CS201A

Foundations of Data Science

Practical

Task 1: Data visualisation and pre-processing

Housing is a central part of the New Zealand economy and accounts for around half of the assets of New Zealand households. Data is available from 1979. The value of housing stock includes all private sector residential dwellings (detached houses, flats and apartments), lifestyle blocks (with a dwelling), detached houses converted to flats and ‘home and income' properties. It does not include vacant land. This is an estimate of the current market value of houses in New Zealand and is based on current house prices. The data is compiled by CoreLogic and published by the Reserve Bank. Data from 1979 is available in the key graph data file.

How many records are official QV data?

There are total of official QV data is 81

How many records are RBNZ estimate?

There are total of 88 records in RBNZ estimate

Read the CSV file as a Pandas data frame

```
In [ ]: import numpy as np
        import pandas as pd

        df = pd.read_excel("graphdata.xlsx", sheet_name ="HOUSING")
```

I am formatting the data here to make it easier to read. I converted the graphdata.xlsx to 'csv' and added some parameter of which rows and columns I want to display. I added a header for the date and some slight formatting of the other headers

```
In [ ]: df.to_csv("HOUSING")
```

In [ ]:
```
housing = pd.read_csv('HOUSING', header = 5, usecols = (2,3,4,5), skiprows=[17
5,176,177,178,179])
```

In [ ]:
```
housing.columns = ['Date','Value of Housing $Billion','House Prices - RBNZ Lin
ked all Residential HPI Series A%','HPI for Houses, Index']
housing['Date'] = pd.to_datetime(housing['Date'])
```

In [ ]:
```
housing
```

Out[ ]:

	Date	Value of Housing $Billion	House Prices - RBNZ Linked all Residential HPI Series A%	HPI for Houses, Index
0	1979-12-01	25.0	NaN	NaN
1	1980-03-01	25.0	NaN	NaN
2	1980-06-01	26.0	NaN	NaN
3	1980-09-01	27.0	NaN	NaN
4	1980-12-01	28.0	NaN	NaN
...	...	...	...	...
164	2020-12-01	1385.7	16.1	3080.9
165	2021-03-01	1513.0	22.7	3379.1
166	2021-06-01	1591.5	28.5	3495.0
167	2021-09-01	1663.1	28.7	3704.3
168	2021-12-01	1763.1	25.2	3893.5

169 rows × 4 columns

Get statistics of the data using python

```
In [ ]: housing.describe()
```

Out[ ]:

	Value of Housing $Billion	House Prices - RBNZ Linked all Residential HPI Series A%	HPI for Houses, Index
count	169.000000	125.000000	129.000000
mean	425.053254	7.076000	1337.831783
std	394.275427	7.385987	802.662676
min	25.000000	-9.000000	466.300000
25%	123.000000	2.300000	695.900000
50%	232.000000	6.400000	1299.900000
75%	613.700000	12.300000	1714.900000
max	1763.100000	28.700000	3893.500000

Does the data contain missing values?

Yes, we do have missing values

```
In [ ]: housing.isnull().values.any()

Out[ ]: True
```

This are the amount of missing values for each column

```
In [ ]: housing.isnull().sum()

Out[ ]: Date                                                        0
        Value of Housing $Billion                                   0
        House Prices - RBNZ Linked all Residential HPI Series A%   44
        HPI for Houses, Index                                      40
        dtype: int64
```

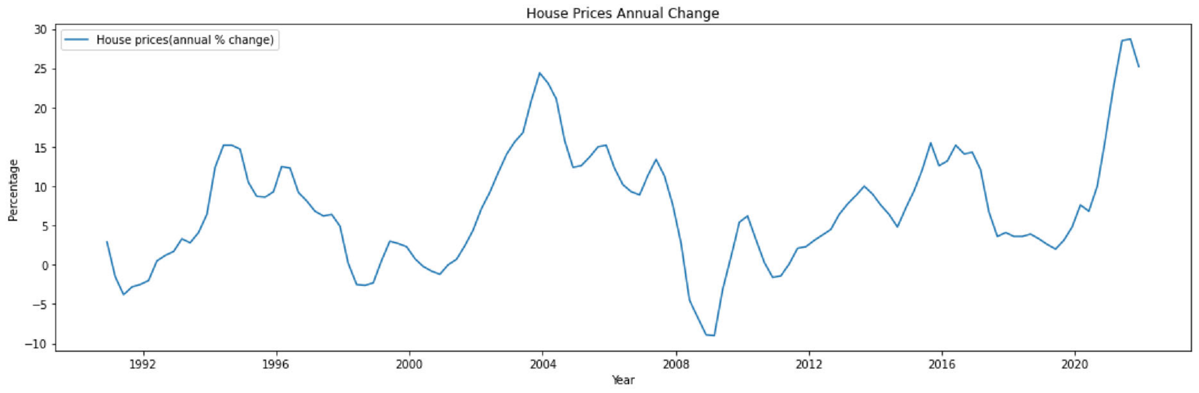
This is the total summation of all missing values in the Dataframe

```
In [ ]: housing.isnull().sum().sum()

Out[ ]: 84
```

Draw the graph of House prices annual change (in percentage) using matplotlib or seaborn using a suitable chart of your choice.

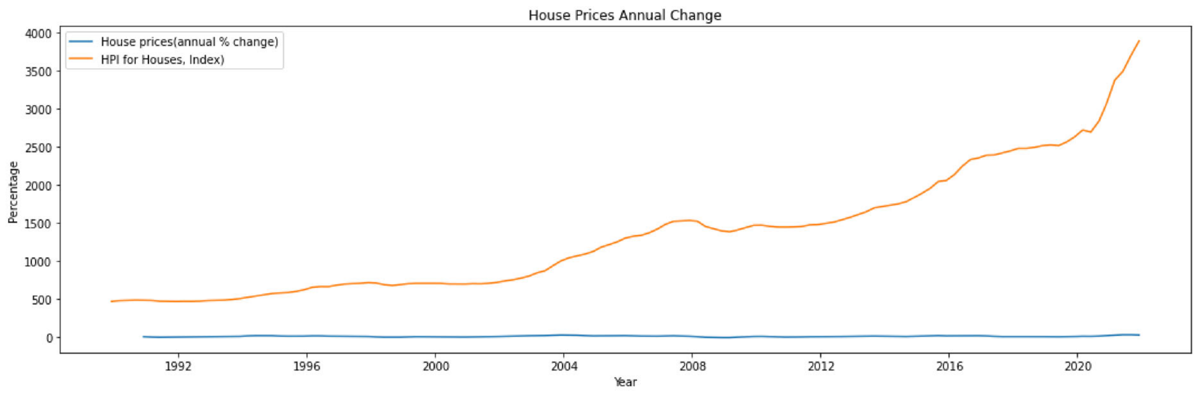
```
In [ ]: from matplotlib import pyplot as plt
        import seaborn as sns
```

```
In [ ]: plt.figure(figsize=(15,5))
        plt.title('House Prices Annual Change')
        plt.ylabel('Percentage')
        plt.xlabel('Year')


        plt.plot(housing['Date'] ,housing['House Prices - RBNZ Linked all Residential
         HPI Series A%'],Label="House prices(annual % change)")
        plt.legend()
        plt.tight_layout()
        plt.show()
```



