In this example, we will explore the use of various classifiers from the scikit-learn package. Again, we'll use the modified Video Store data.

In [53]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
vstable = pd.read_csv("http://facweb.cs.depaul.edu/mobasher/classes/csc478/c

vstable.shape
```

Out[2]:
```
(50, 7)
```

In [49]:
```
vstable.head()
```

Out[49]:

	Gender	Income	Age	Rentals	Avg Per Visit	Genre	Incidentals
Cust ID							
1	M	45000	25	32	2.5	Action	Yes
2	F	54000	33	12	3.4	Drama	No
3	F	32000	20	42	1.6	Comedy	No
4	F	59000	70	16	4.2	Drama	Yes
5	M	37000	35	25	3.2	Action	Yes

Let's separate the target attribute and the attributes used for model training

In [4]:
```
vs_records = vstable[['Gender','Income','Age','Rentals','Avg Per Visit','Ger
vs_records.head()
```

Out[4]:

	Gender	Income	Age	Rentals	Avg Per Visit	Genre
Cust ID						
1	M	45000	25	32	2.5	Action
2	F	54000	33	12	3.4	Drama
3	F	32000	20	42	1.6	Comedy
4	F	59000	70	16	4.2	Drama
5	M	37000	35	25	3.2	Action

In [5]:
```
vs_target = vstable.Incidentals
vs_target.head()
```

Out[5]:
```
Cust ID
1    Yes
2     No
3     No
4    Yes
5    Yes
Name: Incidentals, dtype: object
```

Next, we use Pandas "get_dummies" function to create dummy variables.

In [6]:
```
vs_matrix = pd.get_dummies(vs_records[['Gender','Income','Age','Rentals','Av
vs_matrix.head(10)
```

Out[6]:

Cust ID	Income	Age	Rentals	Avg Per Visit	Gender_F	Gender_M	Genre_Action	Genre_Comedy	Genr
1	45000	25	32	2.5	0	1	1	0	
2	54000	33	12	3.4	1	0	0	0	
3	32000	20	42	1.6	1	0	0	1	
4	59000	70	16	4.2	1	0	0	0	
5	37000	35	25	3.2	0	1	1	0	
6	18000	20	29	1.7	0	1	1	0	
7	29000	45	19	3.8	1	0	0	0	
8	74000	25	31	2.4	0	1	1	0	
9	38000	21	18	2.1	0	1	0	1	
10	65000	40	21	3.3	1	0	0	0	

Next, we divide the data into randomized training and test partitions (note that the same split should also be perfromed on the target attribute). The easiest way to do this is to use the "train_test_split" module of "sklearn.cross_validation".

In [7]:

```
from sklearn.model_selection import train_test_split
vs_train, vs_test, vs_target_train, vs_target_test = train_test_split(vs_mat

print(vs_test.shape)
vs_test[0:5]
```

(10, 9)

Out[7]:

Cust ID	Income	Age	Rentals	Avg Per Visit	Gender_F	Gender_M	Genre_Action	Genre_Comedy	Genr
6	18000	20	29	1.7	0	1	1	0	
28	57000	52	22	4.1	0	1	0	1	
38	41000	38	20	3.3	0	1	0	0	
16	17000	19	26	2.2	0	1	1	0	
41	50000	33	17	1.4	1	0	0	0	

In [8]:

```
print(vs_train.shape)
vs_train[0:5]
```

(40, 9)

Out[8]:

Cust ID	Income	Age	Rentals	Avg Per Visit	Gender_F	Gender_M	Genre_Action	Genre_Comedy	Genr
30	41000	25	17	1.4	0	1	1	0	
35	74000	29	43	4.6	0	1	1	0	
18	6000	16	39	1.8	1	0	1	0	
40	17000	19	32	1.8	0	1	1	0	
2	54000	33	12	3.4	1	0	0	0	

Performing min-max normalization to rescale numeric attributes.

In [9]:

```
from sklearn import preprocessing
```

In [10]:
```
min_max_scaler = preprocessing.MinMaxScaler().fit(vs_train)

vs_train_norm = min_max_scaler.transform(vs_train)
vs_train_norm = pd.DataFrame(vs_train_norm, columns=vs_train.columns, index=

