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 [1]:
```python
import numpy as np
import pandas as pd
```

In [2]:
```python
vstable = pd.read_csv("Video_Store_2.csv", index_col=0)

vstable.shape
```

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

In [3]:
```python
vstable.head()
```

Out[3]:

	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]:
```python
vs_records = vstable[['Gender','Income','Age','Rentals','Avg Per Visit','Genre']]
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]:
```python
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]:
```python
vs_matrix = pd.get_dummies(vs_records[['Gender','Income','Age','Rentals','Avg Per Visit','Genre']])
vs_matrix.head(10)
```

Out[6]:

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

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_matrix, vs_target, test_size=0.2, rand

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

```
(10, 9)
```

Out[7]:

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

In [8]:

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

```
(40, 9)
```

Out[8]:

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

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_train.index)

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

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_Comedy	Genre_Drama
30	0.454545	0.181818	0.162162	0.057143	0.0	1.0	1.0	0.0	0.0
35	0.829545	0.254545	0.864865	0.971429	0.0	1.0	1.0	0.0	0.0
18	0.056818	0.018182	0.756757	0.171429	1.0	0.0	1.0	0.0	0.0
40	0.181818	0.072727	0.567568	0.171429	0.0	1.0	1.0	0.0	0.0
2	0.602273	0.327273	0.027027	0.628571	1.0	0.0	0.0	0.0	1.0

In [12]:

```
vs_test_norm.head()
```

Out[12]:

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

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
KNeighborsClassifier(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=3)
```

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]:

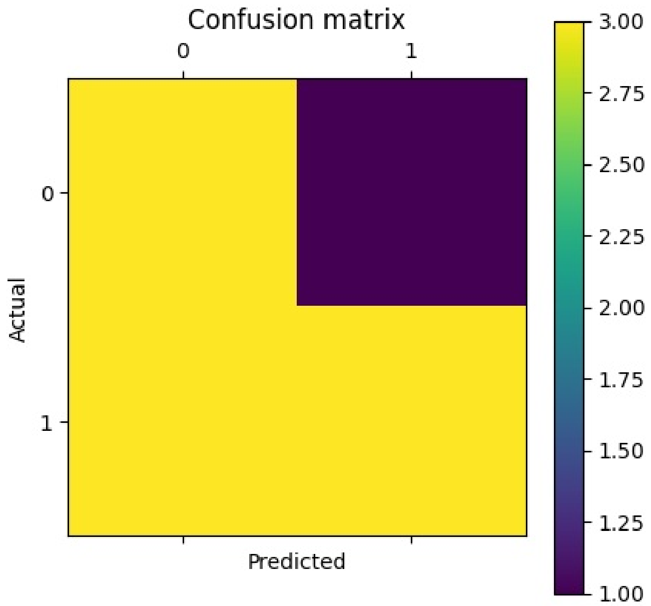
```
treecm = confusion_matrix(vs_target_test, treepreds_test)
print(treecm)
```

```
[[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 [31]:

```
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 [32]:

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

```
0.675
```

In [33]:

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

```
0.8
```

Finally, let's try linear discriminant analysis:

In [34]:

```
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']
```

In [35]:

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

```
0.725
```

In [36]:

```
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 [37]:

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

In [38]:

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

```
[0.5 0.4 0.8 0.4 0.7]
```

In [39]:

```
print("Overall Accuracy: %0.2f (+/- %0.2f)" % (cv_scores.mean(), cv_scores.std() * 2))
```

```
Overall Accuracy: 0.56 (+/- 0.32)
```

Visualizing the decision tree

In [40]:

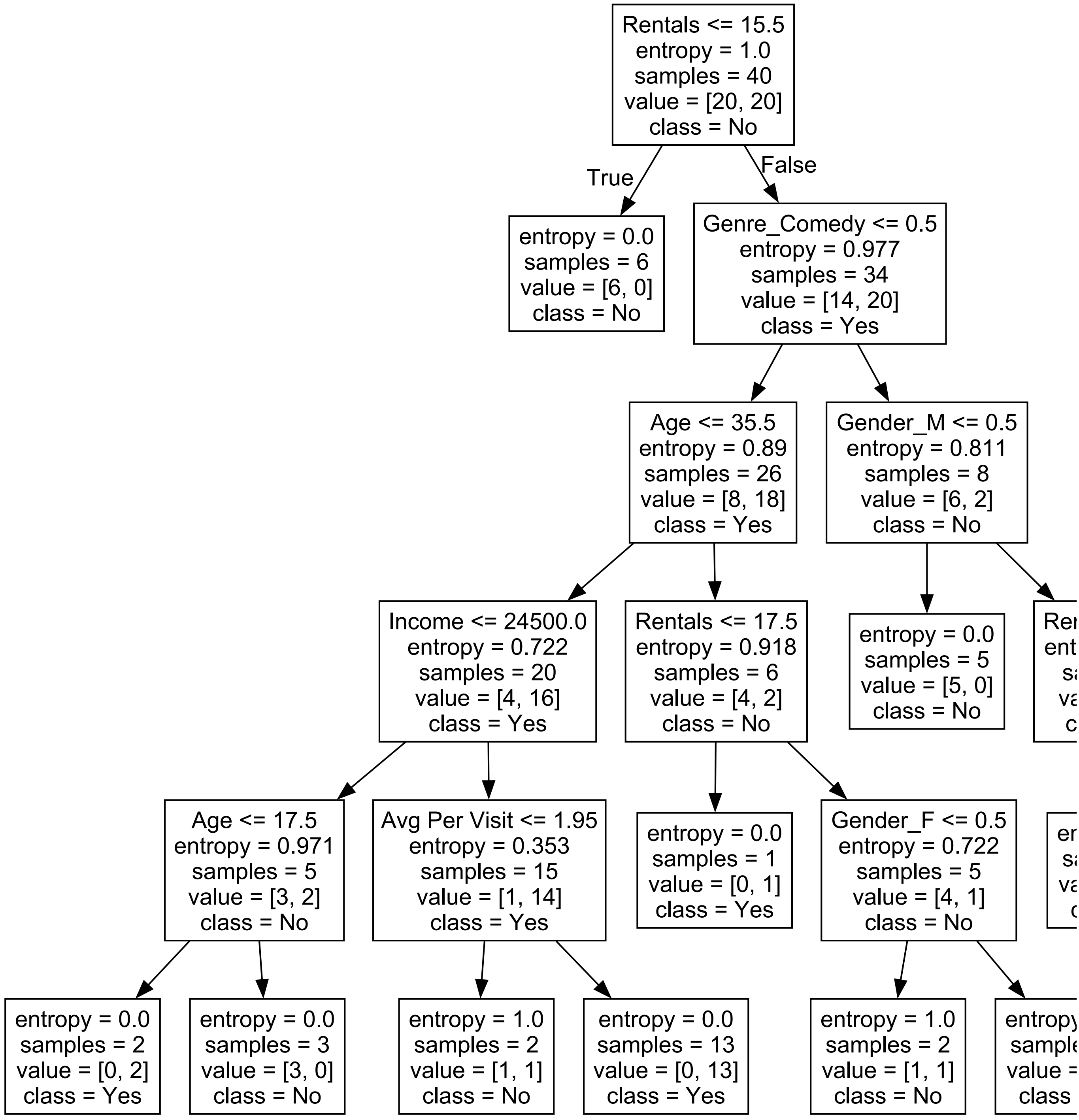
```
from sklearn.tree import export_graphviz

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.columns, class_names=['No','Yes'])
graph = Source(tree)
```

