

```

1 #import libraries
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import seaborn as sns
5 %matplotlib inline

1 #Get the data and define col names
2 colnames=["sepal_length_in_cm", "sepal_width_in_cm", "petal_length_in_cm", "petal_width_in_cm", "class"]
3
4 #Read the dataset
5 dataset = pd.read_csv("https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data", header = None, names= colnames )
6
7 #See the Data
8 dataset.head()

```

	sepal_length_in_cm	sepal_width_in_cm	petal_length_in_cm	petal_width_in_cm	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

```

1 #Use pandas to encode the categorized columns
2
3 dataset = dataset.replace({"class": {"Iris-setosa":1,"Iris-versicolor":2, "Iris-virginica":3}})
4 #Read the new dataset
5 dataset.head()
6

```

	sepal_length_in_cm	sepal_width_in_cm	petal_length_in_cm	petal_width_in_cm	class
0	5.1	3.5	1.4	0.2	1
1	4.9	3.0	1.4	0.2	1
2	4.7	3.2	1.3	0.2	1
3	4.6	3.1	1.5	0.2	1
4	5.0	3.6	1.4	0.2	1

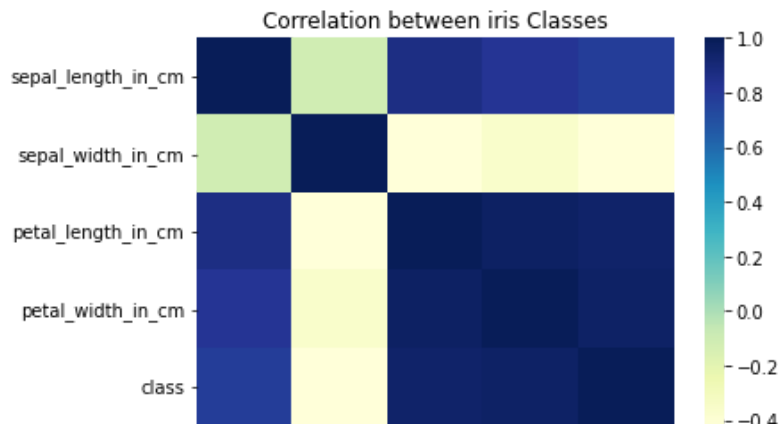
▼ Analyze the Data: There are no more than 50 rows for each type of Iris. It may be useful to look at the correlation between them.

```

1 plt.figure(1)
2 sns.heatmap(dataset.corr(), cmap="YlGnBu")
3 plt.title('Correlation between iris Classes')

```

Text(0.5, 1.0, 'Correlation between iris Classes')



▼ Split the Data

```
1 X = dataset.iloc[:, :-1]
2 y = dataset.iloc[:, -1].values
3
4 from sklearn.model_selection import train_test_split
5 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
```

▼ Create the SVM Classifier

```
1 #Create the SVM classifier model
2 from sklearn.svm import SVC
3 classifier = SVC(kernel = 'linear', random_state = 0)
4 #Fit the model for the data
5
6 classifier.fit(X_train, y_train)
7
8 #Make the prediction
9 y_pred = classifier.predict(X_test)
```

▼ Verify the accuracy of the model , using the confusion matrix and the cross validation

```
1 from sklearn.metrics import confusion_matrix
2 cm = confusion_matrix(y_test, y_pred)
3 print(cm)
4
5 from sklearn.model_selection import cross_val_score
6 accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv = 10)
7 print("Accuracy: {:.2f} %".format(accuracies.mean()*100))
8 print("Standard Deviation: {:.2f} %".format(accuracies.std()*100))
```

```
[[13  0  0]
 [ 0 15  1]
 [ 0  0  9]]
Accuracy: 98.18 %
Standard Deviation: 3.64 %
```

A 98% of accuracy is derived which is acceptable. The confusion matrix shows that there is one misclassified data.

```
1 kernels = ['Polynomial', 'RBF', 'Sigmoid', 'Linear'] #A function which returns the corresponding SVC model
2 def getClassifier(ktype):
3     if ktype == 0:
```

```

4      # Polynomial kernel
5      return SVC(kernel='poly', degree=8, gamma="auto")
6  elif ktype == 1:
7      # Radial Basis Function kernel
8      return SVC(kernel='rbf', gamma="auto")
9  elif ktype == 2:
10     # Sigmoid kernel
11     return SVC(kernel='sigmoid', gamma="auto")
12 elif ktype == 3:
13     # Linear kernel
14     return SVC(kernel='linear', gamma="auto")

```

Comparing four kernel models

```

1  from sklearn.metrics import classification_report
2  for i in range(4):
3      # Separate data into test and training sets
4      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20)# Train a SVC model using different kernel
5      classifier = getClassifier(i)
6      classifier.fit(X_train, y_train)# Make prediction
7      y_pred = classifier.predict(X_test)# Evaluate our model
8      print("Evaluation:", kernels[i], "kernel")
9      print(classification_report(y_test,y_pred))