vs_test_norm = min_max_scaler.transform(vs_test)
vs_test_norm = pd.DataFrame(vs_test_norm, columns=vs_test.columns, index=vs_
```

In [11]:
```
# np.set_printoptions(precision=2, linewidth=80, suppress=True)
vs_train_norm.head()
```

Out[11]:

Cust ID	Income	Age	Rentals	Avg Per Visit	Gender_F	Gender_M	Genre_Action	Genre_Co
30	0.454545	0.181818	0.162162	0.057143	0.0	1.0	1.0	
35	0.829545	0.254545	0.864865	0.971429	0.0	1.0	1.0	
18	0.056818	0.018182	0.756757	0.171429	1.0	0.0	1.0	
40	0.181818	0.072727	0.567568	0.171429	0.0	1.0	1.0	
2	0.602273	0.327273	0.027027	0.628571	1.0	0.0	0.0	

In [12]:
```
vs_test_norm.head()
```

Out[12]:

Cust ID	Income	Age	Rentals	Avg Per Visit	Gender_F	Gender_M	Genre_Action	Genre_Co
6	0.193182	0.090909	0.486486	0.142857	0.0	1.0	1.0	
28	0.636364	0.672727	0.297297	0.828571	0.0	1.0	0.0	
38	0.454545	0.418182	0.243243	0.600000	0.0	1.0	0.0	
16	0.181818	0.072727	0.405405	0.285714	0.0	1.0	1.0	
41	0.556818	0.327273	0.162162	0.057143	1.0	0.0	0.0	

We will use the KNN, decision tree, and naive Bayes classifiers from sklearn.

In [13]:
```
from sklearn import neighbors, tree, naive_bayes
```

First, we'll use KNN classifer. You can vary K and monitor the accuracy metrics (see below) to find the best value.

In [14]:
```
n_neighbors = 5

knnclf = neighbors.KNeighborsClassifier(n_neighbors, weights='distance')
knnclf.fit(vs_train_norm, vs_target_train)
```

Out[14]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                     weights='distance')
```

Next, we call the predict function on the test intances to produce the predicted classes.

In [15]:
```
knnpreds_test = knnclf.predict(vs_test_norm)
```

In [16]:
```
print(knnpreds_test)
```

```
['No' 'No' 'Yes' 'Yes' 'No' 'No' 'Yes' 'Yes' 'Yes' 'Yes']
```

scikit-learn has various modules that can be used to evaluate classifier accuracy

In [17]:
```
from sklearn.metrics import classification_report
```

In [18]:
```
print(classification_report(vs_target_test, knnpreds_test))
```

```
              precision    recall  f1-score   support

          No       1.00      1.00      1.00         4
         Yes       1.00      1.00      1.00         6

    accuracy                           1.00        10
   macro avg       1.00      1.00      1.00        10
weighted avg       1.00      1.00      1.00        10
```

In [19]:
```
from sklearn.metrics import confusion_matrix
```

In [20]:
```
knncm = confusion_matrix(vs_target_test, knnpreds_test)
print(knncm)
```

```
[[4 0]
 [0 6]]
```

We can also compute the average accuracy score across the test instances

In [21]:
```
print(knnclf.score(vs_test_norm, vs_target_test))
```

```
1.0
```

This can be compared to the performance on the training data itself (to check for over- or under-fitting)

In [22]:
```
print(knnclf.score(vs_train_norm, vs_target_train))
```
```
1.0
```

Next, let's use a decision tree classifier:

In [23]:
```
treeclf = tree.DecisionTreeClassifier(criterion='entropy', min_samples_split
```

In [24]:
```
treeclf = treeclf.fit(vs_train, vs_target_train)
```

In [25]:
```
treepreds_test = treeclf.predict(vs_test)
print(treepreds_test)
```
```
['No' 'Yes' 'No' 'No' 'No' 'No' 'Yes' 'Yes' 'Yes' 'No']
```

In [26]:
```
print(treeclf.score(vs_test, vs_target_test))
```
```
0.6
```

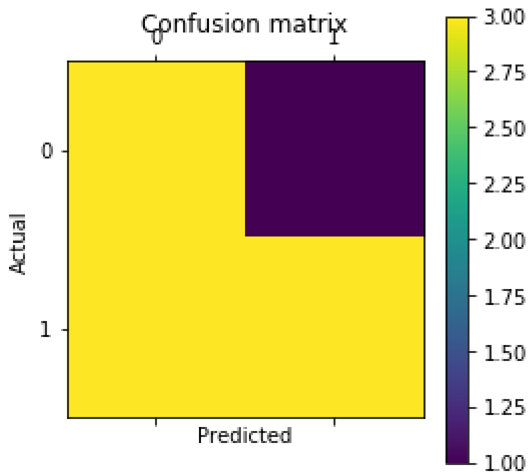
In [27]:
```
print(treeclf.score(vs_train, vs_target_train))
```
```
0.95
```