In [41]:

```
display(SVG(graph.pipe(format='svg')))
```



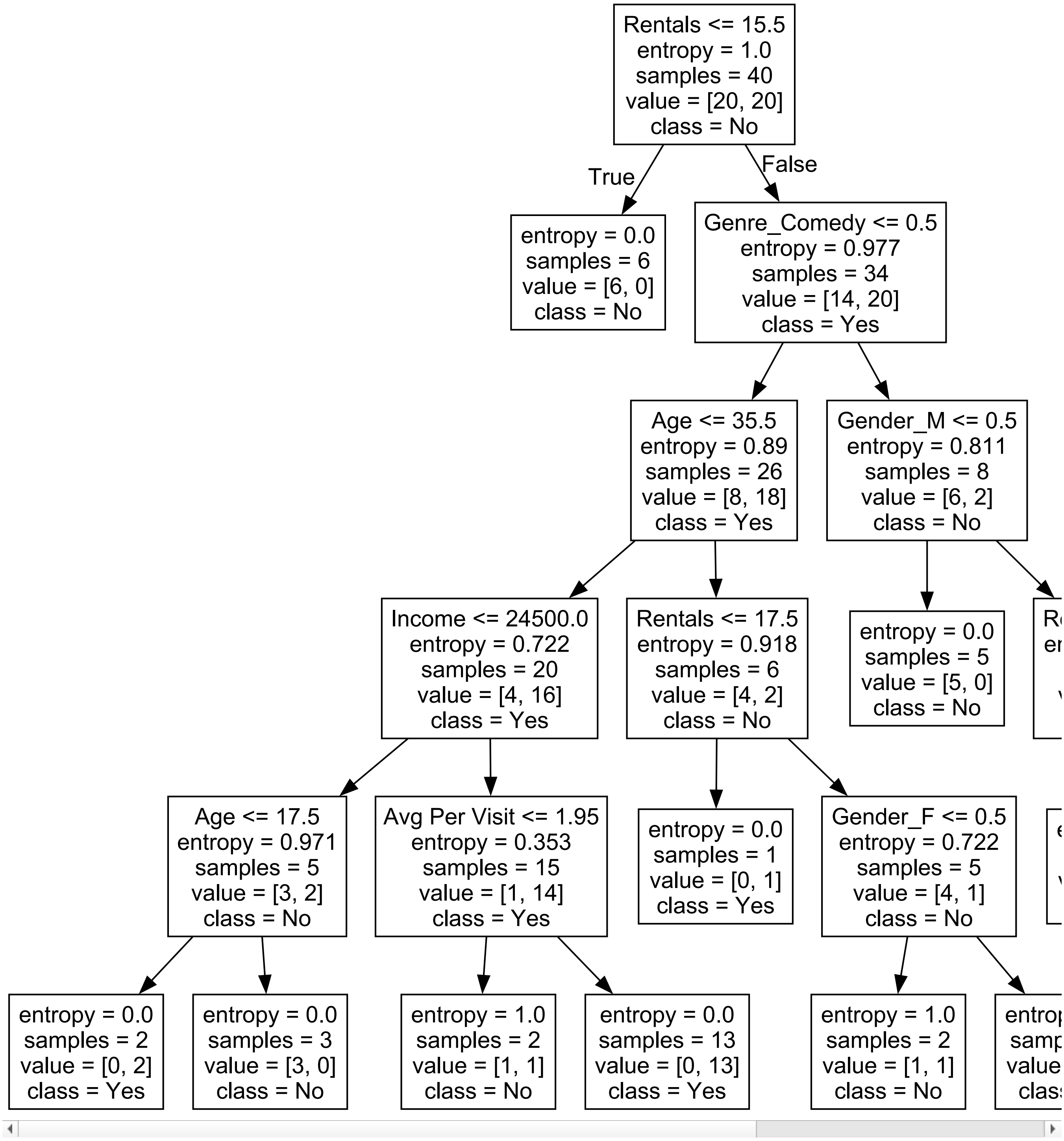
In [42]:

```
tree = export_graphviz(treeclf,out_file='tree.dot', feature_names=vs_train.columns, class_names=['No','Yes'])

import graphviz

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

Out[42]:



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 [43]:

```
system(dot -Tpng tree.dot -o dtree.png)
```

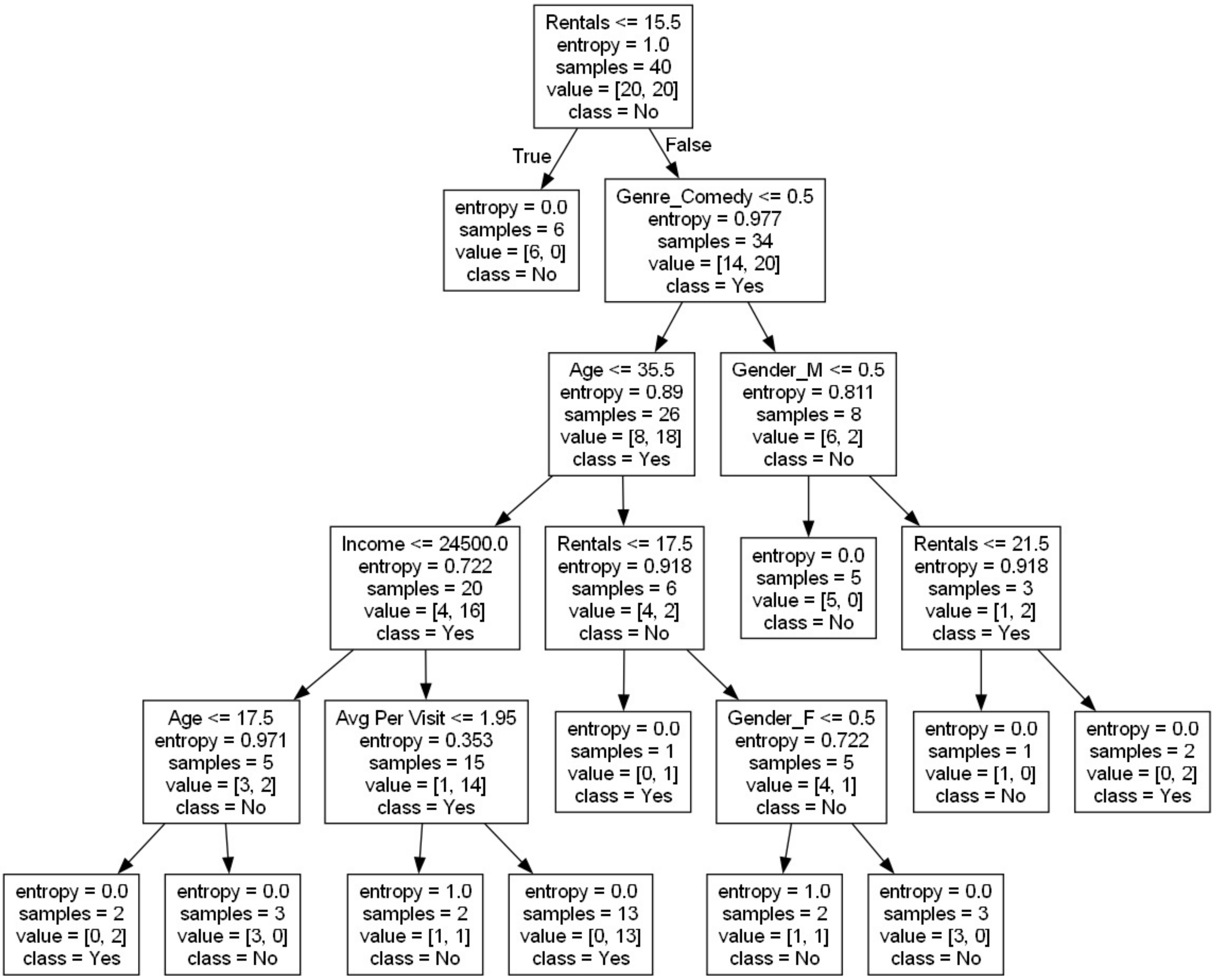
Out[43]:

```
[]
```

In [44]:

```
from IPython.display import Image
Image(filename='dtree.png', width=900)
```

Out[44]:



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