	0	1
10	0	1
12	0	0

[5 rows x 90 columns]

In [34]: target in test_data.columns

Out[34]: True

In [35]: binary_features = train_data.columns

In [36]: target in train_data.columns

Out[36]: True

In [37]: np.unique(train_data[target])

Out[37]: array([0, 1])

0.4 Calculate the Mistakes

```
In [38]: def intermediate_node_num_mistakes(labels_in_node):
        if len(labels_in_node)==0:
            return (0)

        #Find the number of -1s
        neg_count = len([ele for ele in labels_in_node if(ele==-1)])
```

```

#Find the number of 1s
pos_count = len([ele for ele in labels_in_node if(ele==1)])

# Return the number of mistakes that the majority classifier makes.

if(neg_count>pos_count):
    max_class = -1
else:
    max_class = 1

#Get the prediction array
predicted = np.array(len(labels_in_node) * [max_class])

mistakes = 0
for act, pred in zip(labels_in_node, predicted):
    if(act!=pred):
        mistakes += 1

return mistakes

```

```

In [39]: # Test case 1
example_labels = np.array([-1, -1, 1, 1, 1])
if intermediate_node_num_mistakes(example_labels) == 2:
    print ('Test passed!')
else:
    print ('Test 1 failed... try again!')

# Test case 2
example_labels = np.array([-1, -1, 1, 1, 1, 1, 1])
if intermediate_node_num_mistakes(example_labels) == 2:
    print ('Test passed!')
else:
    print ('Test 3 failed... try again!')

# Test case 3
example_labels = np.array([-1, -1, -1, -1, -1, 1, 1])
if intermediate_node_num_mistakes(example_labels) == 2:
    print ('Test passed!')
else:
    print ('Test 3 failed... try again!')

```

Test passed!
Test passed!
Test passed!

0.5 9. Follow these steps to implement best_splitting_feature:

Step 1: Loop over each feature in the feature list

Step 2: Within the loop, split the data into two groups: one group where all of the data has f

Step 3: Calculate the number of misclassified examples in both groups of data and use the above

Step 4: If the computed error is smaller than the best error found so far, store this feature a

```
In [40]: def split_on(feature):
```

```
    intermediate_node_num_mistakes(labels_in_node)
```

```
In [41]: def best_splitting_feature(data, features, target):
```

```
    target_values = data[target]
```

```
    best_feature = None # Keep track of the best feature
```

```
    best_error = 10 # Keep track of the best error so far
```

```
    # Note: Since error is always <= 1, we should initialize it with something larger
```

```
    # Convert to float to make sure error gets computed correctly.
```

```
    num_data_points = float(len(data))
```

```
    # Loop through each feature to consider splitting on that feature
```

```
    for feature in features:
```

```
        # The left split will have all data points where the feature value is 0  
        left_split = data.loc[data[feature] == 0, feature]
```

```
        # The right split will have all data points where the feature value is 1  
        ## YOUR CODE HERE
```

```
        right_split = data.loc[data[feature] == 1, feature]
```

```
        # Calculate the number of misclassified examples in the left split.
```

```
        # Remember that we implemented a function for this! (It was called intermediate_node_num_mistakes)
```

```
        # YOUR CODE HERE
```

```
        left_mistakes = intermediate_node_num_mistakes(left_split)
```

```
        # Calculate the number of misclassified examples in the right split.
```

```
        ## YOUR CODE HERE
```

```
        right_mistakes = intermediate_node_num_mistakes(right_split)
```

```
        # Compute the classification error of this split.
```

```
        # Error = (# of mistakes (left) + # of mistakes (right)) / (# of data points)
```

```
        ## YOUR CODE HERE
```

```
        error = (left_mistakes + right_mistakes)/num_data_points
```

```
        # If this is the best error we have found so far, store the feature as best_feature
```

```
        ## YOUR CODE HERE
```

```
        if error < best_error:
```

```
            best_error = error
```