In [32]:

```
import sklearn
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
```

Question 4

In [12]:

```
data = [(1, .98), (0, .92), (1, .85), (0, .77), (0, .71), (1, .64), (1, .5), (1, .39), (0, .34), (0, .31)]

neg = pos = 5

# [[thresh, TP, FP, TN, FN], ...]
out = []
for i in range(len(data)):
    tp = fp = tn = fn = 0
    thresh = data[i][1]
    for n in range(len(data)):
        if data[n][1] >= thresh:
            if data[n][0] == 1: tp += 1
            else: fp += 1
        else:
            if data[n][0] == 0: tn += 1
            else: fn += 1
    out += [[thresh, tp, fp, tn, fn]]

# [[thresh, TPR, FPR, acc], ...]
out2 = []
for i in range(len(data)):
    acc = (out[i][1] + out[i][3]) / len(data)
    tpr = out[i][1] / pos
    fpr = out[i][2] / pos

    out2 += [[out[i][0], acc, tpr, fpr]]

out2 = pd.DataFrame(out2, columns=['Threshold', 'Accuracy', 'True Pos Rate', 'False Pos Rate'],
                    index= ['' for i in range(10)])
display(out2)
```

Threshold	Accuracy	True Pos Rate	False Pos Rate
0.98	0.6	0.2	0.0
0.92	0.5	0.2	0.2
0.85	0.6	0.4	0.2
0.77	0.5	0.4	0.4
0.71	0.4	0.4	0.6
0.64	0.5	0.6	0.6
0.50	0.6	0.8	0.6
0.39	0.7	1.0	0.6
0.34	0.6	1.0	0.8
0.31	0.5	1.0	1.0

Question 5

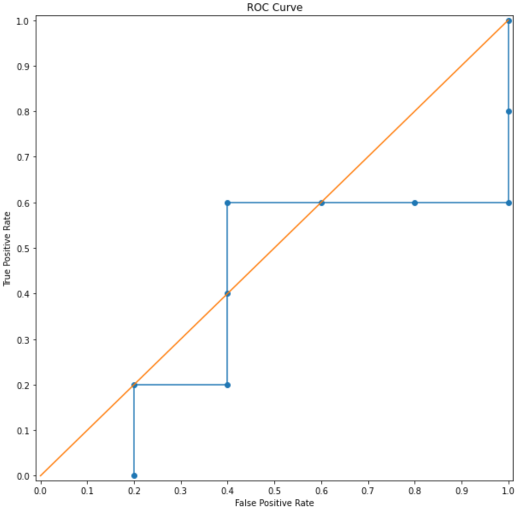
ROC Curve

In [13]:

```
plt.figure(figsize=(10,10))
plt.scatter(out2['True Pos Rate'], out2['False Pos Rate'])

plt.plot(out2['True Pos Rate'], out2['False Pos Rate'])
plt.plot([0,1], [0,1])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.xticks([.1 * i for i in range(11)])
plt.yticks([.1 * i for i in range(11)])
plt.title('ROC Curve')
plt.margins(x=.01, y=0.01)

plt.show()
```



Question 6

Part A

In [15]:

```
# Import Data
data = pd.read_csv("spam.csv")
data = data.drop(['isuid', 'id', 'domain', 'spampct', 'category', 'cappct'], axis=1)
```

Part B

i.

In [16]:

```
spamCount = 0
for i in data['spam']:
    if i == 'yes': spamCount += 1

print("%.2f%% of emails are spam." % (100*spamCount/len(data['spam'])))
```

```
32.70% of emails are spam.
```

ii.

The constant classifier will predict that 100% of emails are spam.

iii.

The constant classifier will have an error rate of 67.30%.

Part C

In [17]:

```python
# Split Data into training and test groups
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OrdinalEncoder
from sklearn import tree

enc = OrdinalEncoder()
enc.fit(data)
ord_data = pd.DataFrame(enc.transform(data))

data_train, data_test, spam_train, spam_test = train_test_split(ord_data.iloc[:, 0:14], ord_data[14
], test_size=0.2, train_size=0.8, random_state=124)
```

