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19BCP130

Classification using K-Nearest Neighbors

Load the IRIS data

```
import pandas as pd
import numpy as np
import warnings
from sklearn.datasets import load_iris

iris = pd.read_csv('./iris.csv')
# iris = pd.DataFrame(data=np.c_[iris['data'], iris['target']], columns=iris['feature_names']+['targ
iris.rename(columns={'species':'target'}, inplace=True)

iris.head()
```

	sepal_length	sepal_width	petal_length	petal_width	target
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

Create class label/vector.

```
class_labels = iris["target"].unique()

print(f'Class labels are {class_labels}')
```

```
Class labels are ['setosa' 'versicolor' 'virginica']
```

Splitting data into Train, cross-validation and test sets with Stratified Sampling using *train_test_split()*

```
df = iris.drop(['target'], axis=1)
df.head()
```

	sepal_length	sepal_width	petal_length	petal_width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2

```
from sklearn.model_selection import train_test_split

X = iris.iloc[: , :-1]
y = iris.iloc[: , -1:]

X_train, X_test_valid, y_train, y_test_valid = train_test_split(X, y, test_size=0.2, random_state=42
X_test, X_valid, y_test, y_valid = train_test_split(X_test_valid, y_test_valid, test_size=0.2, rando
```

Data Preprocessing using column standardisation. Use sklearn.preprocessing.StandardScaler().

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
X_valid = sc.transform(X_valid)
```

Write your own implementation of K-NN

```
def getEuclideanDistance(a, b):
  return np.sqrt(np.sum((a - b) ** 2))
```

```
def getAccuracyAndError(A, B):
  correct_predictions = 0

  for i in range(len(A)):
    if A[i] == B[i]:
      correct_predictions += 1

  accuracy = correct_predictions / len(A)
  error = (len(A) - correct_predictions) / len(A)

  return accuracy, error
```

```
def knn(X_train, y_train, X_input, y_input, k):
  y_pred = []

  for x_input in X_input:
    distances = []

    for i in range(len(X_train)):
      distances.append([ getEuclideanDistance(np.array(x_input) , np.array(X_train[i])), y_train["ta

    distances.sort(key = lambda x: x[0])
    k_nearest_points = distances[:k]

    classes = [ ['setosa', 0], ['versicolor', 0], ['virginica', 0] ]
```

```
    for point in k_nearest_points:
      if point[1] == 'setosa':
        classes[0][1] += 1
      elif point[1] == 'versicolor':
        classes[1][1] += 1
      else:
        classes[2][1] += 1

    classes.sort(key = lambda x: x[1], reverse=True)

    y_pred.append(classes[0][0])

  accuracy, error = getAccuracyAndError(y_pred, y_input["target"].to_numpy())

  return accuracy, error
```

Perform hyper-parameter tuning. Here, K is a hyperparameter.

Compute training accuracy and cross-validation accuracy for every value of K in [1,3,5,7,9,11,13,15,17,19,21,23,25] and choose the best K.

```
def getResults(X_train, y_train, X_valid, y_valid):
  K = [1,3,5,7,9,11,13,15,17,19,21,23,25]
  accuraciesAndErrors = []
  errors = []

  for k in K:
    train_accuracy, train_error = knn(X_train, y_train, X_train, y_train, k)
    crossval_accuracy, crossval_error = knn(X_train, y_train, X_valid, y_valid, k)

    accuraciesAndErrors.append([ k, round(train_accuracy * 100, 2), round(crossval_accuracy * 100, 2

  results = pd.DataFrame(accuraciesAndErrors, columns = ['K', 'Training Accuracy', 'Cross-Validation

  return results
```

```
print(f"Displaying Training and Cross-Validation Accuracies for different values of K:\n")

results = getResults(X_train, y_train, X_valid, y_valid)
display(results[['K', 'Training Accuracy', 'Cross-Validation Accuracy']])
```

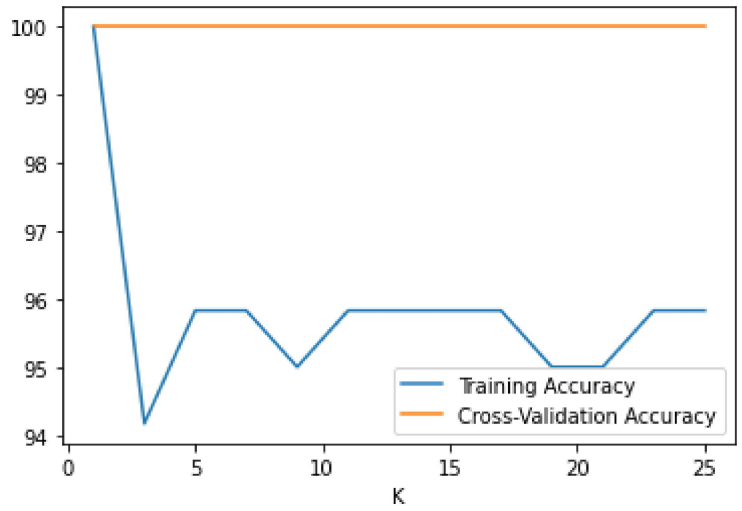
```
Displaying Training and Cross-Validation Accuracies for different values of K:
```

	K	Training Accuracy	Cross-Validation Accuracy
0	1	100.00	100.0
1	3	94.17	100.0
2	5	95.83	100.0
3	7	95.83	100.0

Plot the "Hyperparameter vs. accuracy" graph for training and CV sets.

```
import matplotlib.pyplot as plt
```

```
results.plot(x='K', y=['Training Accuracy', 'Cross-Validation Accuracy'], kind="line")
plt.show()
```



Plot the training and CV errors graphs w.r.t. different values of K. Write your observations for overfitting and underfitting.

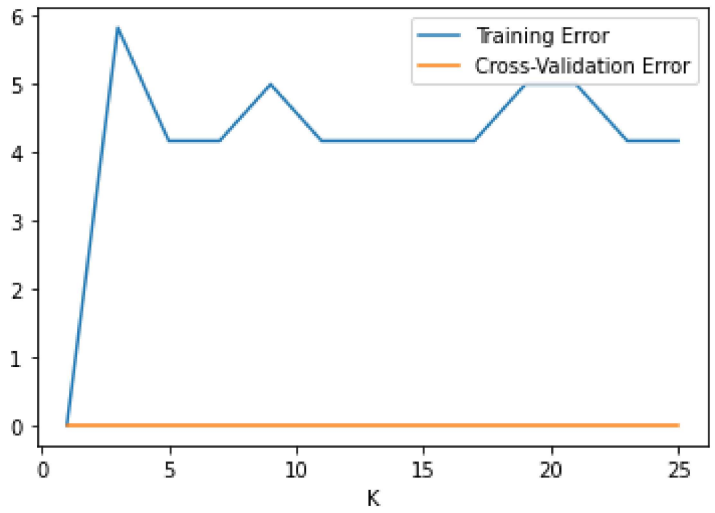
```
print(f"Displaying Training and Cross-Validation Errors for different values of K:\n")

display(results[['K', 'Training Error', 'Cross-Validation Error']])
```

```
Displaying Training and Cross-Validation Errors for different values of K:
```

	K	Training Error	Cross-Validation Error
0	1	0.00	0.0
1	3	5.83	0.0
2	5	4.17	0.0
3	7	4.17	0.0

```
results.plot(x='K', y=['Training Error', 'Cross-Validation Error'], kind="line")
plt.show()
```



From the graph, we can make the following observations:

- For k=21, the graph is giving max error in both training and cross-validation sets, there it is a case of underfitting.
- For k=3,5,7,9 , the cross-validation set is giving min error of 0.00 %, therefore it is a case of overfitting.

Test the performance of your model on Test sets.

```
accuracy, error = knn(X_train, y_train, X_test, y_test, 5)
print(f"We are selecting k=3 as optimal number of neighbors.")
print(f"  Accuracy = {round(accuracy * 100, 2)} %")
print(f"  Error = {round(error * 100, 2)} %")
```

```
We are selecting k=3 as optimal number of neighbors.
  Accuracy = 100.0 %
  Error = 0.0 %
```

Compare your implementation with sk-learn's implementation of KNN

```
from sklearn.neighbors import KNeighborsClassifier
```

```
clf = KNeighborsClassifier(n_neighbors = 3)
clf.fit(X_train, y_train)

train_accuracy = clf.score(X_train, y_train)
valid_accuracy = clf.score(X_valid, y_valid)
```

```
test_accuracy = clf.score(X_test, y_test)

print(f"Results using sklearn's KNN implementation are:")
print(f"  Train Accuracy = {round(train_accuracy * 100, 2)} %")
print(f"  Cross-Validation Accuracy = {round(valid_accuracy * 100, 2)} %")
print(f"  Test Accuracy = {round(test_accuracy * 100, 2)} %")
```

```
Results using sklearn's KNN implementation are:
  Train Accuracy = 94.17 %
  Cross-Validation Accuracy = 100.0 %
  Test Accuracy = 100.0 %
c:\Users\siddh\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\neighbors\_cla
  return self._fit(X, y)
```

Thus, our model and sklearn's KNN model are giving the same results.