In [28]:
```
print(classification_report(vs_target_test, treepreds_test))
```
```
              precision    recall  f1-score   support

          No       0.50      0.75      0.60         4
         Yes       0.75      0.50      0.60         6

    accuracy                           0.60        10
   macro avg       0.62      0.62      0.60        10
weighted avg       0.65      0.60      0.60        10
```

In [29]:
```
treecm = confusion_matrix(vs_target_test, treepreds_test)
print(treecm)
```
```
[[3 1]
 [3 3]]
```

We can actually plot the confusion matrix for better visualization:

In [30]:
```
import pylab as plt
%matplotlib inline
plt.matshow(treecm)
plt.title('Confusion matrix')
plt.colorbar()
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```



Now, let's try the (Gaussian) naive Bayes classifier:

In [38]:
```
nbclf = naive_bayes.GaussianNB()
nbclf = nbclf.fit(vs_train, vs_target_train)
nbpreds_test = nbclf.predict(vs_test)
print(nbpreds_test)
```

```
['Yes' 'No' 'No' 'Yes' 'No' 'No' 'Yes' 'Yes' 'Yes' 'Yes']
```

In [39]:
```
print(nbclf.score(vs_train, vs_target_train))
```

```
0.675
```

In [40]:
```
print(nbclf.score(vs_test, vs_target_test))
```

```
0.8
```

Finally, let's try linear discriminant analysis:

In [42]:

```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

ldclf = LinearDiscriminantAnalysis()
ldclf = ldclf.fit(vs_train, vs_target_train)
ldpreds_test = ldclf.predict(vs_test)
print(ldpreds_test)
```

```
['Yes' 'No' 'Yes' 'Yes' 'No' 'No' 'Yes' 'Yes' 'Yes' 'Yes']

C:\Users\bmobashe\AppData\Local\Continuum\anaconda3\lib\site-packages\sklear
  warnings.warn("Variables are collinear.")
```

In [43]:

```
print(ldclf.score(vs_train, vs_target_train))
```

```
0.725
```

In [44]:

```
print(ldclf.score(vs_test, vs_target_test))
```

```
0.9
```

Next, let's see how we can use the cross-validation module from scikit-learn. This allows for n-fold cross validation without the necessity to split the data set manually.

In [46]:

```
from sklearn.model_selection import cross_val_score
```

In [47]:

```
cv_scores = cross_val_score(treeclf, vs_matrix, vs_target, cv=5)
print(cv_scores)
```

```
[0.45454545 0.3        0.8        0.6        0.88888889]
```

In [48]:

```
print("Overall Accuracy: %0.2f (+/- %0.2f)" % (cv_scores.mean(), cv_scores.s
```

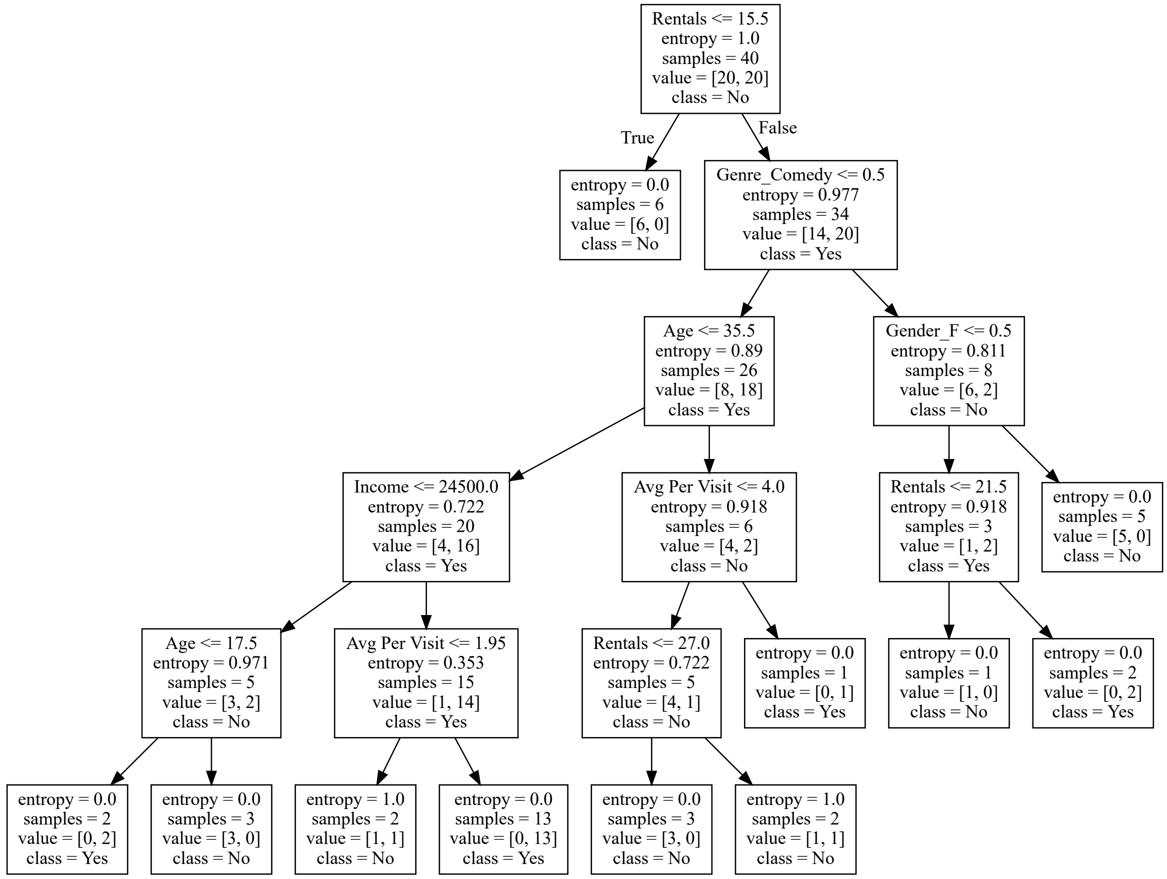
```
Overall Accuracy: 0.61 (+/- 0.43)
```

Visualizing the decision tree

In [44]:

```
from sklearn.tree import export_graphviz

from IPython.display import SVG
from graphviz import Source
from IPython.display import display

tree = export_graphviz(treeclf, out_file=None, feature_names=vs_train.columr
graph = Source(tree)
```

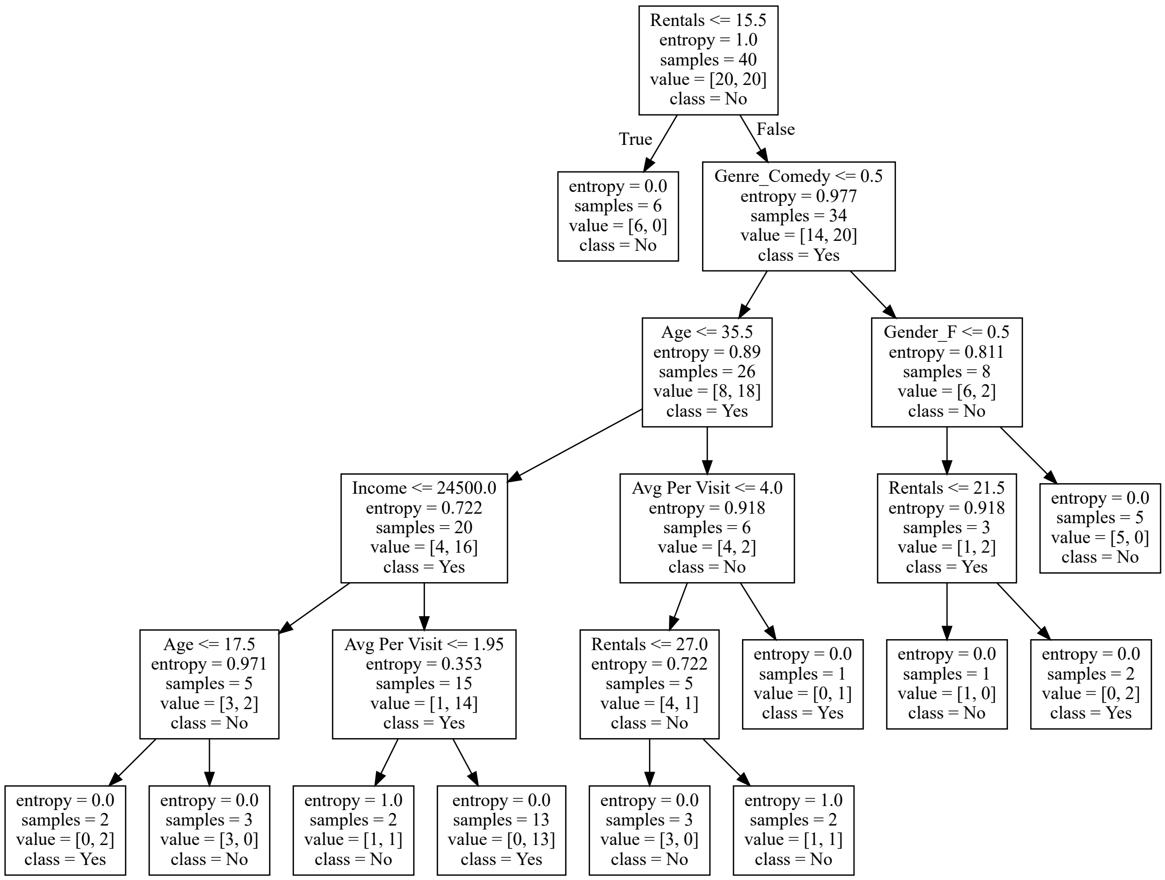
In [45]:
```
display(SVG(graph.pipe(format='svg')))
```



In [50]:

```
tree = export_graphviz(treeclf,out_file='tree.dot', feature_names=vs_train.c

import graphviz

with open("tree.dot") as f:
    dot_graph = f.read()
graphviz.Source(dot_graph, format="png")
```

Out[50]:



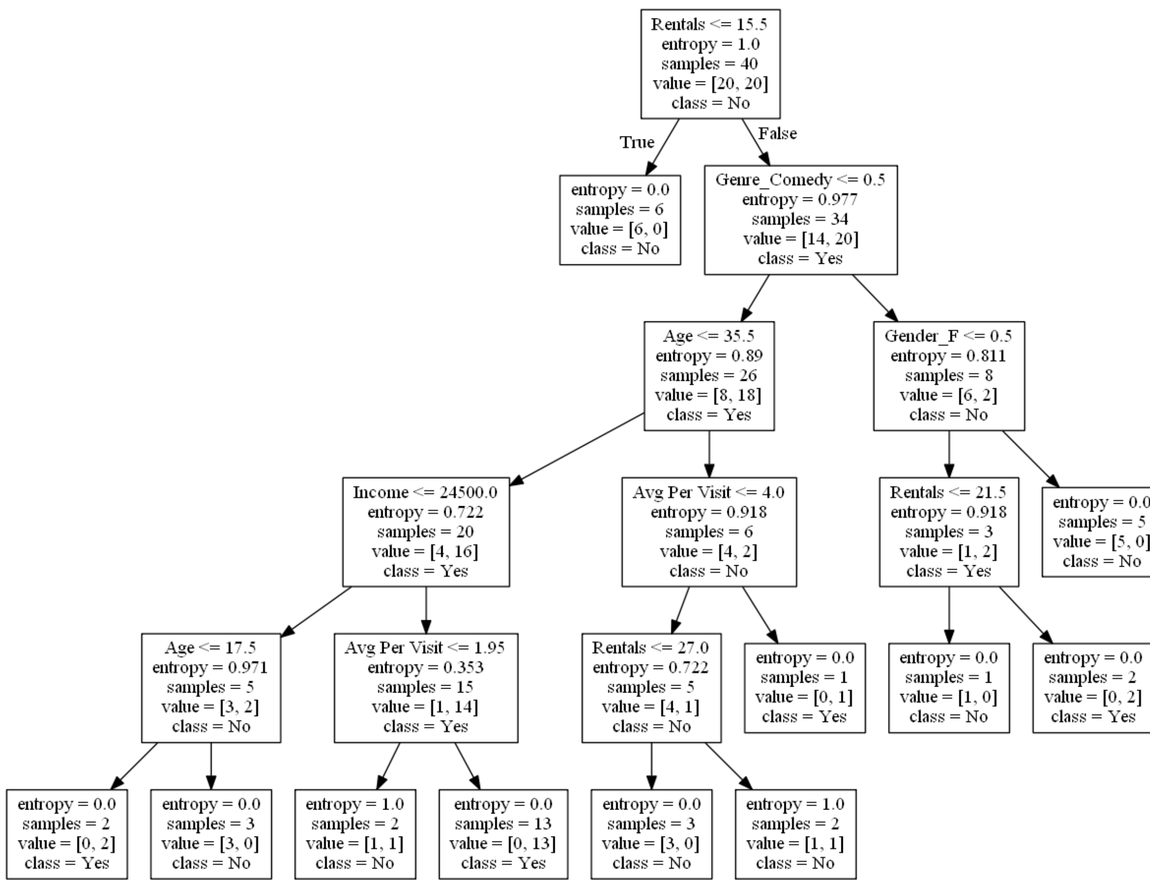
Alternatively, you can use GraphViz or some other tool outside Jupyter environment to convert the dot file into an image file (e.g., a .png file) and save it to a local directory. Then, the image can be displayed in Jupyter as follows.

In [51]:
```
system(dot -Tpng tree.dot -o dtree.png)
```

Out[51]:
```
[]
```

In [52]:
```
from IPython.display import Image
Image(filename='dtree.png', width=900)
```

Out[52]:



In [ ]: