Data Warehousing and Data Mining

Labs

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Week 3 - Decision Trees in Python

Additional Reference Resources:

http://scikit-learn.org/stable/modules/tree.html (http://scikit-learn.org/stable/modules/tree.html)

Objectives

```
> Data Selection
> Data Preprocessing
    > Noisy Data - Invalid Attribute Values
    > Casewise Deletion
> Data Transformation
    > Dummy Encoding
> Data Mining
     > Decision Trees
> Model Evaluation and Prediction
     > Train/Test Split - 70/30
> Presentation
     > Tree Chart
     > Tree Rules
     > Confusion Matrix
```

Import required libraries and acquire data

NB. The data required was retrieved from the required text for this course. This should assist you in following the concepts from the book better

In [1]:
```
# import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:
```
data_path = './data/Creditcardprom.xls' # Path to data file
data = pd.read_excel(data_path)  # read data from an excel file
```

In [45]:
```
data #view the data
```

Out[45]:

	Income Range	Magazine Promo	Watch Promo	Life Ins Promo	Credit Card Ins.	Sex	Age
2	40-50,000	Yes	No	No	No	Male	45
3	30-40,000	Yes	Yes	Yes	No	Female	40
4	40-50,000	No	No	No	No	Male	42
5	30-40,000	Yes	Yes	Yes	Yes	Male	43
6	50-60,000	Yes	No	Yes	No	Female	38
7	20-30,000	No	No	No	No	Female	55
8	30-40,000	Yes	No	Yes	Yes	Male	35
9	20-30,000	No	Yes	No	No	Male	27
10	30-40,000	Yes	No	No	No	Male	43
11	30-40,000	Yes	Yes	Yes	No	Female	41
12	40-50,000	No	Yes	Yes	No	Female	43
13	20-30,000	No	Yes	Yes	No	Male	29
14	50-60,000	Yes	Yes	Yes	No	Female	39
15	40-50,000	No	Yes	No	No	Male	55
16	20-30,000	No	No	Yes	Yes	Female	19

In [5]:
```
# What columns are in the data set ? Do they have spaces that I should cons
ider
data.columns
```

Out[5]:
```
Index(['Income Range', 'Magazine Promo', 'Watch Promo', 'Life Ins Promo',
       'Credit Card Ins.', 'Sex', 'Age'],
      dtype='object')
```

In [6]:
```
# The first two(2) rows have invalid data. Let us perform casewise deletion
to remove these rows from the data set
data = data.drop([0,1],axis=0) # dropping items 0 and 1 from axis 0 or the
x axis (rows)
data #viewing data
```

Out[6]:

	Income Range	Magazine Promo	Watch Promo	Life Ins Promo	Credit Card Ins.	Sex	Age
2	40-50,000	Yes	No	No	No	Male	45
3	30-40,000	Yes	Yes	Yes	No	Female	40
4	40-50,000	No	No	No	No	Male	42
5	30-40,000	Yes	Yes	Yes	Yes	Male	43
6	50-60,000	Yes	No	Yes	No	Female	38
7	20-30,000	No	No	No	No	Female	55
8	30-40,000	Yes	No	Yes	Yes	Male	35
9	20-30,000	No	Yes	No	No	Male	27
10	30-40,000	Yes	No	No	No	Male	43
11	30-40,000	Yes	Yes	Yes	No	Female	41
12	40-50,000	No	Yes	Yes	No	Female	43
13	20-30,000	No	Yes	Yes	No	Male	29
14	50-60,000	Yes	Yes	Yes	No	Female	39
15	40-50,000	No	Yes	No	No	Male	55
16	20-30,000	No	No	Yes	Yes	Female	19

In [7]:
```
# We are only interested in a few columns
# extracting only sex, age and income,range, watch promo and life insurance
promo
data2 = data[['Income Range','Sex','Age', 'Watch Promo', 'Life Ins Promo']]
data2
```

Out[7]:

	Income Range	Sex	Age	Watch Promo	Life Ins Promo
2	40-50,000	Male	45	No	No
3	30-40,000	Female	40	Yes	Yes
4	40-50,000	Male	42	No	No
5	30-40,000	Male	43	Yes	Yes
6	50-60,000	Female	38	No	Yes
7	20-30,000	Female	55	No	No
8	30-40,000	Male	35	No	Yes
9	20-30,000	Male	27	Yes	No
10	30-40,000	Male	43	No	No
11	30-40,000	Female	41	Yes	Yes
12	40-50,000	Female	43	Yes	Yes
13	20-30,000	Male	29	Yes	Yes
14	50-60,000	Female	39	Yes	Yes
15	40-50,000	Male	55	Yes	No
16	20-30,000	Female	19	No	Yes

Aim : Use a decision tree to identify suitable rules for a Life Ins Promo

NB. The decision tree from sklearn library (http://scikit-learn.org/stable/modules/tree.html (http://scikit-learn.org/stable/modules/tree.html)) only accepts float/integer values for variables. We must therefore transform the data before applying the algorithm

I have created a function below `create_label_encoder_dict` to assist with this. The function accepts a dataframe object and uses the `LabelEncoder` class from `sklearn.preprocessing` to encode (dummy encoding) or transform non-numerical columns to numbers. Finally it returns a dictionary object of all the encoders created for each column.

The LabelEncoder is a useful resource as it not only automatically transforms all values in a column but also keeps a track of what values were transformed from. i.e. It will change all `Female` to `0` and all `Male` to `1`

In [8]:
```
def create_label_encoder_dict(df):
    from sklearn.preprocessing import LabelEncoder

    label_encoder_dict = {}
    for column in df.columns:
        # Only create encoder for categorical data types
        if not np.issubdtype(df[column].dtype, np.number) and column != 'Ag
e':
            label_encoder_dict[column]= LabelEncoder().fit(df[column])
    return label_encoder_dict
```

In [9]:
```
label_encoders = create_label_encoder_dict(data2)
print("Encoded Values for each Label")
print("="*32)
for column in label_encoders:
    print("="*32)
    print('Encoder(%s) = %s' % (column, label_encoders[column].classes_ ))
    print(pd.DataFrame([range(0,len(label_encoders[column].classes_))], col
umns=label_encoders[column].classes_, index=['Encoded Values']  ).T)
```

```
Encoded Values for each Label
================================
================================
Encoder(Watch Promo) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
================================
Encoder(Life Ins Promo) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
================================
Encoder(Sex) = ['Female' 'Male']
        Encoded Values
Female               0
Male                 1
================================
Encoder(Income Range) = ['20-30,000' '30-40,000' '40-50,000' '50-60,000']
           Encoded Values
20-30,000               0
30-40,000               1
40-50,000               2
50-60,000               3
```

In [10]:
```
# Apply each encoder to the data set to obtain transformed values
data3 = data2.copy() # create copy of initial data set
for column in data3.columns:
    if column in label_encoders:
        data3[column] = label_encoders[column].transform(data3[column])

print("Transformed data set")
print("="*32)
data3
```

```
Transformed data set
================================
```

Out[10]:

	Income Range	Sex	Age	Watch Promo	Life Ins Promo
2	2	1	45	0	0
3	1	0	40	1	1
4	2	1	42	0	0
5	1	1	43	1	1
6	3	0	38	0	1
7	0	0	55	0	0
8	1	1	35	0	1
9	0	1	27	1	0
10	1	1	43	0	0
11	1	0	41	1	1
12	2	0	43	1	1
13	0	1	29	1	1
14	3	0	39	1	1
15	2	1	55	1	0
16	0	0	19	0	1

In [11]:
```
# separate our data into dependent (Y) and independent(X) variables
X_data = data3[['Income Range','Sex','Age', 'Watch Promo']]
Y_data = data3['Life Ins Promo']
```

70/30 Train Test Split

We will split the data using a 70/30 split. i.e. 70% of the data will be randomly chosen to train the model and 30% will be used to evaluate the model

In [15]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_data, Y_data, test_si
ze=0.30)
```

In [12]:
```
# import Decision Tree Classifier
```

In [13]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
```

In [46]:
```
# Create the classifier with a maximum depth of 2 using entropy as the crit
erion for choosing most significant nodes
# to build the tree
clf = DecisionTreeClassifier(criterion='entropy',min_samples_split=2)
# Hint : Change the max_depth to 10 or another number to see how this affec
ts the tree
```

In [47]:
```
# Build the classifier  by training it on the training data
clf.fit(X_train, y_train)
```

Out[47]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=No
ne,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

Tree Visualization

In [16]:
```
# What were the determinant features?
```

In [48]:
```
pd.DataFrame([ "%.2f%%" % perc for perc in (clf.feature_importances_ * 100)
], index = X_data.columns, columns = ['Feature Significance in Decision Tre
e'])
```

Out[48]:

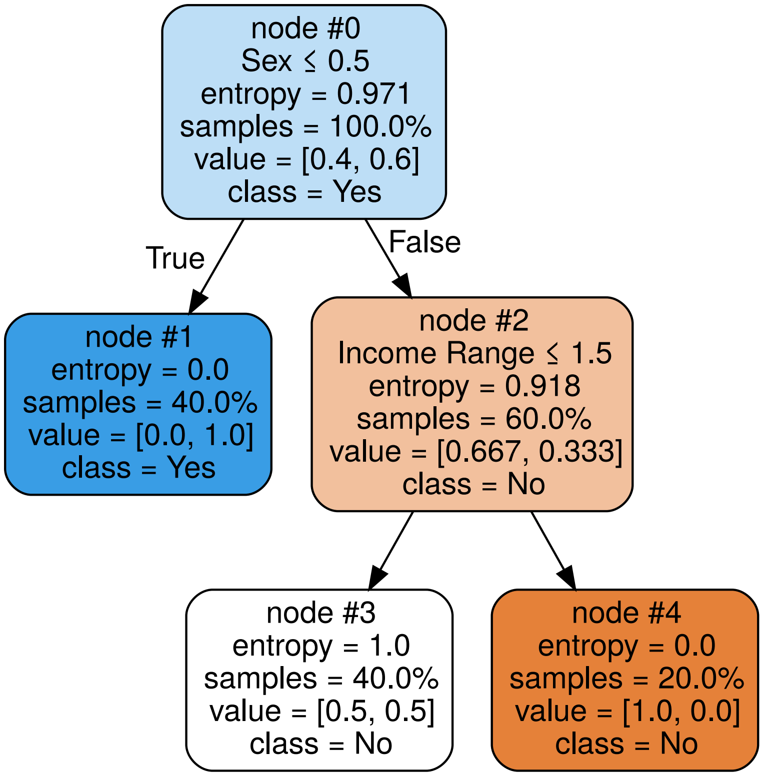
	Feature Significance in Decision Tree
Income Range	15.55%
Sex	43.25%
Age	20.60%
Watch Promo	20.60%

In [49]:
```
import graphviz
```

In [20]:
```
dot_data = tree.export_graphviz(clf,out_file=None,
                                feature_names=X_data.columns,
                         class_names=label_encoders[Y_data.name].classes_,
                         filled=True, rounded=True,  proportion=True,
                                node_ids=True, #impurity=False,
                         special_characters=True)
```

In [22]:
```
graph = graphviz.Source(dot_data)
graph
```

Out[22]:



In [26]:
```
def tree_to_code(tree, feature_names, label_encoders={}):
    from sklearn.tree import _tree

    '''
    Outputs a decision tree model as a Python function

    Parameters:
    -----------
    tree: decision tree model
        The decision tree to represent as a function
    feature_names: list
        The feature names of the dataset used for building the decision tre
e
    '''

    tree_ = tree.tree_
    feature_name = [
        feature_names[i] if i != _tree.TREE_UNDEFINED else "undefined!"
        for i in tree_.feature
    ]
    print("def decision_tree({}):".format(", ".join(feature_names)))

    def recurse(node, depth):
        indent = "  " * depth
        if tree_.feature[node] != _tree.TREE_UNDEFINED:
            name = feature_name[node]
            threshold = tree_.threshold[node]
            print("{}if {} <= {}:".format(indent, name, threshold))
            recurse(tree_.children_left[node], depth + 1)
            print("{}else:  # if {} > {}".format(indent, name, threshold))
            recurse(tree_.children_right[node], depth + 1)
        else:
            #print(node)

            name = tree_.feature[node]
            if name in label_encoders:
                if isinstance(label_encoders[name] , LabelEncoder) or True:
                    print ("{}-return {}".format(indent, label_encoders[nam
e].inverse_transform(tree_.value[node])))
                    return
            print("{}return {} # Distribution of samples in node".format(in
dent, tree_.value[node]))

    recurse(0, 1)
```

In [27]:
```
print("Decision Tree Rules")
print("="*32)
tree_to_code(clf, X_data.columns, label_encoders)
```

```
Decision Tree Rules
================================
def decision_tree(Income Range, Sex, Age, Watch Promo):
  if Sex <= 0.5:
    return [[0. 4.]] # Distribution of samples in node
  else:  # if Sex > 0.5
    if Income Range <= 1.5:
      return [[2. 2.]] # Distribution of samples in node
    else:  # if Income Range > 1.5
      return [[2. 0.]] # Distribution of samples in node
```

In [28]:
```
label_encoders = create_label_encoder_dict(data2)
print("Encoded Values for each Label")
print("="*32)
for column in label_encoders:
    print("="*32)
    print('Encoder(%s) = %s' % (column, label_encoders[column].classes_ ))
    print(pd.DataFrame([range(0,len(label_encoders[column].classes_))], col
umns=label_encoders[column].classes_, index=['Encoded Values']  ).T)
```

```
Encoded Values for each Label
================================
================================
Encoder(Watch Promo) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
================================
Encoder(Life Ins Promo) = ['No' 'Yes']
     Encoded Values
No                0
Yes               1
================================
Encoder(Sex) = ['Female' 'Male']
        Encoded Values
Female               0
Male                 1
================================
Encoder(Income Range) = ['20-30,000' '30-40,000' '40-50,000' '50-60,000']
           Encoded Values
20-30,000               0
30-40,000               1
40-50,000               2
50-60,000               3
```

Evaluation

Building a Confusion Matrix

NB. Data should be split in training and test data. The model built should be evaluated using unseen or test data

In [35]:
```
k=(clf.predict(X_test) == y_test) # Determine how many were predicted corre
ctly
```

In [36]:
```
k.value_counts()
```

Out[36]:
```
True     3
False    2
Name: Life Ins Promo, dtype: int64
```

In [37]:
```
from sklearn.metrics import confusion_matrix
```

In [38]:
```
cm=confusion_matrix(y_test, clf.predict(X_test), labels=y_test.unique())
cm
```

Out[38]:
```
array([[1, 1],
       [1, 2]])
```

In [39]:
```
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    import itertools
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [40]:
```
plot_confusion_matrix(cm,data2['Life Ins Promo'].unique())
```

```
Confusion matrix, without normalization
[[1 1]
 [1 2]]
```