Homework2 Report

course: COMP9417

term: 2020T1

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Question 1

part(a). [0.5 mark]

the accuracy has a general tendency to increase with a larger training size

```
                             DecisionTreeClassifier
-----------------------------------------------------------------------------------------------------------------
   Dataset     |  5%    |  10%   |  15%   |  20%   |  25%   |  30%   |  35%   |  40%   |  45%   |  50%   |
-----------------------------------------------------------------------------------------------------------------
australian     | 72.61% | 74.63% | 75.52% | 77.53% | 77.97% | 79.86% | 83.05% | 81.29% | 80.14% | 82.91% |
balance-scale  | 70.10% | 72.47% | 71.20% | 75.69% | 73.77% | 75.67% | 77.74% | 75.99% | 78.09% | 76.98% |
hypothyroid    | 94.94% | 96.31% | 97.77% | 99.18% | 99.21% | 99.42% | 99.42% | 99.52% | 99.34% | 99.20% |
```

```
                             BernoulliNB with priors
-----------------------------------------------------------------------------------------------------------------
   Dataset     |  5%    |  10%   |  15%   |  20%   |  25%   |  30%   |  35%   |  40%   |  45%   |  50%   |
-----------------------------------------------------------------------------------------------------------------
australian     | 73.47% | 79.85% | 81.72% | 80.43% | 79.69% | 79.84% | 80.12% | 81.14% | 82.16% | 81.28% |
balance-scale  | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% |
hypothyroid    | 91.38% | 91.81% | 92.23% | 92.23% | 92.23% | 92.26% | 92.23% | 92.23% | 92.23% | 92.23% |
```

part(b). [0.5 mark]

(1) none of the 6 models show a learning curve **False**

(2) all of the 6 models show a learning curve **False**

(3) most of the 6 models show a learning curve **True**

(4) All 3 Decision Tree models are generally better than Bernoulli Naive Bayes models **False**

(5) Some Bernoulli Naive Bayes models are better than Decision Tree models **True**

so all true statements are (3) and (5)

part(c). [0.5 mark]

After adding the new line, BNB model results with and without priors are shown below:

```
                             BernoulliNB with priors
-----------------------------------------------------------------------------------------------------------------
   Dataset     |  5%    |  10%   |  15%   |  20%   |  25%   |  30%   |  35%   |  40%   |  45%   |  50%   |
-----------------------------------------------------------------------------------------------------------------
australian     | 73.47% | 79.85% | 81.72% | 80.43% | 79.69% | 79.84% | 80.12% | 81.14% | 82.16% | 81.28% |
balance-scale  | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% |
hypothyroid    | 91.38% | 91.81% | 92.23% | 92.23% | 92.23% | 92.26% | 92.23% | 92.23% | 92.23% | 92.23% |
```

```
               BernoulliNB without priors(with uniform probabilities)
-----------------------------------------------------------------------------------------------------------------
   Dataset     |  5%    |  10%   |  15%   |  20%   |  25%   |  30%   |  35%   |  40%   |  45%   |  50%   |
-----------------------------------------------------------------------------------------------------------------
australian     | 73.62% | 79.27% | 81.44% | 78.98% | 78.40% | 79.69% | 78.52% | 79.83% | 80.41% | 80.41% |
balance-scale  | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% | 46.08% |
hypothyroid    | 83.88% | 79.59% | 77.44% | 74.79% | 73.12% | 65.05% | 53.60% | 51.30% | 51.09% | 50.26% |
```

(1) BNB preforms better with priors **True**

(2) BNB preforms better without priors **False**

(3) there is no difference in performance when using BNB with or without priors **False**

so the true statement is (1)

Question 2

part(a). [1 mark]