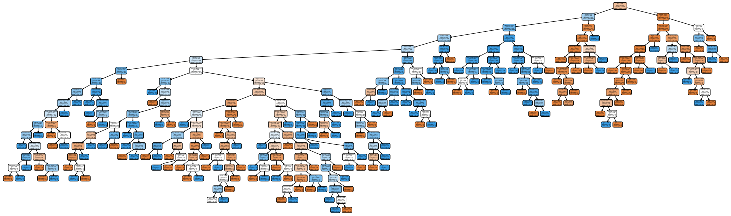
Part D

In [18]:

```python
# Display Decision Tree
import graphviz

out = tree.DecisionTreeClassifier()
out = out.fit(data_train, spam_train)
tree_graph = tree.export_graphviz(out, out_file=None,
                                  feature_names=data.iloc[:, 0:14].columns,
                                  filled = True, rounded=True,
                                  special_characters = True)
tree_graph = graphviz.Source(tree_graph)
tree_graph
```

Out[18]:



Part E

```
Gini value is the default selection criteria when learning the tree.
```

Part F

In [19]:

```python
from sklearn import metrics
#Accuracy = TP + TN / n
#Sensitivity = TP / TP + FN
#Specificity = TN / FP + TN
#AUC
predicted_train = out.predict(data_train)
predicted_test = out.predict(data_test)

matrix_train = metrics.confusion_matrix(spam_train, predicted_train)
matrix_test = metrics.confusion_matrix(spam_test, predicted_test)

acc_train = (matrix_train[1][1] + matrix_train[0][0]) / len(spam_train)
sens_train = matrix_train[1][1] / (matrix_train[1][1] + matrix_train[1][0])
spec_train = matrix_train[0][0] / (matrix_train[0][0] + matrix_train[0][1])
auc_train = metrics.roc_auc_score(spam_train, predicted_train)

acc_test = (matrix_test[1][1] + matrix_test[0][0]) / len(spam_test)
sens_test = matrix_test[1][1] / (matrix_test[1][1] + matrix_test[1][0])
spec_test = matrix_test[0][0] / (matrix_test[0][0] + matrix_test[0][1])
auc_test = metrics.roc_auc_score(spam_test, predicted_test)
```

```
performance_full = pd.DataFrame([[acc_train, sens_train, spec_train, auc_train],
                                 [acc_test, sens_test, spec_test, auc_test]],
                               columns = ['Accuracy', 'Sensitivity', 'Specificity', 'AUC'],
                               index = ['Training Data', 'Testing Data'])
performance_full
```

Out[19]:

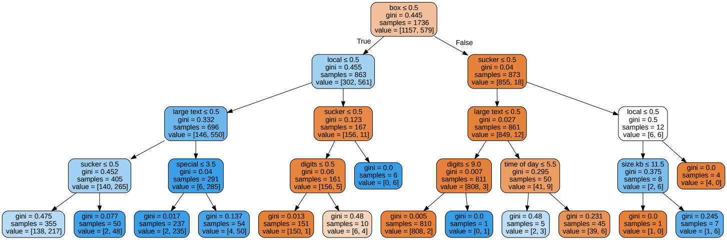
	Accuracy	Sensitivity	Specificity	AUC
Training Data	0.998848	0.996546	1.000000	0.998273
Testing Data	0.898851	0.778626	0.950658	0.864642

Part G

In [20]:

```
out = tree.DecisionTreeClassifier(max_depth=4)
out = out.fit(data_train, spam_train)
tree_graph = tree.export_graphviz(out, out_file=None,
                                 feature_names=data.iloc[:, 0:14].columns,
                                 filled = True, rounded=True,
                                 special_characters = True)
tree_graph = graphviz.Source(tree_graph)
tree_graph
```

Out[20]:



In [28]:

```
predicted_train = out.predict(data_train)
predicted_test = out.predict(data_test)

matrix_train = metrics.confusion_matrix(spam_train, predicted_train)
matrix_test = metrics.confusion_matrix(spam_test, predicted_test)

acc_train = (matrix_train[1][1] + matrix_train[0][0]) / len(spam_train)
sens_train = matrix_train[1][1] / (matrix_train[1][1] + matrix_train[1][0])
spec_train = matrix_train[0][0] / (matrix_train[0][0] + matrix_train[0][1])
auc_train = metrics.roc_auc_score(spam_train, predicted_train)

acc_test = (matrix_test[1][1] + matrix_test[0][0]) / len(spam_test)
sens_test = matrix_test[1][1] / (matrix_test[1][1] + matrix_test[1][0])
spec_test = matrix_test[0][0] / (matrix_test[0][0] + matrix_test[0][1])
auc_test = metrics.roc_auc_score(spam_test, predicted_test)

performance_trim = pd.DataFrame([[acc_train, sens_train, spec_train, auc_train],
                                 [acc_test, sens_test, spec_test, auc_test]],
                               columns = ['Accuracy', 'Sensitivity', 'Specificity', 'AUC'],
                               index = ['Training Data', 'Testing Data'])
performance_trim
```

