Homework 5

Introduction to Data Science

Spring 2023

`pulsar.csv` (source) contains statistics from two types of signal from pulsar candidates: integrated profile and dispersion-measure signal-to-noise curve.

In [2]:
```
import pandas as pd

data = pd.read_csv("pulsar.csv")
display(data)
X = data.iloc[:,:8]
y = data.iloc[:,8]

from sklearn.model_selection import StratifiedShuffleSplit

# Split.
split = StratifiedShuffleSplit(n_splits=1, test_size=1/3, random_state=0)
for train_idx, test_idx in split.split(X, y):
    X_train, y_train = X.iloc[train_idx], y.iloc[train_idx]
    X_test, y_test = X.iloc[test_idx], y.iloc[test_idx]
```

	IP_Mean	IP_SD	IP_Kurt	IP_Skew	DMSNR_Mean	DMSNR_SD	DMSNR_Kurt
0	140.562500	55.683782	-0.234571	-0.699648	3.199833	19.110426	7.975532
1	102.507812	58.882430	0.465318	-0.515088	1.677258	14.860146	10.576487
2	103.015625	39.341649	0.323328	1.051164	3.121237	21.744669	7.735822
3	136.750000	57.178449	-0.068415	-0.636238	3.642977	20.959280	6.896499
4	88.726562	40.672225	0.600866	1.123492	1.178930	11.468720	14.269573
...	...	...	...	...	...	...	...
17893	136.429688	59.847421	-0.187846	-0.738123	1.296823	12.166062	15.450260
17894	122.554688	49.485605	0.127978	0.323061	16.409699	44.626893	2.945244
17895	119.335938	59.935939	0.159363	-0.743025	21.430602	58.872000	2.499517
17896	114.507812	53.902400	0.201161	-0.024789	1.946488	13.381731	10.007967
17897	57.062500	85.797340	1.406391	0.089520	188.306020	64.712562	-1.597527