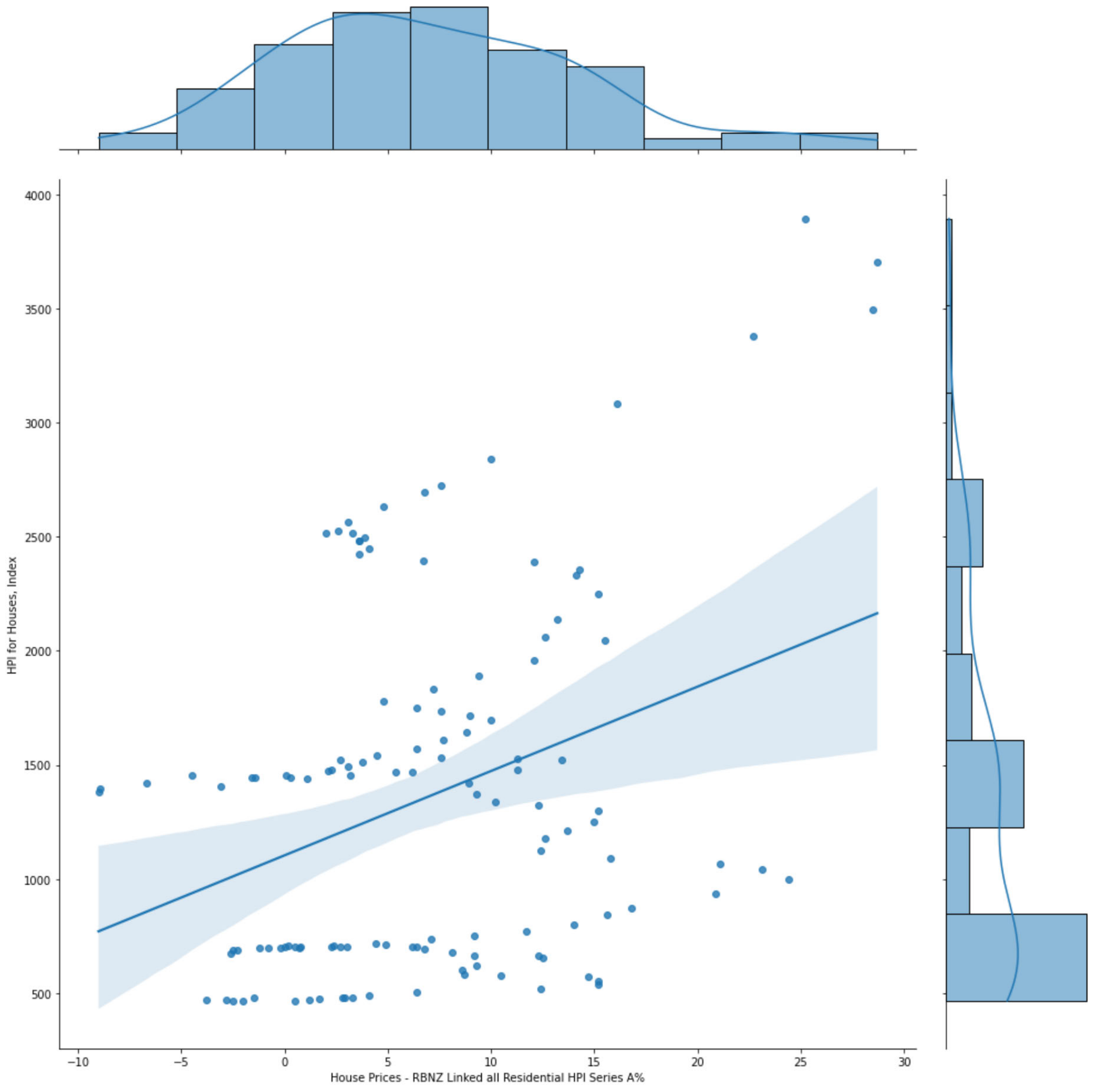
Combine the previous graph with a graph of HPI for houses

In [ ]:
```
plt.figure(figsize=(15,5))
plt.title('House Prices Annual Change')
plt.ylabel('Percentage')
plt.xlabel('Year')

plt.plot(housing['Date'] ,housing['House Prices - RBNZ Linked all Residential
 HPI Series A%'],Label="House prices(annual % change)")
plt.plot(housing['Date'] ,housing['HPI for Houses, Index'],Label="HPI for Hous
es, Index)")
plt.legend()
plt.tight_layout()
plt.show()
```

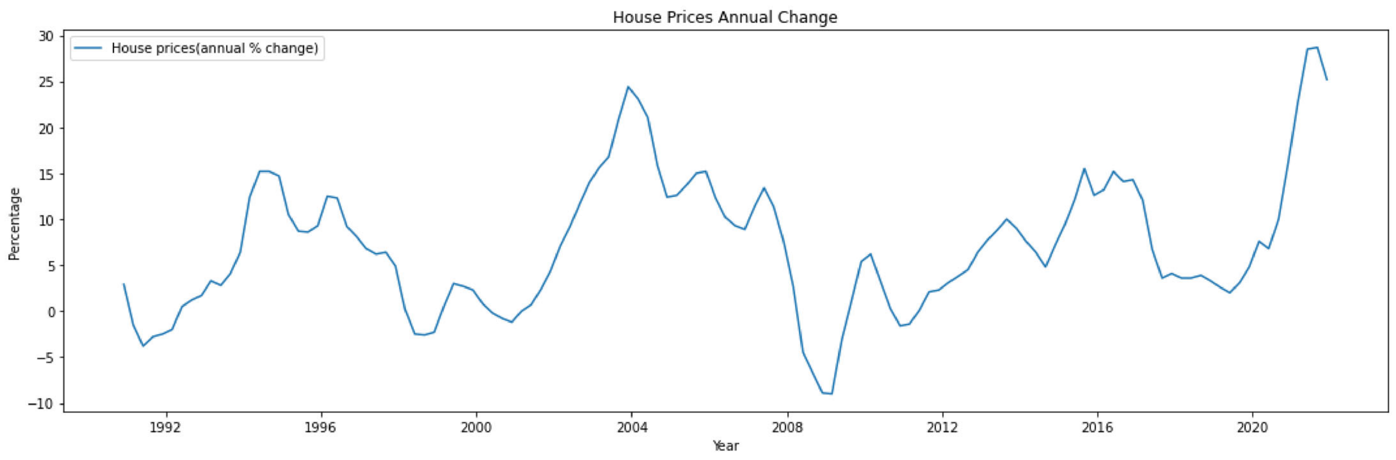


In [ ]:
```
import seaborn as sns
```

In [ ]:
```
anual = housing['House Prices - RBNZ Linked all Residential HPI Series A%']
hpi = housing['HPI for Houses, Index']

df1 = sns.jointplot(x=anual,y=hpi,data=hpi,kind='reg')
#df2 = sns.jointplot(x=hpi,y=hpi,data=anual,kind='reg')

df1.fig.set_size_inches(15,15)
#df2.fig.set_size_inches(15,15)
```



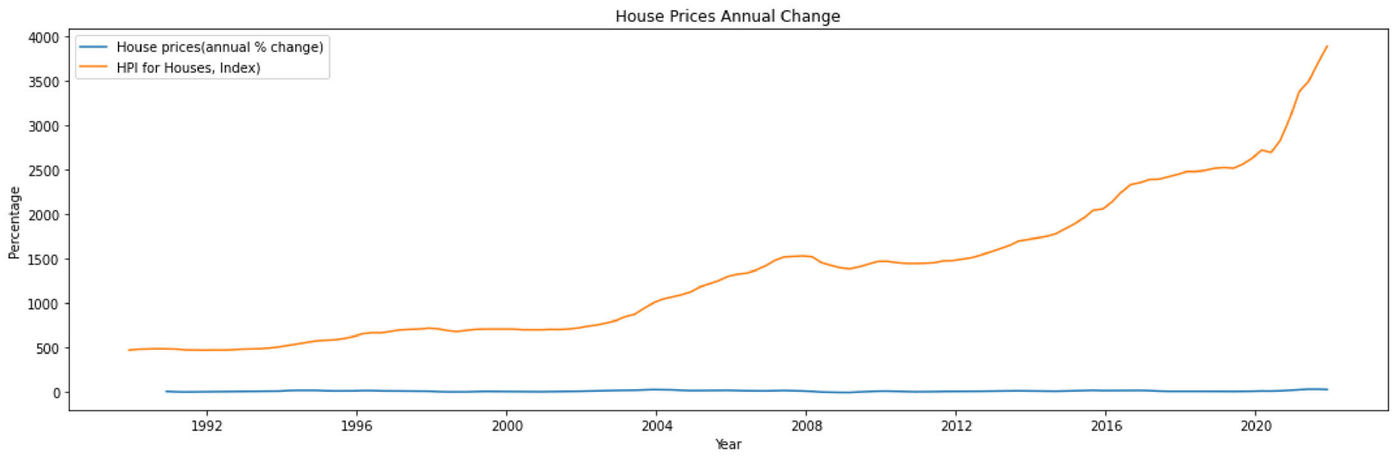
What can you tell about the trend of the housing price in New Zealand?



Throughout 1990 to 2022 the house prices had some irregular changes. Between 1990 and 1996 it had a spiked in house price in 1995 but after 1996 it slowly went down which in 1999 we saw decline of house price.

During 2001 the house price was going up and we got a huge spike on housing price between 2001 and 2004 then it slowly went down and in 2009 it had the lowest house price throughout 1990 to 2022.

After 2009 to 2019 prices was going up and down but on 2020 we saw another spike on house prices.



The HPI for house was slowly going on the rise from 1990 to 2020

Task 2

Random Forest

In [ ]:
```
from sklearn.datasets import load_digits
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

df_test = pd.read_csv("/content/mnist_test.csv")
df_train = pd.read_csv("/content/mnist_train.csv")
```

In [ ]:
```
df_train['target'] = df_train.iloc[:, 0]
```

In [ ]:
```
df_train.head()
```

Out[ ]:

	5	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	...	0.609	0.610	0.611	0.612	0.613	0.614	0.615
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
1	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
3	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
4	2	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0

5 rows × 786 columns

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df_train.drop(['target'],
axis='columns'),df_train.iloc[:, 0],test_size = 0.333,random_state=10, stratif
y=df_train.iloc[:, 0])
```

In [ ]:
```
X_train.shape,y_train.shape
```

Out[ ]:
```
((40019, 785), (40019,))
```

In [ ]:
```
X_test.shape,y_test.shape
```

Out[ ]:
```
((19980, 785), (19980,))
```

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier()
model.fit(X_train, y_train)
```

Out[ ]:
```
RandomForestClassifier()
```

In [ ]:
```
model.score(X_test, y_test)
```

Out[ ]:
```
0.9855355355355355
```

In [ ]:
```
y_predicted = model.predict(X_test)
```

In [ ]:
```
from sklearn.metrics import accuracy_score
accuracy_score(y_predicted,y_test)
```

Out[ ]:
```
0.9855355355355355
```

In [ ]:
```
train_accuracy_default_params = model.score(X_train, y_train)
test_accuracy_default_params = model.score(X_test, y_test)

print(f'Train Accuracy - : {train_accuracy_default_params:.3f}')
print(f'Test Accuracy - : {test_accuracy_default_params:.3f}')
```

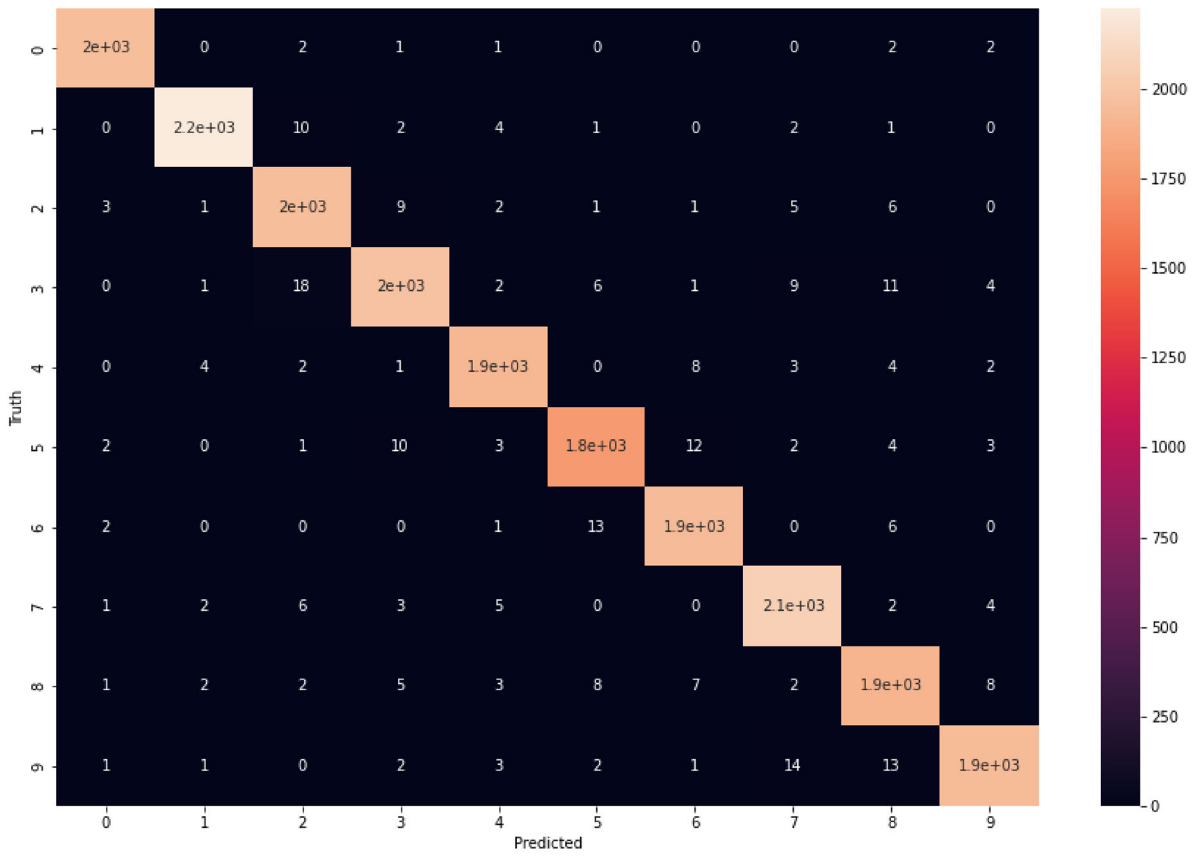
```
Train Accuracy - : 1.000
Test Accuracy - : 0.986
```

In [ ]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_predicted)
cm
```

Out[ ]:
```
array([[1964,    0,    2,    1,    1,    0,    0,    0,    2,    2],
       [   0, 2225,   10,    2,    4,    1,    0,    2,    1,    0],
       [   3,    1, 1956,    9,    2,    1,    1,    5,    6,    0],
       [   0,    1,   18, 1990,    2,    6,    1,    9,   11,    4],
       [   0,    4,    2,    1, 1922,    0,    8,    3,    4,    2],
       [   2,    0,    1,   10,    3, 1768,   12,    2,    4,    3],
       [   2,    0,    0,    0,    1,   13, 1949,    0,    6,    0],
       [   1,    2,    6,    3,    5,    0,    0, 2063,    2,    4],
       [   1,    2,    2,    5,    3,    8,    7,    2, 1910,    8],
       [   1,    1,    0,    2,    3,    2,    1,   14,   13, 1944]])
```

In [ ]:
```
import seaborn as sn

plt.figure(figsize=(15,10))
sn.heatmap(cm,annot=True)
plt.xlabel("Predicted")
plt.ylabel("Truth")
```

Out[ ]:
```
Text(114.0, 0.5, 'Truth')
```



In [ ]:
```
from sklearn.metrics import classification_report
# View the classification report for test data and predictions
print(classification_report(y_test, y_predicted))
```

```
              precision    recall  f1-score   support

           0       0.99      1.00      1.00      1972
           1       1.00      0.99      0.99      2245
           2       0.98      0.99      0.98      1984
           3       0.98      0.97      0.98      2042
           4       0.99      0.99      0.99      1946
           5       0.98      0.98      0.98      1805
           6       0.98      0.99      0.99      1971
           7       0.98      0.99      0.99      2086
           8       0.97      0.98      0.98      1948
           9       0.99      0.98      0.98      1981

    accuracy                           0.99     19980
   macro avg       0.99      0.99      0.99     19980
weighted avg       0.99      0.99      0.99     19980
```

Evaluation

Using the default parameters with Random Forest we were able to get a good accuracy score for our model. It doesn't seem our Training test is overfitting. The confusion matrix shows that the predicted value is high.

Random Forest Hyperparameter Tuning

In [ ]:
```
#Number of tress in random forest
n_estimators = np.arange(10,210,10)
# Number of features to consider at every split
max_features=['auto','sqrt']
# Maximum number of levels in tree
max_depth = np.arange(10,60,10)
# Mininum number of samples requried to split a node
min_samples_split = np.arange(1,11,1)
# Minimum number of samples required at each leaf node
min_samples_leaf = np.arange(1,11,1)
# Method of selecting samples for training each tree
bootstrap = [True,False]
```

In [ ]:
```
#Create param grid

param_grid = {'n_estimators' :n_estimators,
              'max_features' :max_features,
              'max_depth' :max_depth,
              'min_samples_split' :min_samples_split,
              'min_samples_leaf' :min_samples_leaf,
              'bootstrap' :bootstrap}
print(param_grid)
```

```
{'n_estimators': array([ 10,  20,  30,  40,  50,  60,  70,  80,  90, 100, 11
0, 120, 130,
       140, 150, 160, 170, 180, 190, 200]), 'max_features': ['auto', 'sqrt'],
'max_depth': array([10, 20, 30, 40, 50]), 'min_samples_split': array([ 1,  2,
3,  4,  5,  6,  7,  8,  9, 10]), 'min_samples_leaf': array([ 1,  2,  3,  4,
5,  6,  7,  8,  9, 10]), 'bootstrap': [True, False]}
```

In [ ]:
```
rf_model = RandomForestClassifier()
```

GridSearchCV find the the best hyperparamter

In [ ]:
```
from sklearn.model_selection import GridSearchCV
rf_Grid = GridSearchCV(estimator = rf_model, param_grid = param_grid, cv = 5,
verbose = 2, n_jobs = 4)
```

In [ ]:
```
rf_Grid.fit(X_train,y_train)
```

In [ ]:
```
rf_Grid.best_params_
```

Important

The GridSearchCV is taking way to long to compile I have it running for 3 hours but it is still going it had to do Fitting 5 folds for each of 40000 candidates, totalling 200000 fits. So I decided to use another way for tuning

Randomized Search CV

In [ ]:
```
from sklearn.model_selection import RandomizedSearchCV
rf_RandomGrid = RandomizedSearchCV(estimator = rf_model, param_distributions = 
param_grid, cv = 10, verbose = 2, n_jobs = 4)
```

In [ ]:
```
rf_RandomGrid.fit(X_train, y_train)
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_validation.p
y:372: FitFailedWarning:
10 fits failed out of a total of 100.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting erro
r_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
---
10 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_valid
ation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.7/dist-packages/sklearn/ensemble/_forest.py",
line 467, in fit
    for i, t in enumerate(trees)
  File "/usr/local/lib/python3.7/dist-packages/joblib/parallel.py", line 104
3, in __call__
    if self.dispatch_one_batch(iterator):
  File "/usr/local/lib/python3.7/dist-packages/joblib/parallel.py", line 861,
in dispatch_one_batch
    self._dispatch(tasks)
  File "/usr/local/lib/python3.7/dist-packages/joblib/parallel.py", line 779,
in _dispatch
    job = self._backend.apply_async(batch, callback=cb)
  File "/usr/local/lib/python3.7/dist-packages/joblib/_parallel_backends.py",
line 208, in apply_async
    result = ImmediateResult(func)
  File "/usr/local/lib/python3.7/dist-packages/joblib/_parallel_backends.py",
line 572, in __init__
    self.results = batch()
  File "/usr/local/lib/python3.7/dist-packages/joblib/parallel.py", line 263,
in __call__
    for func, args, kwargs in self.items]
  File "/usr/local/lib/python3.7/dist-packages/joblib/parallel.py", line 263,
in <listcomp>
    for func, args, kwargs in self.items]
  File "/usr/local/lib/python3.7/dist-packages/sklearn/utils/fixes.py", line
216, in __call__
    return self.function(*args, **kwargs)
  File "/usr/local/lib/python3.7/dist-packages/sklearn/ensemble/_forest.py",
line 185, in _parallel_build_trees
    tree.fit(X, y, sample_weight=curr_sample_weight, check_input=False)
  File "/usr/local/lib/python3.7/dist-packages/sklearn/tree/_classes.py", lin
e 942, in fit
    X_idx_sorted=X_idx_sorted,
  File "/usr/local/lib/python3.7/dist-packages/sklearn/tree/_classes.py", lin
e 254, in fit
    % self.min_samples_split
ValueError: min_samples_split must be an integer greater than 1 or a float in
(0.0, 1.0]; got the integer 1

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search.py:97
```

```
2: UserWarning: One or more of the test scores are non-finite: [0.9657664  0.
97131374 0.9764613  0.97773569        nan 0.97733591
 0.97958482 0.98333298 0.9801845  0.9712887 ]
  category=UserWarning,
```

Out[ ]:
```
RandomizedSearchCV(cv=10, estimator=RandomForestClassifier(), n_jobs=4,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': array([10, 20, 30, 40, 5
0]),
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': array([ 1,  2,
3,  4,  5,  6,  7,  8,  9, 10]),
                                        'min_samples_split': array([ 1,  2,
3,  4,  5,  6,  7,  8,  9, 10]),
                                        'n_estimators': array([ 10,  20,  30,
40,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140, 150, 160, 170, 180, 190, 200])},
                   verbose=2)
```

Fitting 10 folds for each of 10 candidates, totalling 100 fits.

In [ ]:
```
rf_RandomGrid.best_params_
```

Out[ ]:
```
{'bootstrap': False,
 'max_depth': 50,
 'max_features': 'sqrt',
 'min_samples_leaf': 3,
 'min_samples_split': 7,
 'n_estimators': 110}
```

In [ ]:
```
model = RandomForestClassifier(n_estimators = 110, max_features = 'sqrt',boots
trap = False, max_depth = 50, min_samples_leaf = 3, min_samples_split = 7)
model.fit(X_train, y_train)
```

Out[ ]:
```
RandomForestClassifier(bootstrap=False, max_depth=50, max_features='sqrt',
                       min_samples_leaf=3, min_samples_split=7,
                       n_estimators=110)
```

In [ ]:
```
model.score(X_test, y_test)
```

Out[ ]:
```
0.9853853853853853
```

In [ ]:
```
train_accuracy_hyper_params = model.score(X_train, y_train)
test_accuracy_hyper_params = model.score(X_test, y_test)
print(f'Train Accuracy - : {train_accuracy_hyper_params:.3f}')
print(f'Test Accuracy - : {test_accuracy_hyper_params:.3f}')
```

```
Train Accuracy - : 1.000
Test Accuracy - : 0.985
```

In [ ]:
```
y_predicted = model.predict(X_test)
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_predicted)
cm
```

Out[ ]:
```
array([[1962,    0,    3,    0,    3,    0,    0,    0,    4,    0],
       [   0, 2221,   11,    4,    4,    0,    0,    2,    3,    0],
       [   4,    0, 1956,    8,    4,    0,    2,    5,    5,    0],
       [   0,    1,   22, 1985,    1,    6,    0,   13,    9,    5],
       [   1,    4,    2,    0, 1918,    0,    8,    4,    4,    5],
       [   1,    0,    1,   13,    3, 1766,   11,    2,    5,    3],
       [   0,    1,    0,    0,    2,   15, 1951,    0,    2,    0],
       [   1,    3,    6,    2,    2,    0,    0, 2063,    2,    7],
       [   0,    1,    1,    8,    4,    7,    4,    1, 1919,    3],
       [   1,    0,    0,    3,    2,    3,    0,   12,   13, 1947]])
```

In [ ]:
```
from sklearn.metrics import classification_report
# View the classification report for test data and predictions
print(classification_report(y_test, y_predicted))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1972
           1       1.00      0.99      0.99      2245
           2       0.98      0.99      0.98      1984
           3       0.98      0.97      0.98      2042
           4       0.99      0.99      0.99      1946
           5       0.98      0.98      0.98      1805
           6       0.99      0.99      0.99      1971
           7       0.98      0.99      0.99      2086
           8       0.98      0.99      0.98      1948
           9       0.99      0.98      0.99      1981

    accuracy                           0.99     19980
   macro avg       0.99      0.99      0.99     19980
weighted avg       0.99      0.99      0.99     19980
```

Cross Validation

In [ ]:
```
from sklearn.model_selection import cross_val_score
```

In [ ]:
```
k = cross_val_score(RandomForestClassifier(), X_train, y_train)
```

In [ ]:
```
cvs_score  = k.mean()
cvs_std  = k.std()
```

In [ ]:
```
from sklearn.metrics import classification_report
# View the classification report for test data and predictions
print(classification_report(y_test, y_predicted))
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1972
           1       1.00      0.99      0.99      2245
           2       0.98      0.99      0.98      1984
           3       0.98      0.97      0.98      2042
           4       0.99      0.99      0.99      1946
           5       0.98      0.98      0.98      1805
           6       0.99      0.99      0.99      1971
           7       0.98      0.99      0.99      2086
           8       0.98      0.99      0.98      1948
           9       0.99      0.98      0.99      1981

    accuracy                           0.99     19980
   macro avg       0.99      0.99      0.99     19980
weighted avg       0.99      0.99      0.99     19980
```

Evaluation

Unlike GridSearchCV were it will take all the estimators and combination and do a number of folds, The time it will take to find the best model will depend on how many estimators and combination and folds you have.

While Randomized Search CV it will go through random parameter combination and it will have significantly lower combination to run through to find the best model which is I think is better because Google Colab has a limit on how long you can run you notebook hence using Randomized Search CV in this situation is a better choice.

In [ ]:
```
test_outcome = {'Model':['Random Forest Default Parameters', 'Random Forest Hy
pertuning','Random Forest Cross Validation'],
                'Train Accuracy': [train_accuracy_default_params,train_accurac
y_hyper_params,train_accuracy_hyper_params],
                'Test Accuracy': [test_accuracy_default_params,test_accuracy_h
yper_params,cvs_score ],
                }
```

In [ ]:
```
pd.DataFrame(test_outcome)
```

Out[ ]:

	Model	Train Accuracy	Test Accuracy
0	Random Forest Default Parameters	1.000000	0.985536
1	Random Forest Hypertuning	0.999925	0.985385
2	Random Forest Cross Validation	0.999925	0.982433

As you can see in the table there isn't much difference when it comes to the outcome. With the default parameters I was still able to get a good score of my test and the same thing can be said by the other model that was used.

The default parameter did well compared to the other 2 probably fine tuning the parameters will get us a better result

Did the training overfit? I dont believe it did the training score and test score shows this and we can also see it in the classification report.

Based in my understanding the RandomForest uses multiple decision tree and takes a majority vote which in turn creates a low variance so thats why our training score is very close witht the test score.

Decision Tree

In [ ]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

df_test = pd.read_csv("/content/mnist_test.csv")
df_train = pd.read_csv("/content/mnist_train.csv")
```

In [ ]:
```
df_data = df_train.iloc[:,1:]
```

In [ ]:
```
df_data.shape
```

Out[ ]:
```
(59999, 784)
```

In [ ]:
```
df_data
```

Out[ ]:

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	...	0.608	0.609	0.610	0.611	0.612	0.613
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
59994	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
59995	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
59996	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
59997	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
59998	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0

59999 rows × 784 columns

In [ ]:
```
df_label = df_train.iloc[:,0]
```

In [ ]:
```
df_label
```

Out[ ]:
```
0        0
1        4
2        1
3        9
4        2
        ..
59994    8
59995    3
59996    5
59997    6
59998    8
Name: 5, Length: 59999, dtype: int64
```

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df_data, df_label, test_si
ze = 0.333, random_state = 101,stratify =df_label)#
```

In [ ]:
```
X_train.shape, X_test.shape
```

Out[ ]:
```
((40019, 784), (19980, 784))
```

In [ ]:
```
y_train.shape, y_test.shape
```

Out[ ]:
```
((40019,), (19980,))
```

```
In [ ]: from sklearn import tree
```

```
In [ ]: from sklearn.tree import DecisionTreeClassifier
        dt_model = DecisionTreeClassifier()
```

```
In [ ]: dt_model.fit(X_train,y_train)

Out[ ]: DecisionTreeClassifier()
```

```
In [ ]: dt_model.score(X_test,y_test)

Out[ ]: 0.8582082082082082
```

Check the training if we are overfitting

```
In [ ]: dt_train_accuracy_default_params = dt_model.score(X_train, y_train)
        dt_test_accuracy_default_params = dt_model.score(X_test, y_test)
        print(f'Train Accuracy - : {dt_train_accuracy_default_params:.3f}')
        print(f'Test Accuracy - : {dt_test_accuracy_default_params:.3f}')

        Train Accuracy - : 1.000
        Test Accuracy - : 0.858
```

Training score is perfect as predicted but the test accuracy is far from desirable our model is overfitting.

Decision Tree Hyperparameter Tuning

```
In [ ]: from sklearn.tree import DecisionTreeClassifier
        from sklearn.model_selection import RandomizedSearchCV
```

```
In [ ]: parameters = {'max_depth': np.arange(10,210,10),
                      'criterion':('gini','entropy'),
                      'max_leaf_nodes':np.arange(1,11,1),
                      'max_features':('auto','sqrt','log2'),
                      'min_samples_split':(2,4,6,8)
                      }
```

```
In [ ]: DT_grid = RandomizedSearchCV(DecisionTreeClassifier(),param_distributions = pa
        rameters, cv = 5, verbose = True)
```

In [ ]:
```
DT_grid.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

Out[ ]:
```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(),
                   param_distributions={'criterion': ('gini', 'entropy'),
                                        'max_depth': array([ 10,  20,  30,  4
0,  50,  60,  70,  80,  90, 100, 110, 120, 130,
       140, 150, 160, 170, 180, 190, 200]),
                                        'max_features': ('auto', 'sqrt',
                                                         'log2'),
                                        'max_leaf_nodes': array([ 1,  2,  3,
4,  5,  6,  7,  8,  9, 10]),
                                        'min_samples_split': (2, 4, 6, 8)},
                   verbose=True)
```

In [ ]:
```
DT_grid.best_estimator_
```

Out[ ]:
```
DecisionTreeClassifier(max_depth=190, max_features='sqrt', max_leaf_nodes=9,
                       min_samples_split=4)
```

Check Accuracy

In [ ]:
```
DT_Model = DecisionTreeClassifier(max_depth=190, max_features='sqrt', max_leaf
_nodes=9,
                       min_samples_split=4)
```

In [ ]:
```
DT_Model.fit(X_train,y_train)
```

Out[ ]:
```
DecisionTreeClassifier(max_depth=190, max_features='sqrt', max_leaf_nodes=9,
                       min_samples_split=4)
```

In [ ]:
```
dt_train_accuracy_hyper_params  = DT_Model.score(X_train, y_train)
dt_test_accuracy_hyper_params  = DT_Model.score(X_test, y_test)
print(f'Train Accuracy - : {dt_train_accuracy_hyper_params:.3f}')
print(f'Test Accuracy - : {dt_test_accuracy_hyper_params:.3f}')
```

```
Train Accuracy - : 0.409
Test Accuracy - : 0.409
```

Changing the max_depth

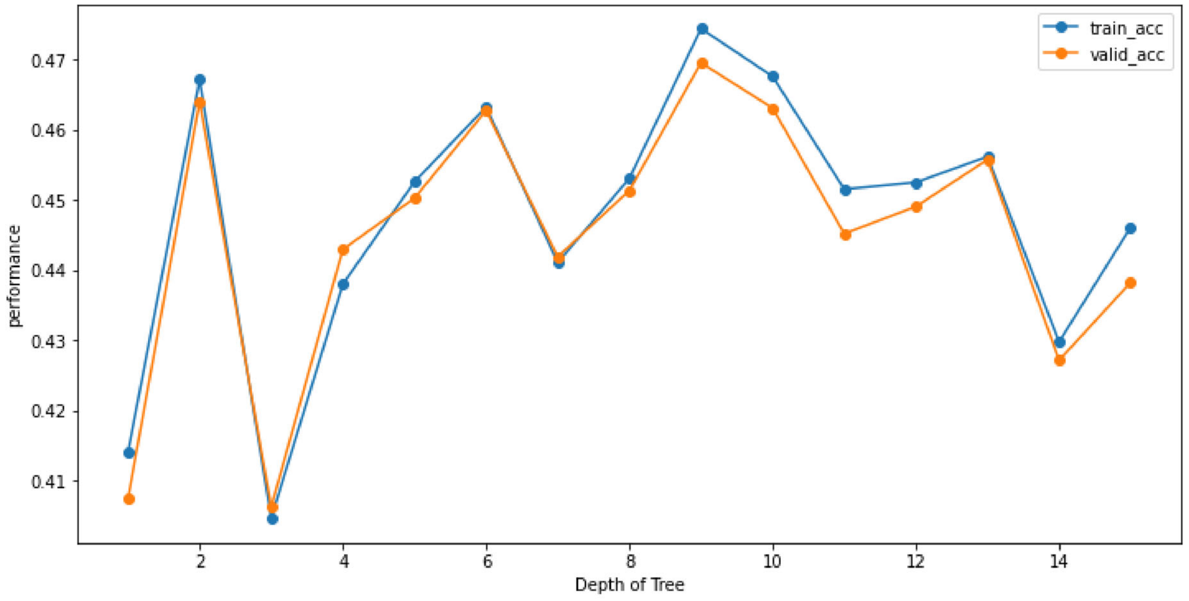
In [ ]:
```
train_accuracy = []
validation_accuracy  = []
for depth in range(1,16):
  DT_Model = DT_Model = DecisionTreeClassifier(max_depth=16, max_features='sqr
t', max_leaf_nodes=9,
                       min_samples_split=4)
  DT_Model.fit(X_train,y_train)
  train_accuracy.append(DT_Model.score(X_train, y_train))
  validation_accuracy.append(DT_Model.score(X_test, y_test))
```

In [ ]:
```
frame = pd.DataFrame({'max_depth':range(1,16),'train_acc':train_accuracy,'vali
d_acc':validation_accuracy})
frame
```

Out[ ]:
```
    max_depth  train_acc  valid_acc
 0          1   0.414053   0.407407
 1          2   0.467153   0.464064
 2          3   0.404608   0.406206
 3          4   0.437992   0.442943
 4          5   0.452585   0.450250
 5          6   0.463280   0.462763
 6          7   0.441065   0.441892
 7          8   0.453085   0.451351
 8          9   0.474450   0.469570
 9         10   0.467628   0.463113
10         11   0.451536   0.445195
11         12   0.452510   0.449049
12         13   0.456183   0.455756
13         14   0.429771   0.427127
14         15   0.446113   0.438238
```

In [ ]:
```
plt.figure(figsize=(12,6))
plt.plot(frame['max_depth'],frame['train_acc'],marker='o',label=('train_acc'))
plt.plot(frame['max_depth'],frame['valid_acc'],marker='o',label=('valid_acc'))
plt.xlabel('Depth of Tree')
plt.ylabel('performance')
plt.legend()
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x7f2997437110>
```



This is just testing how changing the parameter will change the outcome of the test.

Evaluation

In [ ]:
```
test_outcome2 = {'Model':['Decision Tree Default Parameters', 'Decision Tree w
ith Hyperparameters'],
                'Train Accuracy': [dt_train_accuracy_default_params ,dt_train_
accuracy_hyper_params  ],
                'Test Accuracy': [dt_test_accuracy_default_params ,dt_test_acc
uracy_hyper_params]}
```

In [ ]:
```
pd.DataFrame(test_outcome2)
```

Out[ ]:

	Model	Train Accuracy	Test Accuracy
0	Decision Tree Default Parameters	1.000000	0.858208
1	Decision Tree with Hyperparameters	0.409131	0.408559

With the default parameter of Decision Tree we are overfitting our training to combat this I used hypertuning to lower the bias but the result wasn't as desirable as I hoped it would be. Fine tuning the parameters again might increase the result but not much,is my guess I believe decision tree isn't a best fit for this type of training.

K Nearest Neighbors

In [ ]:
```
from sklearn.datasets import load_digits
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

df_test = pd.read_csv("/content/mnist_test.csv")
df_train = pd.read_csv("/content/mnist_train.csv")
```

In [ ]:
```
knn_data = df_train.iloc[:,1:]
knn_label = df_train.iloc[:,0]
```

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(knn_data, knn_label, test_
size = 0.333, random_state = 101, stratify = knn_label)
```

In [ ]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [ ]:
```
knn = KNeighborsClassifier()
```

In [ ]:
```
knn.fit(X_train,y_train)
```

Out[ ]:
```
KNeighborsClassifier()
```

In [ ]:
```
knn.score(X_test,y_test)
```

Out[ ]:
```
0.9684184184184185
```

In [ ]:
```
knn_train_accuracy_def_params  = knn.score(X_train, y_train)
knn_test_accuracy_def_params  = knn.score(X_test, y_test)
```

In [ ]:
```
print(f'Train Accuracy - : {knn_train_accuracy_def_params:.3f}')
print(f'Test Accuracy - : {knn_test_accuracy_def_params:.3f}')
```

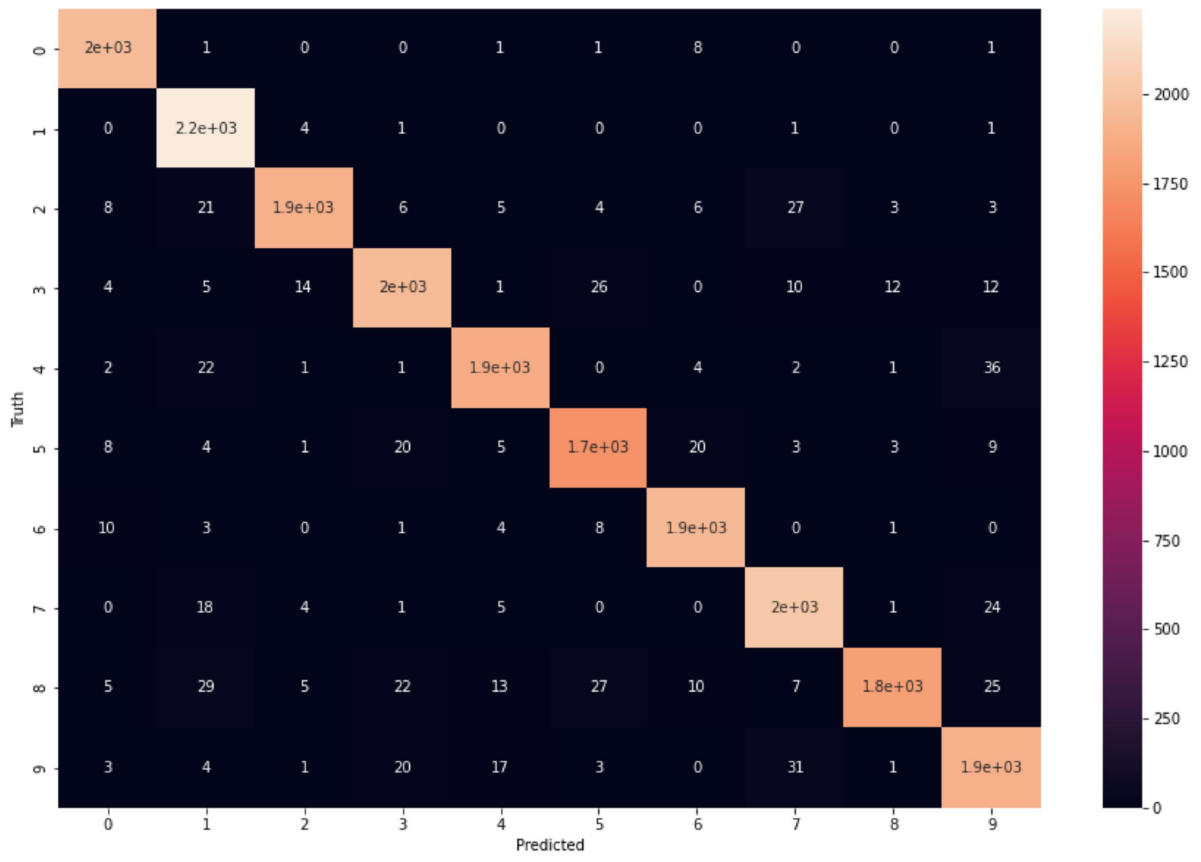
```
Train Accuracy - : 0.979
Test Accuracy - : 0.968
```

In [ ]:
```
from sklearn.metrics import confusion_matrix

y_pred = knn.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
cm
```

Out[ ]:
```
array([[1960,    1,    0,    0,    1,    1,    8,    0,    0,    1],
       [   0, 2238,    4,    1,    0,    0,    0,    1,    0,    1],
       [   8,   21, 1901,    6,    5,    4,    6,   27,    3,    3],
       [   4,    5,   14, 1958,    1,   26,    0,   10,   12,   12],
       [   2,   22,    1,    1, 1877,    0,    4,    2,    1,   36],
       [   8,    4,    1,   20,    5, 1732,   20,    3,    3,    9],
       [  10,    3,    0,    1,    4,    8, 1944,    0,    1,    0],
       [   0,   18,    4,    1,    5,    0,    0, 2033,    1,   24],
       [   5,   29,    5,   22,   13,   27,   10,    7, 1805,   25],
       [   3,    4,    1,   20,   17,    3,    0,   31,    1, 1901]])
```

In [ ]:
```
import seaborn as sn

plt.figure(figsize=(15,10))
sn.heatmap(cm,annot=True)
plt.xlabel("Predicted")
plt.ylabel("Truth")
```

Out[ ]:
```
Text(114.0, 0.5, 'Truth')
```



In [ ]:
```
from sklearn.metrics import classification_report
```

In [ ]:
```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1972
           1       0.95      1.00      0.98      2245
           2       0.98      0.96      0.97      1984
           3       0.96      0.96      0.96      2042
           4       0.97      0.96      0.97      1946
           5       0.96      0.96      0.96      1805
           6       0.98      0.99      0.98      1971
           7       0.96      0.97      0.97      2086
           8       0.99      0.93      0.96      1948
           9       0.94      0.96      0.95      1981

    accuracy                           0.97     19980
   macro avg       0.97      0.97      0.97     19980
weighted avg       0.97      0.97      0.97     19980
```

Evaluation

Using the default parameters for K Nearest Neighbor we also see a good turn out just like the random forest. We can see that we are getting a high accuracy score.

K Nearest Neighbors Hyperparameter Tuning

In [ ]:
```
train_accuracy = []
validation_accuracy  = []
for n in range(1,16):
  knn_Model  = KNeighborsClassifier(n_neighbors=n)
  knn_Model.fit(X_train,y_train)
  train_accuracy.append(knn_Model.score(X_train, y_train))
  validation_accuracy.append(knn_Model.score(X_test, y_test))
```

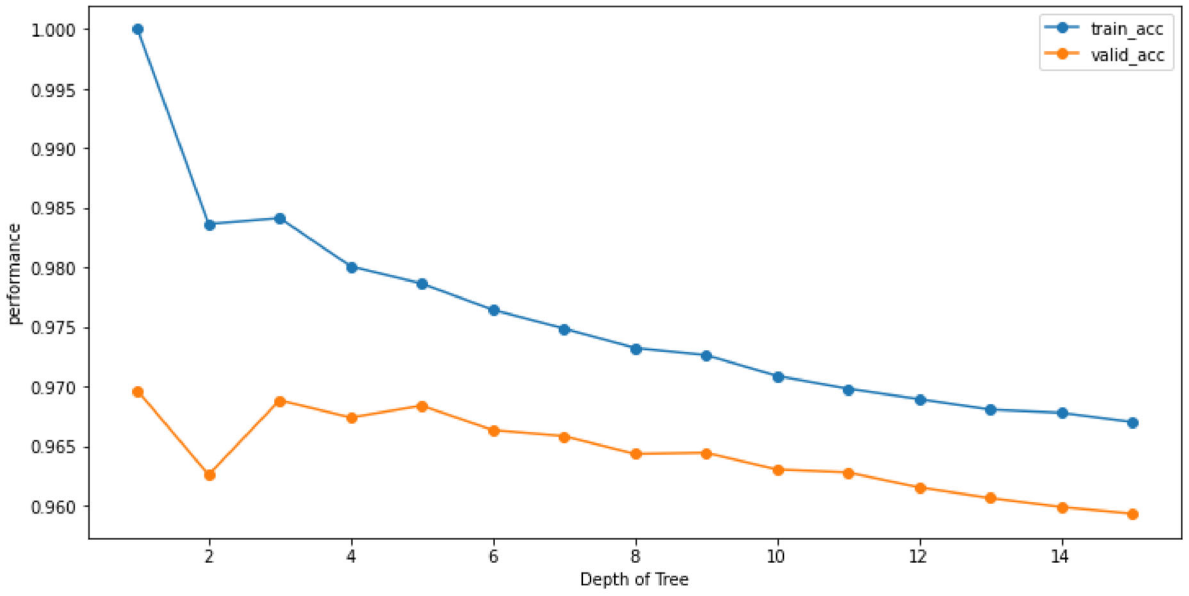
In [ ]:
```
frame = pd.DataFrame({'max_depth':range(1,16),'train_acc':train_accuracy,'vali
d_acc':validation_accuracy})
frame
```

Out[ ]:

	max_depth	train_acc	valid_acc
0	1	1.000000	0.969670
1	2	0.983658	0.962613
2	3	0.984158	0.968869
3	4	0.980109	0.967417
4	5	0.978660	0.968418
5	6	0.976461	0.966366
6	7	0.974887	0.965866
7	8	0.973263	0.964364
8	9	0.972663	0.964464
9	10	0.970914	0.963063
10	11	0.969839	0.962813
11	12	0.968965	0.961562
12	13	0.968090	0.960661
13	14	0.967815	0.959910
14	15	0.967041	0.959359

In [ ]:
```
plt.figure(figsize=(12,6))
plt.plot(frame['max_depth'],frame['train_acc'],marker='o',label=('train_acc'))
plt.plot(frame['max_depth'],frame['valid_acc'],marker='o',label=('valid_acc'))
plt.xlabel('Depth of Tree')
plt.ylabel('performance')
plt.legend()
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x7f2997515990>
```



Evaluation

In this test we check how changing the n_neighbors will drastically change the model. We got the highest test score by having the n_neighbors to 1

In [ ]:
```
knn_train_accuracy_hyper_params = train_accuracy[0]
knn_test_accuracy_hyper_params = validation_accuracy[0]

knn_train_accuracy_def_params  = knn.score(X_train, y_train)
knn_test_accuracy_def_params  = knn.score(X_test, y_test)
```

Conclusion

In [ ]:
```
final_outcome = {'Model':['Default Parameters', 'Hyperparameter Tuning'],
                'Decision Tree Train Accuracy': [dt_train_accuracy_default_par
ams ,dt_train_accuracy_hyper_params  ],
                'Decision Tree Test Accuracy': [dt_test_accuracy_default_param
s ,dt_test_accuracy_hyper_params],
                'Random Forest Train Accuracy': [train_accuracy_default_params
,train_accuracy_hyper_params],
                'Random Forest Test Accuracy': [test_accuracy_default_params,t
est_accuracy_hyper_params],
                'K Nearest Neighbors Train Accuracy': [knn_train_accuracy_def_
params,knn_train_accuracy_hyper_params],
                'K Nearest Neighbors Test Accuracy': [knn_test_accuracy_def_pa
rams,knn_test_accuracy_hyper_params]}
```

In [ ]:
```
table = pd.DataFrame(final_outcome)
table.T
```

Out[ ]:

	0	1
Model	Default Parameters	Hyperparameter Tuning
Decision Tree Train Accuracy	1.0	0.409131
Decision Tree Test Accuracy	0.858208	0.408559
Random Forest Train Accuracy	1.0	0.999925
Random Forest Test Accuracy	0.985536	0.985385
K Nearest Neighbors Train Accuracy	0.97866	1.0
K Nearest Neighbors Test Accuracy	0.968418	0.96967

With all the three model tested Random Forest comes at the top. With just the default parameters it had the highest accuracy compared to other models. For this brief testing Random Forest is the best choice.