KNN-With-Python

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1 Implementing KNN

There are few essential libraries for this notebook code to work, please install all of them listed here so the code works fine without any issues

[10]:
```
#pip install scikit-learn pandas matplotlib plotly nbformat ipython seaborn
#pip install --upgrade nbformat
#pip install ipykernel
# Please restart the kernel after installing the ipykernel package
```

[1]:
```
%matplotlib inline
```

[2]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report
from sklearn.model_selection import cross_val_score
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import seaborn as sns
```

The iris data set is imoprted from the provided csv file using the pandas library. To get a insight into the data, I am using the head to list the first few records.

[3]:
```
iris = pd.read_csv('iris.csv')
print(iris.head())
print(iris.Species.unique())
```

```
   Sepal.Length  Sepal.Width  Petal.Length  Petal.Width Species
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
['setosa' 'versicolor' 'virginica']
```

Now, since we have to select species “iris virginica” “iris versicolor”, below is the filtering logic on this data.

For X we are dropping the species column because we want to predict the species based on other metrics

[4]:
```
iris_filtered = iris[iris['Species'].isin(['virginica', 'versicolor'])]

X = iris_filtered.drop('Species', axis=1)
y = iris_filtered['Species']

#sns.pairplot(iris_filtered, hue='Species') #we can use pairplot to see the␣
 ↪relationship between the features
```

E2: Use the kNN-classes of sklearn in Python and the caret package in R with K=5 and a train-test-split of 70-30 for an initial classification and calculate the accuracy using the test set.

Using the train_test_split function from sklearn lets split the data into training and test sets.

X is our feature matrix which has metrics for Sepal and Petal without species column and y is our target variable

We are splitting the data into 70% training and 30% test data

The random_state parameter is used to ensure that the data is split in the same way every time the code is run, popular value being 42, but it can be any value

The value of k if too less will be overfitting, too less will be underfitting

[5]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=1)

# we will use the 5 neighbors for our knn model as instructed
knn = KNeighborsClassifier(n_neighbors=5)

# lets train the model with above data
knn.fit(X_train, y_train)

# Here we will start predicting the species of the iris
y_pred = knn.predict(X_test)

# lets now perform the accuracy calculation
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy with K=5: {accuracy:.2f}")
```

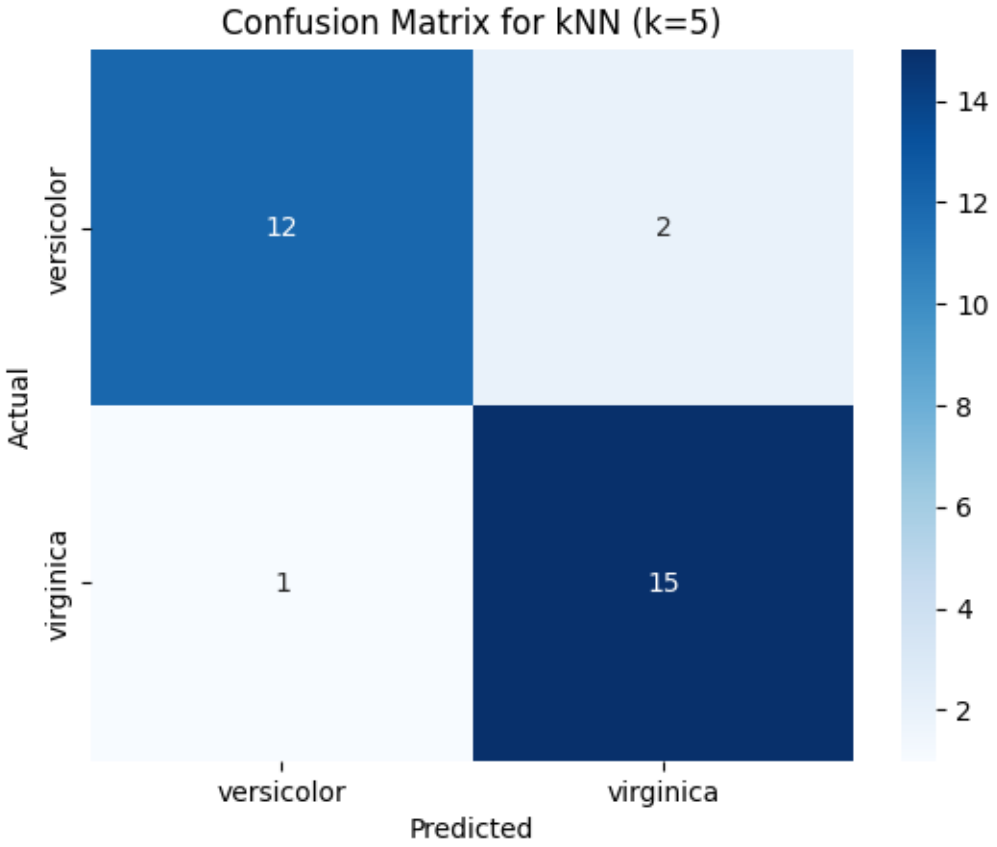
```
Accuracy with K=5: 0.90
```

We can represent the confusion matrix which gives us on overview of where the model was making mistakes. For different value of K, the confusion matrix changes its accuracies