accuracy score for training data: 0.856682769726248

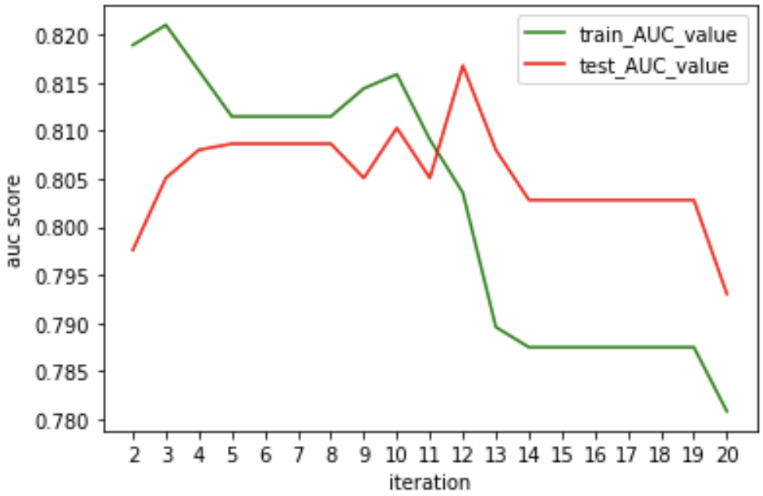
accuracy score for training data: 0.8314606741573034

part(b). [1 mark]

optimal number of min_samples_leaf: 12

part(c). [0.5 mark]

the corresponding plot shown below:



part(d). [1 mark]

posterior probability that part D: 0.36885245901639346

In [220]:

```
import pandas as pd
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import random
import math
import copy
```

In [221]:

```
def pre_processing(dataframe, features):
    for ft in features:
        max_value = dataframe[ft].max()
        min_value = dataframe[ft].min()
        dataframe[ft] = [(x - min_value) / (max_value - min_value) for x in dataframe[ft]]
    return dataframe
```

In [222]:

```
# load data
csv_file = 'titanic.csv'
df = pd.read_csv(csv_file)
feature_vectors = ['Pclass', 'Sex', 'Age', 'Siblings_Spouses_Aboard', 'Parents_Children_Aboard']

df
```

Out[222]:

	Pclass	Sex	Age	Siblings_Spouses_Aboard	Parents_Children_Aboard	Survived
0	3	1	20	1	0	0
1	1	0	30	1	0	1
2	3	0	20	0	0	1
3	1	0	30	1	0	1
4	3	1	30	0	0	0
...	...	...	...	...	...	...
882	2	1	20	0	0	0
883	1	0	10	0	0	1
884	3	0	0	1	2	0
885	1	1	20	0	0	1
886	3	1	30	0	0	0

887 rows × 6 columns

In [223]:

```
# step 1: pre-processing data
df = pre_processing(df, feature_vectors)
df
```

Out[223]:

	Pclass	Sex	Age	Siblings_Spouses_Aboard	Parents_Children_Aboard	Survived
0	1.0	1.0	0.250	0.125	0.000000	0
1	0.0	0.0	0.375	0.125	0.000000	1
2	1.0	0.0	0.250	0.000	0.000000	1
3	0.0	0.0	0.375	0.125	0.000000	1
4	1.0	1.0	0.375	0.000	0.000000	0
...	...	...	...	...	...	...
882	0.5	1.0	0.250	0.000	0.000000	0
883	0.0	0.0	0.125	0.000	0.000000	1
884	1.0	0.0	0.000	0.125	0.333333	0
885	0.0	1.0	0.250	0.000	0.000000	1
886	1.0	1.0	0.375	0.000	0.000000	0

887 rows × 6 columns

In [224]:

```
# split dataset
training_dataset = df.loc[0:620,:]
testing_dataset = df.loc[620:887,:]

# training data and class labels
training_dataset_x = training_dataset.loc[:, feature_vectors]
testing_dataset_x = testing_dataset.loc[:, feature_vectors]
training_dataset_y = training_dataset.loc[:, ['Survived']]
testing_dataset_y = testing_dataset.loc[:, ['Survived']]
```

In [225]:

```
clf = DecisionTreeClassifier() # create DT model
clf.fit(training_dataset_x, training_dataset_y) # train model
```

Out[225]:

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                       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')
```

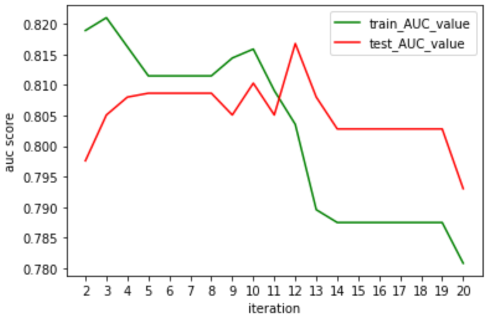
In [226]:

```
from sklearn.metrics import accuracy_score
# for training data
training_predicted = clf.predict(training_dataset_x)
print("accuracy score for training data: ", accuracy_score(training_dataset_y,training_predicted))

