

# K-Nearest-Neighbors Iris Flower Classification Project

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This project uses a built-in seaborn dataset called Iris. It contains 3 classes of 50 instances each, where each class refers to a type of iris plant. The attribute to be predicted is the class of iris plant. The classes are as follows: 1. Iris Setosa, 2. Iris Versicolour, 3. Iris Virginica

There are 4 features:

1. sepalLength: sepal length in cm
2. sepalWidth: sepal width in cm
3. petalLength: petal length in cm
4. petalWidth: petal width in cm

There are 3 classes representing class label of iris flower {1,2,3}

1. Iris Setosa
2. Iris Versicolour
3. Iris Virginica



```
In [233... # import image module
from IPython.display import Image
# get the image
Image(url="iris_flower.png", width=800, height=800)
```

Out[233]:

## Import the needed libraries

```
In [234... import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [235... iris = sns.load_dataset('iris')
```

```
In [236... iris.head()
# No need for data normalization
```

Out[236]:

	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

<b>3</b>	4.6	3.1	1.5	0.2	setosa
<b>4</b>	5.0	3.6	1.4	0.2	setosa

```
In [237... iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  -
 0   sepal_length    150 non-null    float64
 1   sepal_width     150 non-null    float64
 2   petal_length    150 non-null    float64
 3   petal_width     150 non-null    float64
 4   species         150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

```
In [238... iris.describe()
```

Out[238]:

	sepal_length	sepal_width	petal_length	petal_width
<b>count</b>	150.000000	150.000000	150.000000	150.000000
<b>mean</b>	5.843333	3.057333	3.758000	1.199333
<b>std</b>	0.828066	0.435866	1.765298	0.762238
<b>min</b>	4.300000	2.000000	1.000000	0.100000
<b>25%</b>	5.100000	2.800000	1.600000	0.300000
<b>50%</b>	5.800000	3.000000	4.350000	1.300000
<b>75%</b>	6.400000	3.300000	5.100000	1.800000
<b>max</b>	7.900000	4.400000	6.900000	2.500000

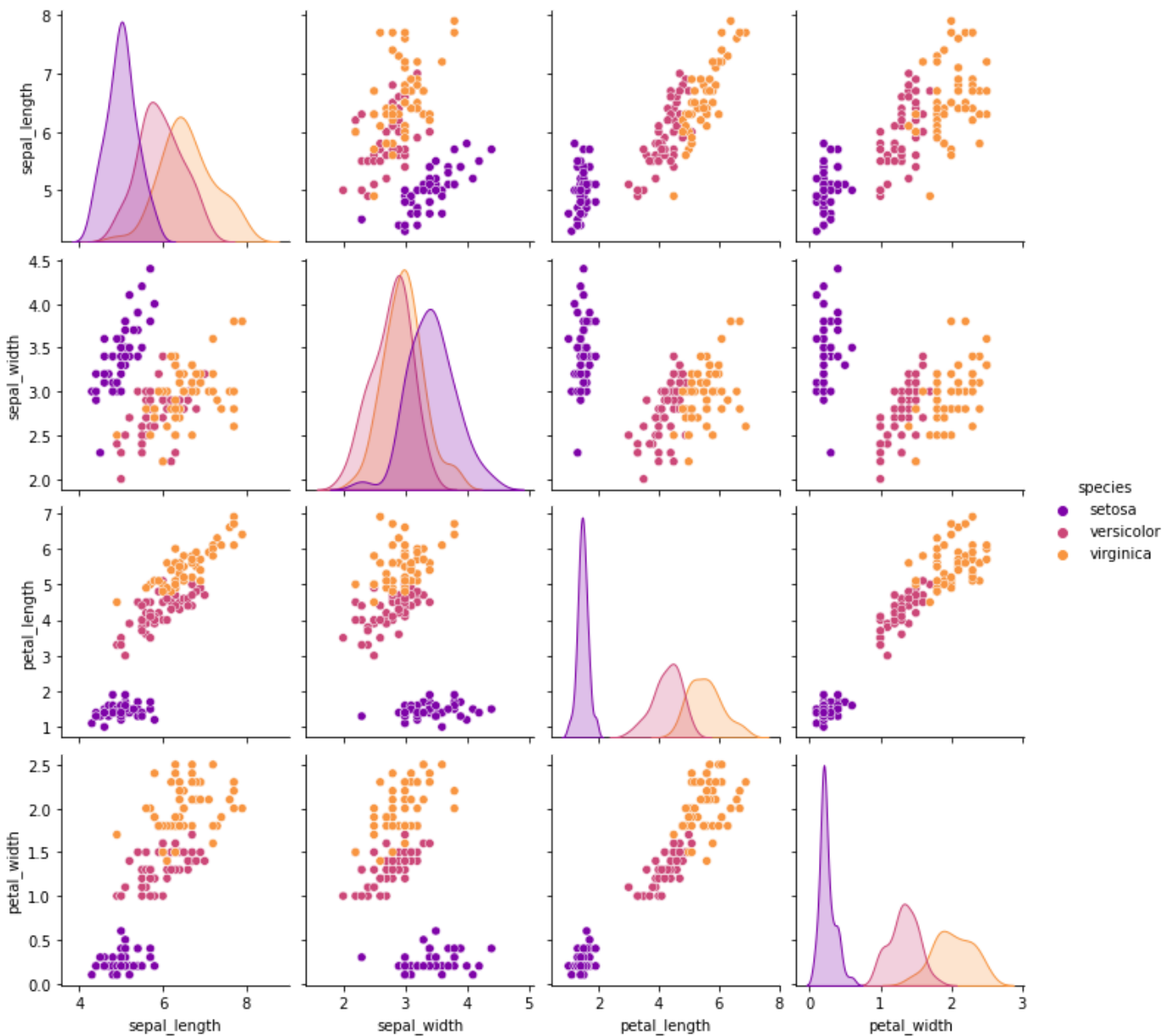
```
In [239... iris['species'].unique()
```

Out[239]: array(['setosa', 'versicolor', 'virginica'], dtype=object)

## Exploratory Data Analysis