Here, we can see that for value k=5 the model predicted 12 species as versicolor and 15 sepcies as virginica correctly. but it has 1 false positive where model incorrectly labled as versicolor and 2 fast negatives where model incorrectly labled as virginica

[6]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['versicolor',␣
 ↪'virginica'], yticklabels=['versicolor', 'virginica'])
plt.title('Confusion Matrix for kNN (k=5)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

print(classification_report(y_test, y_pred, target_names=['versicolor',␣
 ↪'virginica']))
```



	precision	recall	f1-score	support
versicolor	0.92	0.86	0.89	14
virginica	0.88	0.94	0.91	16
accuracy			0.90	30
macro avg	0.90	0.90	0.90	30
weighted avg	0.90	0.90	0.90	30

Below we will use the cross validation to split the data into 3 parts, training part, validation part, predict part using the test data. Here we are using 5 fold meaning we will split the data into 5 part, using 4 parts for training and remaining 5th part for testing it.

[7]:
```
k_values = range(1, 31)
cv_accuracies = []

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X, y, cv=5, scoring='accuracy')
    cv_accuracies.append(scores.mean())  # lets use the mean accuracy across␣
 ↪folds

# Now for the plotting part to see the accuracy for different k values
fig = go.Figure()

# lets add some traces
fig.add_trace(
    go.Scatter(
        x=list(k_values),
        y=cv_accuracies,
        mode='lines+markers',
        name='Accuracy',
        line=dict(color='blue', width=2),
        marker=dict(size=8, color='red')
    )
)

fig.update_layout(
    title='Accuracy vs. k Value',
    xaxis_title='k',
    yaxis_title='Accuracy',
    template='plotly_white',
    #hovermode='x unified',
    dragmode=False,
    hovermode=False,
    showlegend=True
)

fig.show()
```

The graph shows that accuracy is highest at k=1,but this likely overfits the training data.

As k increases, accuracy stabilizes after k=10, indicating better generalization.

A good choice for k is between 5 and 10, as it balances high accuracy and reduces overfitting. Overall, larger k values make the model more robust to noise in the data.

Explain the choice of a good k The best k is the one that maximizes accuracy. From the plot, we

can choose the k with the highest accuracy.

[8]:
```
best_k = k_values[cv_accuracies.index(max(cv_accuracies))]
print(f"Best k value: {best_k} with accuracy: {max(cv_accuracies):.2f}")
```

```
Best k value: 6 with accuracy: 0.97
```

In the above KNN execution we used the default metric i.e, Euclidean.

Now lets use all these metrics Euclidean, Minkowaski and Mahattena.

Lets also plot all the output from these results in a single graph to help us better visualize.

[9]:
```
k_values = range(1, 31)

euclidean_accuracies = []
manhattan_accuracies = []
minkowski_accuracies = []

for k in k_values:
    # Euclidean
    knn_euclidean = KNeighborsClassifier(n_neighbors=k, metric='euclidean')
    scores_euclidean = cross_val_score(knn_euclidean, X, y, cv=5,␣
 ↪scoring='accuracy')
    euclidean_accuracies.append(scores_euclidean.mean())

    # Manhattan
    knn_manhattan = KNeighborsClassifier(n_neighbors=k, metric='manhattan')
    scores_manhattan = cross_val_score(knn_manhattan, X, y, cv=5,␣
 ↪scoring='accuracy')
    manhattan_accuracies.append(scores_manhattan.mean())

    # Minkowski using P more than 2
    #https://www.datacamp.com/tutorial/minkowski-distance
    knn_minkowski = KNeighborsClassifier(n_neighbors=k, metric='minkowski', p=3)
    scores_minkowski = cross_val_score(knn_minkowski, X, y, cv=5,␣
 ↪scoring='accuracy')
    minkowski_accuracies.append(scores_minkowski.mean())


fig = go.Figure()

fig.add_trace(
    go.Scatter(
        x=list(k_values),
        y=euclidean_accuracies,
        mode='lines+markers',
        name='Euclidean',
        line=dict(color='blue', width=2),
```

```
        marker=dict(size=8, color='blue')
    )
)

fig.add_trace(
    go.Scatter(
        x=list(k_values),
        y=manhattan_accuracies,
        mode='lines+markers',
        name='Manhattan',
        line=dict(color='green', width=2),
        marker=dict(size=8, color='green')
    )
)

fig.add_trace(
    go.Scatter(
        x=list(k_values),
        y=minkowski_accuracies,
        mode='lines+markers',
        name='Minkowski (p=3)',
        line=dict(color='red', width=2),
        marker=dict(size=8, color='red')
    )
)

fig.update_layout(
    title='Accuracy vs. k Value for Different Distance Metrics',
    xaxis_title='k',
    yaxis_title='Accuracy',
    template='plotly_white',
    #hovermode='x unified',
    dragmode=False,
    hovermode=False,
    showlegend=True
)

fig.update_xaxes(showgrid=True, gridwidth=1, gridcolor='lightgray')
fig.update_yaxes(showgrid=True, gridwidth=1, gridcolor='lightgray')

fig.show()
```

What can we notice from the above graph ? 1. The sweet spot for k seems to be around 5-10 for all three distance metrics - that's where the accuracy peaks 2. It looks like Minkowski with p=3 (the red line) is the better performer compared to other two 3. All three metrics start pretty similar, then take different paths as k increases 4. There's this sharp dip at k=2 for all three metrics. 5. Manhattan distance (green) is fluctuating quite a bit here compared to others. 6. After about k=20, things generally go downhill for all metrics, too many neighbours might have the impact

here. 7. Euclidean and Manhattan seem to occasionally swap places for second-best performance 8. The high performance for k value 1 and others could indicate that our data is well seperated. 9. The best performer with a better values here are Minkowski with p=3 at k=5 or k=10

1.1 Comparing Plots in R and Python

Further more when we compare the graph with default distance(Euclidean distance) with the result of R, we can notice some differences.

The Python graph shows smoother curves and slightly higher accuracy, while the R graph shows more fluctuations and slightly lower accuracy.

Ee can notice that at around k=10,11 there are some similarities although in python the graph traces around 0.96 and in R around 0.95 for minowski we could see some stabilization.

Apart from this we can see more fluctations in graph from R and in python it looks more smooth.

Hence we can see that there are not much overlaps happening between these two implementations. It could be beacuse of the small data set that we have that is resulting this and also implementation details between the two libraries that could be causing the discrepanceis.

2 E4 and E5

2.0.1 Strengths and Weaknesses of kNN-Classifier (E4)

The Strengths of KNN are 1. It is relatively simple to understand and implement. 2. As we saw in our results, it can hit high accuracy (98% with Minkowski) when tuned right 3. There is no training phase, when we have the data we could start using the model quickly. 4. In our case for the Iris data, the results were commendable, because the classes are fairly well-separated 5. Can handle non-linear boundaries, which is why it works on the tricky Versicolor-Virginica split

The Weakness being 1. Slow at prediction time, with more data it would probably have advese effect. 2. Our results show it's quite sensitive to the k value (example dip at k=2?) 3. Distance metrics matter a lot, here Minkowski outperformed the others 4. Memory-hungry since it stores all training examples 5. Doesn't give you insights into feature importance like some other models would

Good real-world uses:

Anywhere there is a classificaion/grouping involved for example product recomendation on online stores These include finance (predicting stock prices, credit scoring), healthcare (medical diagnosis, analyzing gene expression), recommendation systems, and image processing (facial recognition, object detection).

https://blog.aiensured.com/knn-algorithm-in-real-world/

https://keylabs.ai/blog/k-nearest-neighbors-knn-real-world-applications/#:~:text=What%20are%20some%20real

Bad real-world uses:

KNN is a bad choice when it comes to Very large data sets, higer dimension data etc. For example in autonomous driving, real time decision making systems, where decisions need to be made instantly, the slow nature of KNN could prevent its use in time-sensitive situations.

2.0.2 E5: Biases in the Iris Dataset

Potential biases:

Relatively sample size 1. All collected from the same geographic region 2. Collected by the same person, potentially introducing measurement bias 3. Setosa is way easier to separate than the other two species 4. Just four features, ignoring many other potential flower characteristics 5. Perfectly balanced classes (50 of each) which rarely happens in real life

How these affect results:

1. The high accuracy we're seeing probably wouldn't hold up with more diverse samples
2. Our model looks better than it is because Setosa is so easy to identify
3. The 98% accuracy is misleading - errors are concentrated in the Versicolor-Virginica boundary
4. With such a small dataset, a few outliers can significantly skew results
5. The k sensitivity we observed might be even worse in less pristine real-world data