# for testing data
testing_predicted = clf.predict(testing_dataset_x)
print("accuracy score for testing data: ", accuracy_score(testing_dataset_y,testing_predicted))

# print("accuracy score for training data: ", clf.score(training_dataset_x, training_dataset_y))
# print("accuracy score for testing data: ", clf.score(testing_dataset_x, testing_dataset_y))
```

```
accuracy score for training data:  0.856682769726248
accuracy score for testing data:  0.8314606741573034
```

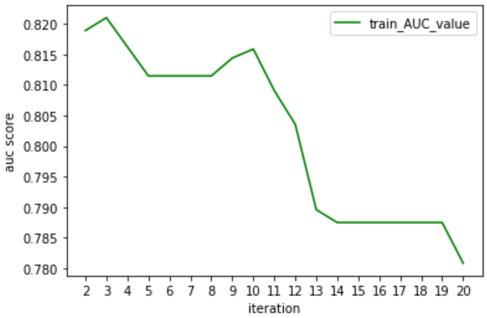
In [227]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score

iter_list = []
auc_train = [] # store train AUC values
auc_test = []  # store test AUC values
for i in range(2,21,1):
    temp_clf = DecisionTreeClassifier(min_samples_leaf=i)
    temp_clf.fit(training_dataset_x, training_dataset_y)
    temp_train_predicted = temp_clf.predict(training_dataset_x)
    temp_test_predicted = temp_clf.predict(testing_dataset_x)
    auc_train_value = roc_auc_score(training_dataset_y, temp_train_predicted)
    auc_test_value = roc_auc_score(testing_dataset_y, temp_test_predicted)
    iter_list.append(int(i))
    auc_test.append(auc_test_value)
    auc_train.append(auc_train_value)
plt.plot(iter_list, auc_train, label="train_AUC_value", color='green')
plt.plot(iter_list, auc_test, label="test_AUC_value", color='red')
plt.xlabel("iteration")
plt.ylabel("auc score")
plt.xticks(iter_list) # show x-coordinate with details
plt.legend() # show label graphic
plt.show()
```



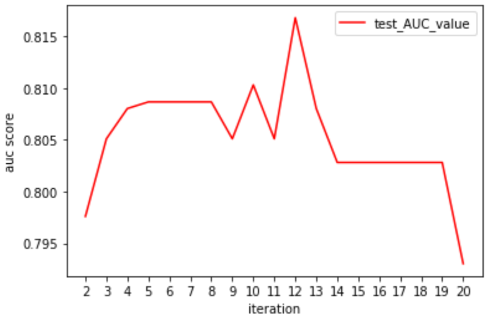
In [228]:

```
# for training data
plt.plot(iter_list, auc_train, label="train_AUC_value", color='green')
plt.xlabel("iteration")
plt.ylabel("auc score")
plt.xticks(iter_list) # show x-coordinate with details
plt.legend() # show label graphic
plt.show()
```



In [229]:

```
# for testing data
plt.plot(iter_list, auc_test, label="test_AUC_value", color='red')
plt.xlabel("iteration")
plt.ylabel("auc score")
plt.xticks(iter_list) # show x-coordinate with details
plt.legend() # show label graphic
plt.show()
```



```
In [230]: iter_list[auc_test.index(max(auc_test))]
```

```
Out[230]: 12
```

```
In [231]: df
```

Out[231]:

	Pclass	Sex	Age	Siblings_Spouses_Aboard	Parents_Children_Aboard	Survived
0	1.0	1.0	0.250	0.125	0.000000	0
1	0.0	0.0	0.375	0.125	0.000000	1
2	1.0	0.0	0.250	0.000	0.000000	1
3	0.0	0.0	0.375	0.125	0.000000	1
4	1.0	1.0	0.375	0.000	0.000000	0
...	...	...	...	...	...	...
882	0.5	1.0	0.250	0.000	0.000000	0
883	0.0	0.0	0.125	0.000	0.000000	1
884	1.0	0.0	0.000	0.125	0.333333	0
885	0.0	1.0	0.250	0.000	0.000000	1
886	1.0	1.0	0.375	0.000	0.000000	0

887 rows × 6 columns

```
In [232]: total = df[(df['Sex']==1.0)&(df['Pclass']==0.0)]
          survived = total[total['Survived']==1]
          len(survived)/len(total)
```

```
Out[232]: 0.36885245901639346
```

```
In [ ]:
```