```
In [240... # Which flower species seems to be the most separable?
# Answer is: A) Setosa
sns.pairplot(data=iris, hue='species', palette = 'plasma')
```

Out[240]: <seaborn.axisgrid.PairGrid at 0x18b955f4ca0>



```
In [241...] corr = iris.corr()
```

```
In [242...] sns.heatmap(corr, annot = True, cmap = 'Purples')
```

```
Out[242]: <AxesSubplot:>
```



```
In [243...] plt.figure(figsize =(15,25))
```

```
plt.subplot(4,4,1)
```

```

sns.violinplot(y = iris['sepal_length'], x= iris['species'], palette = 'plasma')

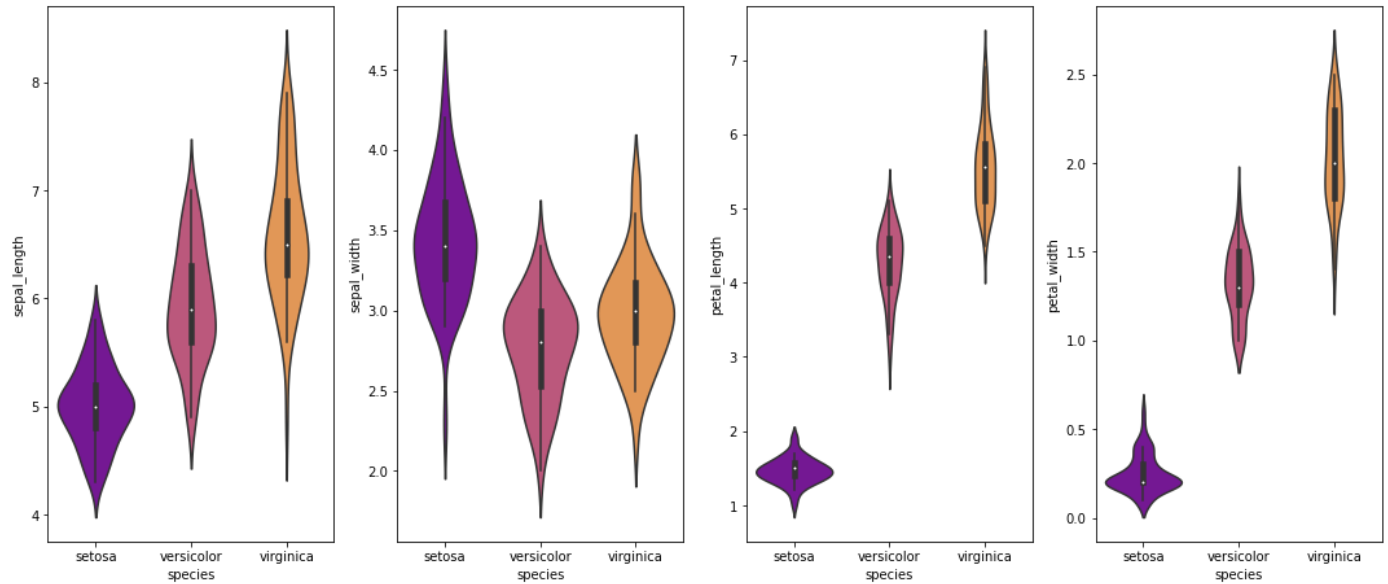
plt.subplot(4,4,2)
sns.violinplot(y = iris['sepal_width'], x= iris['species'], palette = 'plasma')