Out[28]:

	Accuracy	Sensitivity	Specificity	AUC
Training Data	0.906682	0.977547	0.871219	0.924383
Testing Data	0.894253	0.946565	0.871711	0.909138

Question 7:

a)

In [34]:

```python
from sklearn.model_selection import StratifiedKFold
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
import pandas as pd
import numpy as np
```

In [48]:

```python
def spec_test(y, y_pred):
    if(len(y) != len(y_pred)):
        print( "Error in spec_score")
        exit(-1)
    fp = 0.
    tn = 0.
    for i in range(len(y_pred)):
        if y_pred[i] == 0 and y[i] == 0:
            tn += 1
        elif y_pred[i] == 1 and y[i] == 0:
            fp += 1

    return tn / (fp + tn)
```

In [49]:

```python
import csv

spam = []
with open('spam.csv') as csv_file:
    spam_file = csv.reader(csv_file, delimiter=',')
    linenum = 0;
    for row in spam_file:
        if(linenum != 0):
            spam.append(row)
        linenum += 1


#Transform Data to numeric type
enc = OrdinalEncoder()
enc.fit(spam)
t_spam = enc.transform(spam)

#Scale Data [0, 1]
scaler = MinMaxScaler()
scaler.fit(t_spam)
s_spam = scaler.transform(t_spam)

#Split data and target vector
y = np.array(s_spam.T[len(s_spam[0]) - 1]) #target vector
x = np.delete(s_spam, len(s_spam[0]) - 1, 1) #data


skf = StratifiedKFold(n_splits=10)
skf.get_n_splits(x, y)

train_data = []
test_data = []
for train_i, test_i in skf.split(x, y):
    x_train, x_test = x[train_i], x[test_i]
    y_train, y_test = y[train_i], y[test_i]
    train_data.append((x_train, y_train))
    test_data.append((x_test, y_test))
```

b)

In [51]:

```
model_array = [ KNeighborsClassifier(n_neighbors = 3),
                KNeighborsClassifier(n_neighbors = 7),
                KNeighborsClassifier(n_neighbors = 11),
                KNeighborsClassifier(n_neighbors = 15),
                DecisionTreeClassifier(max_depth = 5),
                DecisionTreeClassifier(criterion = "entropy", max_depth = 100, min_samples_split = 2
5),
                GaussianNB()]

for model in model_array:
    print(model)
    total_accuracy = 0.
    total_auc = 0.
    total_recall = 0.
    total_spec = 0.
    split_stats = []
    for i in range(len(train_data)):
        model.fit(train_data[i][0], train_data[i][1])
        y_pred = model.predict(test_data[i][0])

        acc_score = metrics.accuracy_score(test_data[i][1], y_pred)
        auc_score = metrics.roc_auc_score(test_data[i][1], y_pred)
        recall_score = metrics.recall_score(test_data[i][1], y_pred)
        spec_score = spec_test(test_data[i][1], y_pred)

        total_accuracy += acc_score
        total_auc += auc_score
        total_recall += recall_score
        total_spec += spec_score

        split_stats.append([acc_score, auc_score, recall_score, spec_score])


    split_stats.append([total_accuracy / 10, total_auc / 10 , total_recall / 10, total_spec / 10])
    display(pd.DataFrame(split_stats,
                 columns = ['Accuracy', 'AUC', 'Recall', 'Specificity'],
                 index = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 'Averages']))
```

```
KNeighborsClassifier(n_neighbors=3)
```

	Accuracy	AUC	Recall	Specificity
1	0.766055	0.808326	0.929577	0.687075
2	0.972350	0.972217	0.971831	0.972603
3	0.976959	0.979259	0.985915	0.972603
4	0.963134	0.958132	0.943662	0.972603
5	0.940092	0.933774	0.915493	0.952055
6	0.926267	0.916265	0.887324	0.945205
7	0.926267	0.916265	0.887324	0.945205
8	0.958525	0.958325	0.957746	0.958904
9	0.972350	0.964982	0.943662	0.986301
10	0.857143	0.792543	0.605634	0.979452
Averages	0.925914	0.920009	0.902817	0.937201

```
KNeighborsClassifier(n_neighbors=7)
```