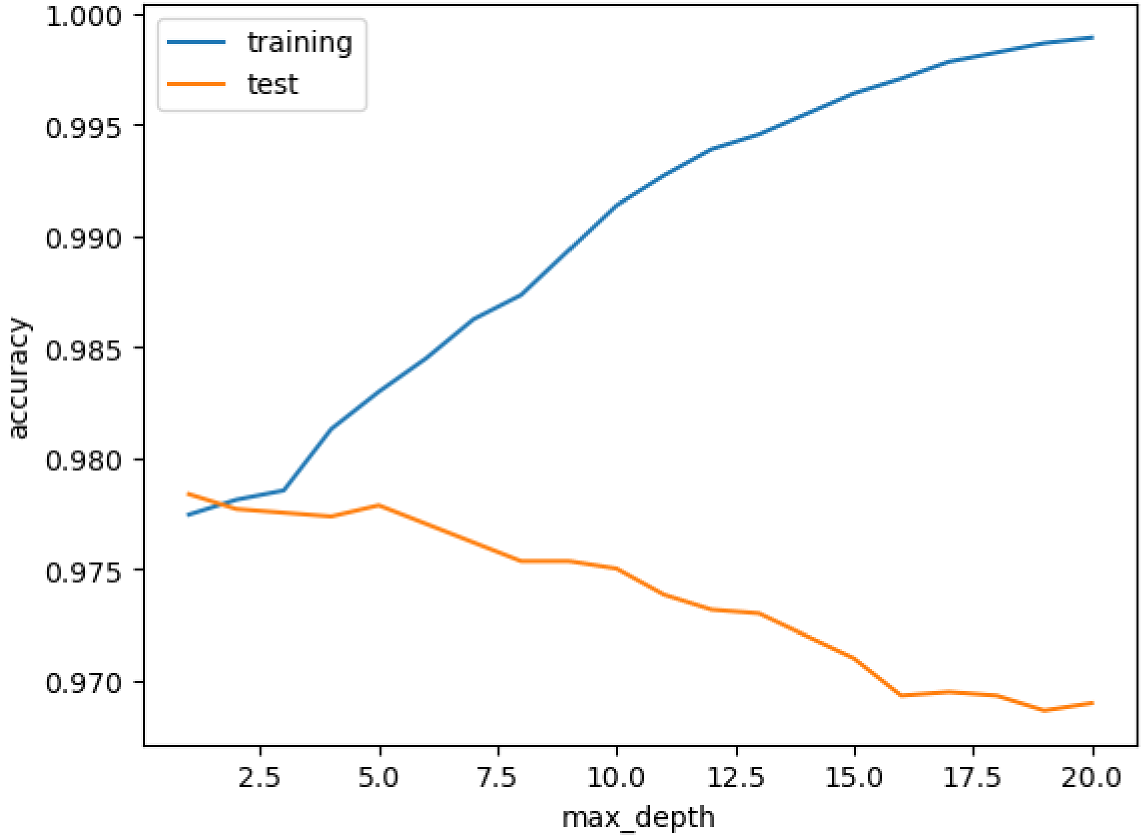
17898 rows × 9 columns

Part 1A [3pts] For `max_depth` ranging from 1 to 20, fit decision tree classifiers using to the training data. Use `random_state=0`. Plot training vs. test accuracy.

In [3]:
```
import numpy as np
from sklearn.tree import DecisionTreeClassifier
```

```python
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

training_acclist = []
test_acclist = []

for max_depth in range(1, 21):
    # Train.
    tree = DecisionTreeClassifier(max_depth=max_depth, random_state=0)
    tree.fit(X_train, y_train)

    # Test.
    y_pred = tree.predict(X_test)
    train_acc = np.sum(tree.predict(X_train) == y_train) / len(y_train)
    training_acclist.append(train_acc)
    test_acc = np.sum(y_pred == y_test) / len(y_test)
    test_acclist.append(test_acc)
    print("max_depth = %d, train_acc = %.3f, test_acc = %.3f" % (max_depth, tra

# Plot training vs. test accuracy
plt.plot(range(1, 21), training_acclist, label="training")
plt.plot(range(1, 21), test_acclist, label="test")
plt.xlabel("max_depth")
plt.ylabel("accuracy")
plt.legend()
plt.show()
```

```
max_depth = 1, train_acc = 0.977, test_acc = 0.978
max_depth = 2, train_acc = 0.978, test_acc = 0.978
max_depth = 3, train_acc = 0.979, test_acc = 0.978
max_depth = 4, train_acc = 0.981, test_acc = 0.977
max_depth = 5, train_acc = 0.983, test_acc = 0.978
max_depth = 6, train_acc = 0.984, test_acc = 0.977
max_depth = 7, train_acc = 0.986, test_acc = 0.976
max_depth = 8, train_acc = 0.987, test_acc = 0.975
max_depth = 9, train_acc = 0.989, test_acc = 0.975
max_depth = 10, train_acc = 0.991, test_acc = 0.975
max_depth = 11, train_acc = 0.993, test_acc = 0.974
max_depth = 12, train_acc = 0.994, test_acc = 0.973
max_depth = 13, train_acc = 0.995, test_acc = 0.973
max_depth = 14, train_acc = 0.995, test_acc = 0.972
max_depth = 15, train_acc = 0.996, test_acc = 0.971
max_depth = 16, train_acc = 0.997, test_acc = 0.969
max_depth = 17, train_acc = 0.998, test_acc = 0.969
max_depth = 18, train_acc = 0.998, test_acc = 0.969
max_depth = 19, train_acc = 0.999, test_acc = 0.969
max_depth = 20, train_acc = 0.999, test_acc = 0.969
```



Part 1B [2pts] What trends do you observe in the training and test accuracies as depth increases? Explain these trends.

Part 1B Answer:

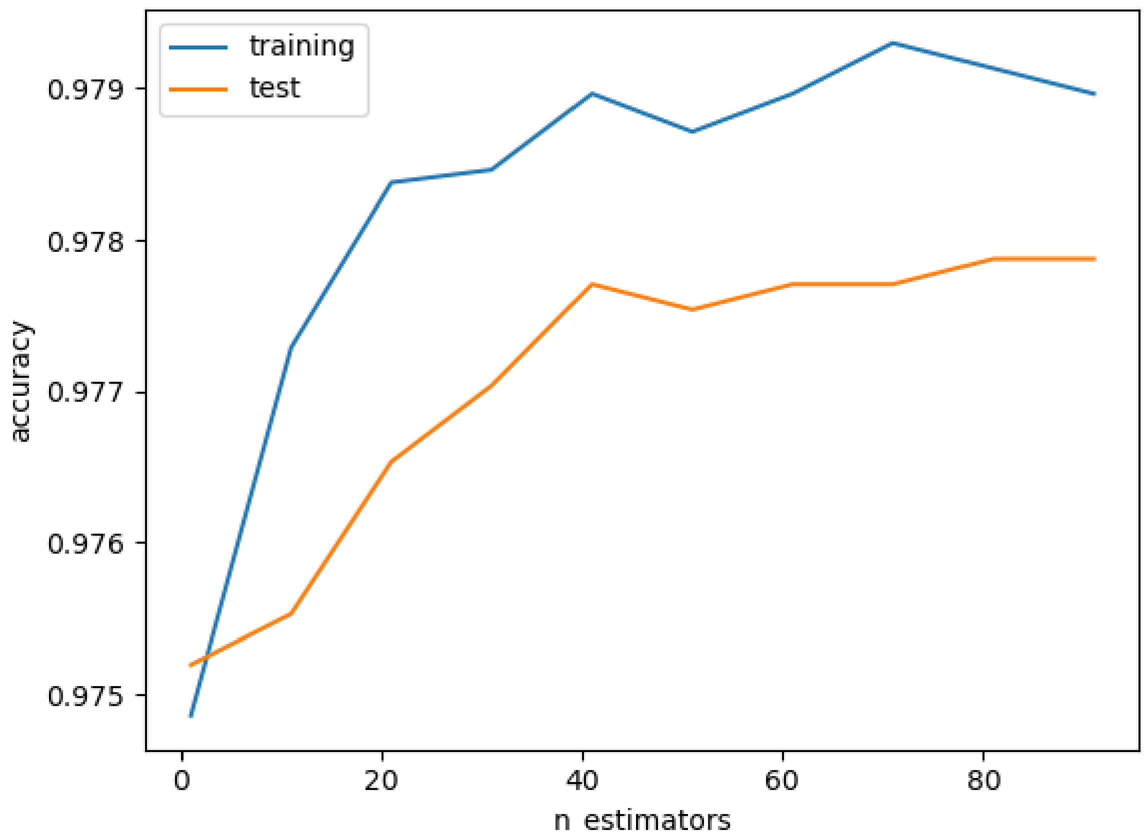
Answer: With the depth increase, the training accuracy increase but the test accuracy decrease. This is because when max_depth is low, the model is not learning the data enough and underfitting the training data, which cause it not generalizing well to the test data. Also, when max_depth is high, the model is overfitting the training data which makes it not generalizing well to the test data.

Part 2A [3pts] For `n_estimators` ranging from 1 to 101 with step size 10, fit random forest classifiers to the training data. Use `random_state=0` and `max_depth=3`. Plot training vs. test accuracy.

In [5]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier

training_acclist = []
test_acclist = []

#step size = 10, max_depth = 3, random_state = 0
for n_estimators in range(1, 101, 10):
    # Train.
    forest = RandomForestClassifier(n_estimators=n_estimators, max_depth=3, rar
    forest.fit(X_train, y_train)
```

```
    # Test.
    y_pred = forest.predict(X_test)

    train_acc = np.sum(forest.predict(X_train) == y_train) / len(y_train)
    training_acclist.append(train_acc)

    test_acc = np.sum(y_pred == y_test) / len(y_test)
    test_acclist.append(test_acc)
    print("n_estimators = %d, train_acc = %.3f, test_acc = %.3f" % (n_estimator

# Plot training vs. test accuracy.
plt.plot(range(1, 101, 10), training_acclist, label="training")
plt.plot(range(1, 101, 10), test_acclist, label="test")
plt.xlabel("n_estimators")
plt.ylabel("accuracy")
plt.legend()
plt.show()
```

```
n_estimators = 1, train_acc = 0.975, test_acc = 0.975
n_estimators = 11, train_acc = 0.977, test_acc = 0.976
n_estimators = 21, train_acc = 0.978, test_acc = 0.977
n_estimators = 31, train_acc = 0.978, test_acc = 0.977
n_estimators = 41, train_acc = 0.979, test_acc = 0.978
n_estimators = 51, train_acc = 0.979, test_acc = 0.978
n_estimators = 61, train_acc = 0.979, test_acc = 0.978
n_estimators = 71, train_acc = 0.979, test_acc = 0.978
n_estimators = 81, train_acc = 0.979, test_acc = 0.978
n_estimators = 91, train_acc = 0.979, test_acc = 0.978
```



Part 2B What trends do you observe in the training and test accuracies as `n_estimators` increases? Explain these trends.

Part 2B Answer:

Answer: With the n_estimators increase, the training accuracy and the test accuracy both increase. The training accuracy increases faster than the test accuracy. This is randon forest is the combination of multiple decision trees, and the more decision trees are used, the more accurate the model is. When the n_estimators increase to a high number, the model will overfitting the training data that will cause training accuracy increases faster than the test accuracy and will have a higher accuracy than the test accuracy.