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

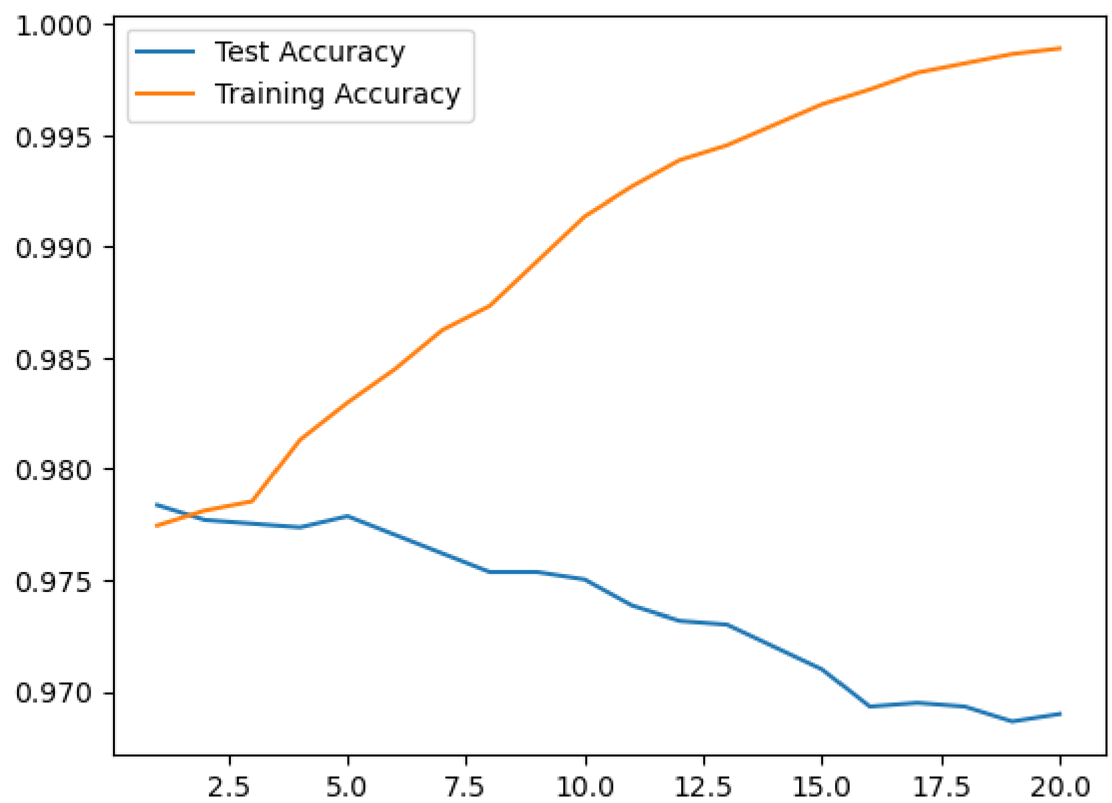
In [1]:
```python
import pandas as pd

data = pd.read_csv("pulsar.csv")
display(data)
X = data.iloc[:,:8] # Predictors: Signal statistics.
y = data.iloc[:,8] # Target: pulsar (1) vs. non-pulsar (0).

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	DMSNR_Skew	Pulsar
0	140.562500	55.683782	-0.234571	-0.699648	3.199833	19.110426	7.975532	74.242225	0
1	102.507812	58.882430	0.465318	-0.515088	1.677258	14.860146	10.576487	127.393580	0
2	103.015625	39.341649	0.323328	1.051164	3.121237	21.744669	7.735822	63.171909	0
3	136.750000	57.178449	-0.068415	-0.636238	3.642977	20.959280	6.896499	53.593661	0
4	88.726562	40.672225	0.600866	1.123492	1.178930	11.468720	14.269573	252.567306	0
...	...	...	...	...	...	...	...	...	...
17893	136.429688	59.847421	-0.187846	-0.738123	1.296823	12.166062	15.450260	285.931022	0
17894	122.554688	49.485605	0.127978	0.323061	16.409699	44.626893	2.945244	8.297092	0
17895	119.335938	59.935939	0.159363	-0.743025	21.430602	58.872000	2.499517	4.595173	0
17896	114.507812	53.902400	0.201161	-0.024789	1.946488	13.381731	10.007967	134.238910	0
17897	57.062500	85.797340	1.406391	0.089520	188.306020	64.712562	-1.597527	1.429475	0

17898 rows × 9 columns

For `max_depth` ranging from 1 to 20, fit decision tree classifiers to the training data. Use `random_state=0`. Plot training vs. test accuracy.

In [29]:
```python
from sklearn.tree import DecisionTreeClassifier as dt
from sklearn.metrics import accuracy_score as acc
import matplotlib.pyplot as plt
import numpy as np
accuracy_test=[]
accuracy_train=[]
for i in range(1,21):
    dt_model = dt(max_depth=i,random_state=0).fit(X_train, y_train)
    accuracy_1 = acc(y_test, dt_model.predict(X_test))
    accuracy_2 = acc(y_train, dt_model.predict(X_train))
    accuracy_test.append(accuracy_1)
    accuracy_train.append(accuracy_2)
depth=np.linspace(1,20, num = 20)
plt.plot(depth,accuracy_test,label="Test Accuracy")
plt.plot(depth,accuracy_train,label="Training Accuracy")
plt.legend(loc="upper left")
plt.show()
```

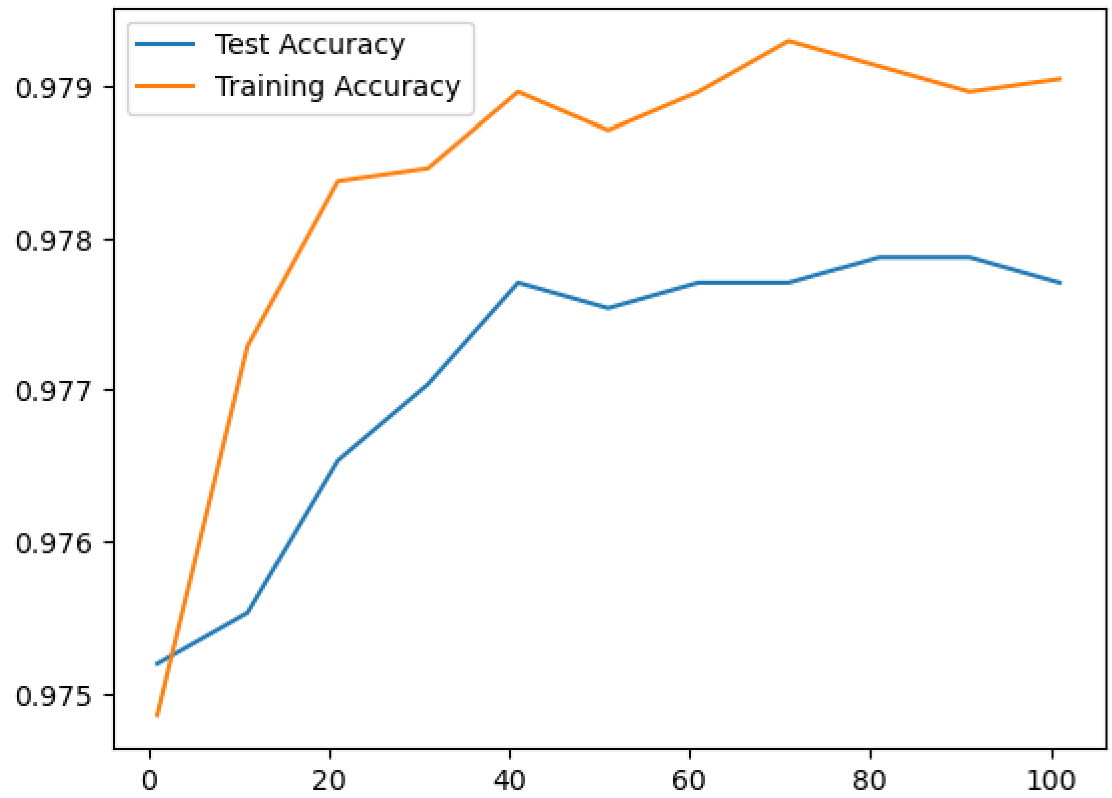


What trend do you observe in the training and test accuracies as `max_depth` increases? Explain the trend.

Answer: We can see from the plot that as max_depth increases, the training accuracy increases while the test accuracy decreases. This happens because depth determine how flexible the model is, increasing the depth will help fitting deeper into the training data and thus increase the accuracy of the training set. However, it will also cause overfitting problem, thus decrease the accuracy for the general performance, and that's why the test accuracy is decreasing.

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 [39]:
```
from sklearn.ensemble import RandomForestClassifier as rf
accuracy_test2=[]
accuracy_train2=[]
for i in range(1,102,10):
    rf_model=rf(n_estimators = i, max_depth = 3, random_state = 0).fit(X_train, y_train)
    accuracy_test2.append(acc(y_test, rf_model.predict(X_test)))
    accuracy_train2.append(acc(y_train, rf_model.predict(X_train)))
n=np.linspace(1,101, num = 11)
plt.plot(n, accuracy_test2,label="Test Accuracy")
plt.plot(n, accuracy_train2,label="Training Accuracy")
plt.legend(loc="upper left")
plt.show()
```



What trend do you observe in the training and test accuracies as `n_estimators` increases? Explain the trend.

Answer: From the plot, we can see that as n_estimators increases, both the training and test accuracies increase, and to some point, the increment slows down(flattened). The n_estimators parameter specifies the number of trees in the forest of the model, and increasing it means adding more subsamples to fit the data, thus result in increasing accuracies for test and training sets. However, as the model's accuracies getting better and better, the increment would slow down since the accuracies are already high enough.