	Accuracy	AUC	Recall	Specificity
1	0.747706	0.794721	0.929577	0.659864
2	0.976959	0.982877	1.000000	0.965753
3	0.972350	0.975834	0.985915	0.965753
4	0.958525	0.954708	0.943662	0.965753
5	0.967742	0.965175	0.957746	0.972603
6	0.921659	0.905605	0.859155	0.952055
7	0.921659	0.912840	0.887324	0.938356
8	0.972350	0.972217	0.971831	0.972603
9	0.967742	0.957939	0.929577	0.986301
10	0.870968	0.817287	0.661972	0.972603

Averages	0.927766	0.923920	0.912676	0.935164

```
KNeighborsClassifier(n_neighbors=11)
```

	Accuracy	AUC	Recall	Specificity
1	0.733945	0.784517	0.929577	0.639456
2	0.972350	0.979452	1.000000	0.958904
3	0.972350	0.975834	0.985915	0.965753
4	0.958525	0.954708	0.943662	0.965753
5	0.972350	0.972217	0.971831	0.972603
6	0.917051	0.905798	0.873239	0.938356
7	0.917051	0.909415	0.887324	0.931507
8	0.972350	0.972217	0.971831	0.972603
9	0.953917	0.940430	0.901408	0.979452
10	0.870968	0.817287	0.661972	0.972603
Averages	0.924086	0.921188	0.912676	0.929699

```
KNeighborsClassifier(n_neighbors=15)
```

	Accuracy	AUC	Recall	Specificity
1	0.715596	0.770911	0.929577	0.612245
2	0.963134	0.972603	1.000000	0.945205
3	0.972350	0.975834	0.985915	0.965753
4	0.967742	0.961557	0.943662	0.979452
5	0.972350	0.975834	0.985915	0.965753
6	0.917051	0.909415	0.887324	0.931507
7	0.912442	0.902373	0.873239	0.931507
8	0.967742	0.965175	0.957746	0.972603
9	0.949309	0.933388	0.887324	0.979452
10	0.861751	0.803203	0.633803	0.972603
Averages	0.919947	0.917029	0.908451	0.925608

```
DecisionTreeClassifier(max_depth=5)
```

	Accuracy	AUC	Recall	Specificity
1	0.986239	0.982514	0.971831	0.993197
2	0.949309	0.922535	0.845070	1.000000
3	0.949309	0.937006	0.901408	0.972603
4	0.972350	0.961364	0.929577	0.993151
5	0.967742	0.961557	0.943662	0.979452
6	0.912442	0.873432	0.760563	0.986301
7	0.972350	0.972217	0.971831	0.972603
8	0.981567	0.982684	0.985915	0.979452
9	0.981567	0.982684	0.985915	0.979452
10	0.880184	0.820519	0.647887	0.993151
Averages	0.955306	0.939651	0.894366	0.984936

```
DecisionTreeClassifier(criterion='entropy', max_depth=100, min_samples_split=25)
```

	Accuracy	AUC	Recall	Specificity
1	0.926606	0.923733	0.915493	0.931973
2	0.940092	0.930156	0.901408	0.958904
3	0.949309	0.937006	0.901408	0.972603
4	0.917051	0.920268	0.929577	0.910959
5	0.921659	0.898370	0.830986	0.965753
6	0.889401	0.859927	0.774648	0.945205
7	0.880184	0.874783	0.859155	0.890411

8	0.963134	0.961750	0.957746	0.965753
9	0.972350	0.972217	0.971831	0.972603
10	0.880184	0.831372	0.690141	0.972603
Averages	0.923997	0.910958	0.873239	0.948677

```
GaussianNB()
```

	Accuracy	AUC	Recall	Specificity
1	0.724771	0.693973	0.605634	0.782313
2	0.912442	0.873432	0.760563	0.986301
3	0.990783	0.993151	1.000000	0.986301
4	0.903226	0.895524	0.873239	0.917808
5	0.958525	0.961943	0.971831	0.952055
6	0.857143	0.821484	0.718310	0.924658
7	0.880184	0.849460	0.760563	0.938356
8	0.917051	0.894945	0.830986	0.958904
9	0.894009	0.863351	0.774648	0.952055
10	0.806452	0.722313	0.478873	0.965753
Averages	0.884459	0.856958	0.777465	0.936450