plt.subplot(4,4,3)
sns.violinplot(y = iris['petal_length'], x= iris['species'], palette = 'plasma')

plt.subplot(4,4,4)
sns.violinplot(y = iris['petal_width'], x= iris['species'], palette = 'plasma')

plt.tight_layout()

```

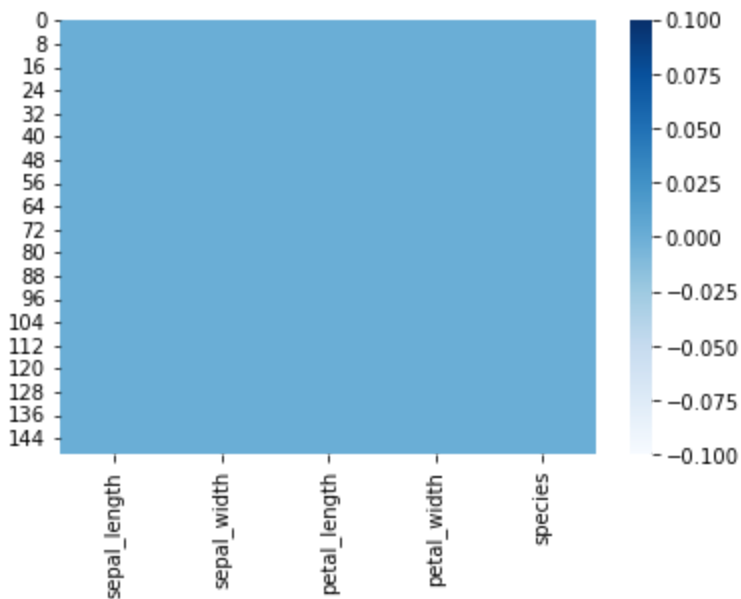


```

In [244...] sns.heatmap(iris.isnull(), fmt="d", cmap='Blues')
# No missing values

```

Out[244]: <AxesSubplot:>



## Train Test Split

```

In [245...] X = iris.drop('species', axis = 1)
y = iris['species']

```

```

In [246...] from sklearn.preprocessing import LabelEncoder
labelencoder_y = LabelEncoder()

```

```
y = labelencoder_y.fit_transform(y)
```

In [247...

y

Out[247]:

```
array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [248...

```
from sklearn.model_selection import train_test_split
```

In [249...

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

In [250...

```
#p : int, default=2 , Power parameter for the Minkowski metric.
#metric : str or callable, default='minkowski'. The default metric is minkowski
#, and with p=2 is equivalent to the standard Euclidean metric.
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=5, metric = 'minkowski', p=2)
```

In [251...

```
classifier = KNeighborsClassifier()
```

In [252...

```
# train/fit the classifier to the dataset
classifier.fit(X_train, y_train)
```

Out[252]:

```
▼ KNeighborsClassifier
KNeighborsClassifier()
```

In [253...

```
# test the classifier and see the predictions
predictions = classifier.predict(X_test)
```

## Model Evaluation

In [254...

```
# let's see the performance of this classifier using confusion atrix and classification
from sklearn.metrics import classification_report, confusion_matrix
```

In [255...

```
print('*****Classification Report*****')
print(classification_report(y_test, predictions))
print('*****Confusion Matrix*****')
print(confusion_matrix(y_test, predictions))
```

```
*****Classification Report*****
              precision    recall  f1-score   support

     0             1.00        1.00        1.00         9
     1             1.00        0.92        0.96        12
     2             0.90        1.00        0.95         9

 accuracy              0.97
 macro avg              0.97
 weighted avg           0.97

*****Confusion Matrix*****
[[ 9  0  0]
 [ 0 11  1]
 [ 0  0  9]]
```

In [256...

```
cm = confusion_matrix(y_test, predictions)
```

```
sns.heatmap(cm, annot = True, fmt = "d", cmap = 'Purples')
```

Out[256]: <AxesSubplot:>