```

Evaluation: Polynomial kernel

	precision	recall	f1-score	support
1	1.00	1.00	1.00	11
2	0.80	1.00	0.89	8
3	1.00	0.82	0.90	11

accuracy			0.93	30
macro avg	0.93	0.94	0.93	30
weighted avg	0.95	0.93	0.93	30

Evaluation: RBF kernel

	precision	recall	f1-score	support
1	1.00	1.00	1.00	12
2	1.00	1.00	1.00	7
3	1.00	1.00	1.00	11

accuracy			1.00	30
macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30

Evaluation: Sigmoid kernel

	precision	recall	f1-score	support
1	0.00	0.00	0.00	12
2	0.00	0.00	0.00	12
3	0.20	1.00	0.33	6

accuracy			0.20	30
macro avg	0.07	0.33	0.11	30
weighted avg	0.04	0.20	0.07	30

Evaluation: Linear kernel

	precision	recall	f1-score	support
1	1.00	1.00	1.00	10
2	0.82	1.00	0.90	9
3	1.00	0.82	0.90	11

accuracy			0.93	30
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macro avg	0.94	0.94	0.93	30
weighted avg	0.95	0.93	0.93	30

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score are ill-defin
_warn_prf(average, modifier, msg_start, len(result))
```

Fine tuning hyperparameters

```
1 from sklearn.model_selection import GridSearchCV
2 param_grid = {'C': [0.1, 1, 10, 100], 'gamma': [1, 0.1, 0.01, 0.001], 'kernel': ['rbf', 'poly', 'sigmoid']}
3 grid = GridSearchCV(SVC(), param_grid, refit=True, verbose=2)
4 grid.fit(X_train, y_train)
5 print(grid.best_estimator_)
```

```
[CV] ..... C=1, gamma=0.1, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.1, kernel=rbf .....
[CV] ..... C=1, gamma=0.1, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.1, kernel=rbf .....
[CV] ..... C=1, gamma=0.1, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.1, kernel=poly .....
[CV] ..... C=1, gamma=0.1, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.1, kernel=poly .....
[CV] ..... C=1, gamma=0.1, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.1, kernel=poly .....
[CV] ..... C=1, gamma=0.1, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.1, kernel=poly .....
[CV] ..... C=1, gamma=0.1, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.1, kernel=poly .....
[CV] ..... C=1, gamma=0.1, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.1, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.1, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.1, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.1, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.1, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.1, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.1, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.1, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.01, kernel=rbf .....
[CV] ..... C=1, gamma=0.01, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.01, kernel=rbf .....
[CV] ..... C=1, gamma=0.01, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.01, kernel=rbf .....
[CV] ..... C=1, gamma=0.01, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.01, kernel=rbf .....
[CV] ..... C=1, gamma=0.01, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.01, kernel=rbf .....
[CV] ..... C=1, gamma=0.01, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.01, kernel=rbf .....
[CV] ..... C=1, gamma=0.01, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.01, kernel=poly .....
[CV] ..... C=1, gamma=0.01, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.01, kernel=poly .....
[CV] ..... C=1, gamma=0.01, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.01, kernel=poly .....
[CV] ..... C=1, gamma=0.01, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.01, kernel=poly .....
[CV] ..... C=1, gamma=0.01, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.01, kernel=poly .....
[CV] ..... C=1, gamma=0.01, kernel=poly, total= 0.0s
[CV] C=1, gamma=0.01, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.01, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.01, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.01, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.01, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.01, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.01, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.01, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.01, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.01, kernel=sigmoid, total= 0.0s
```

```
[CV] C=1, gamma=0.01, kernel=sigmoid .....
[CV] ..... C=1, gamma=0.01, kernel=sigmoid, total= 0.0s
[CV] C=1, gamma=0.001, kernel=rbf .....
[CV] ..... C=1, gamma=0.001, kernel=rbf, total= 0.0s
[CV] C=1, gamma=0.001, kernel=rbf .....
[CV] ..... C=1, gamma=0.001, kernel=rbf, total= 0.0s
```

```
1 grid_predictions = grid.predict(X_test)
2 print(confusion_matrix(y_test,grid_predictions))
3 print(classification_report(y_test,grid_predictions))#Output
```

```
[[10 0 0]
 [ 0 9 0]
 [ 0 1 10]]
```

	precision	recall	f1-score	support
1	1.00	1.00	1.00	10
2	0.90	1.00	0.95	9
3	1.00	0.91	0.95	11
accuracy			0.97	30
macro avg	0.97	0.97	0.97	30
weighted avg	0.97	0.97	0.97	30