Iris Classification Model

Prediction or Interpretation

- This model will be focussed on Prediction rather Interpretaion
- Model will have more explanation over the model prediction performance using performance metrics

In [15]:

```
# Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.datasets import load_iris
# will import regression models later while building it
```

In [16]:

```
# importing iris dataset and creating dataframe

iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)
df.head()
```

Out[16]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

Dataset Description and Attributes summary

In [17]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   sepal length (cm)  150 non-null    float64
 1   sepal width (cm)   150 non-null    float64
 2   petal length (cm)  150 non-null    float64
 3   petal width (cm)   150 non-null    float64
dtypes: float64(4)
memory usage: 4.8 KB
```

In [18]:
```
df.columns
```

Out[18]:
```
Index(['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)',
       'petal width (cm)'],
      dtype='object')
```

In [19]:
```
df.describe()
```

Out[19]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333
std	0.828066	0.435866	1.765298	0.762238
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

- Dataset has 4 features - all are dimensions of a flower(outer layer - sepal, inner layer - Petal)
- sepal length - length of the outer layer of the petal
- sepal width - width of the outer layer of the petal
- petal length - length of the inner layer of the flower
- petal width - width of the inner layer of the flower
- all features has float values
- Our aim is to find out the flower category with given features

Data Cleaning

In [20]:
```
df.isnull().sum()
```

Out[20]:
```
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
dtype: int64
```

This dataset is pretty clean. Since our concern is on the model performance we dive into the next section.

Feature Engineering

Determine if the floating point values need to be scaled

In [24]:

```
df.dtypes.tail()
```

Out[24]:

```
sepal length (cm)    float64
sepal width (cm)     float64
petal length (cm)    float64
petal width (cm)     float64
dtype: object
```

The data are all scaled from -1.0 to 1.0

Feature Correlation

In [ ]:

```
np.round(df.corr(),2)
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
sepal length (cm)	1.00	-0.12	0.87	0.82
sepal width (cm)	-0.12	1.00	-0.43	-0.37
petal length (cm)	0.87	-0.43	1.00	0.96
petal width (cm)	0.82	-0.37	0.96	1.00

In [25]:

```
feature_cols = df.columns[:]
corr_values = df[feature_cols].corr()

# Simplify by emptying all the data below the diagonal
tril_index = np.tril_indices_from(corr_values)

# Make the unused values NaNs
for coord in zip(*tril_index):
    corr_values.iloc[coord[0], coord[1]] = np.NaN

# Stack the data and convert to a data frame
corr_values = (corr_values
               .stack()
               .to_frame()
               .reset_index()
               .rename(columns={'level_0':'feature1',
                                'level_1':'feature2',
                                0:'correlation'}))

# Get the absolute values for sorting
corr_values['abs_correlation'] = corr_values.correlation.abs()
corr_values
```

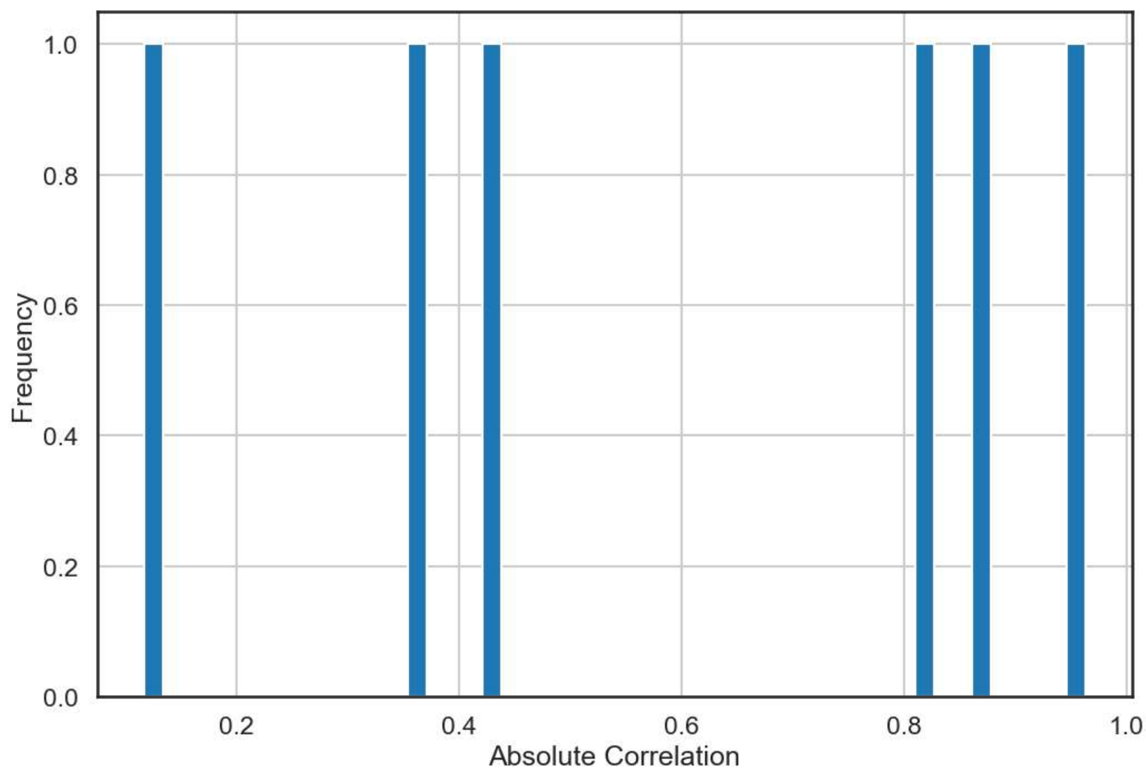
Out[25]:

	feature1	feature2	correlation	abs_correlation
0	sepal length (cm)	sepal width (cm)	-0.117570	0.117570
1	sepal length (cm)	petal length (cm)	0.871754	0.871754
2	sepal length (cm)	petal width (cm)	0.817941	0.817941
3	sepal width (cm)	petal length (cm)	-0.428440	0.428440
4	sepal width (cm)	petal width (cm)	-0.366126	0.366126

	feature1	feature2	correlation	abs_correlation
4	sepal width (cm)	petal width (cm)	0.366126	0.366126
5	petal length (cm)	petal width (cm)	0.962865	0.962865

In [30]:
```
# Histogram representation of correlation
sns.set_context('talk')
sns.set_style('white')

ax = corr_values.abs_correlation.hist(bins=50, figsize=(12, 8))
ax.set(xlabel='Absolute Correlation', ylabel='Frequency');
```



In [29]:
```
# the most correlated features
corr_values.sort_values('correlation', ascending=False).query('abs_correlation>
```

Out[29]:

	feature1	feature2	correlation	abs_correlation
5	petal length (cm)	petal width (cm)	0.962865	0.962865
1	sepal length (cm)	petal length (cm)	0.871754	0.871754
2	sepal length (cm)	petal width (cm)	0.817941	0.817941

Model Creation

Train Test Split

In [31]:
```
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(iris.data, iris.target, random_
```

Stock Logistic Regression

In [36]:
```
from sklearn.linear_model import LogisticRegression
stockmodel = LogisticRegression()
stockmodel.fit(xtrain, ytrain)
stockypred = stockmodel.predict(xtest)
```

SVM Classifier

In [39]:
```
from sklearn.svm import SVC
svcmodel = SVC()
svcmodel.fit(xtrain, ytrain)
svcypred = svcmodel.predict(xtest)
```

Random Forest Classifier

In [41]:
```
from sklearn.ensemble import RandomForestClassifier
rfmodel = RandomForestClassifier()
rfmodel.fit(xtrain, ytrain)
rfypred = rfmodel.predict(xtest)
```

Best Model

In [64]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score
from sklearn.metrics import precision_recall_fscore_support as score
```

Stock LR

In [61]:
```
precision, recall, fscore, _ = score(stockypred, ytest)
print('Stock LR')
print('Accuracy', accuracy_score(ytest, stockypred))
print('Precision : {}, Recall : {}, fscore : {}'.format(precision, recall, fsco
```

```
Stock LR
Accuracy 1.0
Precision : [1. 1. 1.], Recall : [1. 1. 1.], fscore : [1. 1. 1.]
```

SVM Classifier

In [62]:
```
precision, recall, fscore, _ = score(svcypred, ytest)
print('SVM')
print('Accuracy', accuracy_score(ytest, svcypred))
print('Precision : {}, Recall : {}, fscore : {}'.format(precision, recall, fsco
```

```
SVM
Accuracy 0.9666666666666667
Precision : [1.         0.92307692 1.        ], Recall : [1.    1.    0.875], f
score : [1.         0.96       0.93333333]
```

Random Forest Claasifier

In [63]:
```
precision, recall, fscore, _ = score(rfypred, ytest)
print('Random Forest')
print('Accuracy', accuracy_score(ytest, rfypred))
print('Precision : {}, Recall : {}, fscore : {}'.format(precision, recall, fsco
```

```
Random Forest
Accuracy 0.9666666666666667
Precision : [1.         0.92307692 1.        ], Recall : [1.    1.    0.875], f
score : [1.         0.96       0.93333333]
```

Insights on my models

- According to my dataset Stock LR performs the best with maximum accuracy, precision and fscore
- On the other hand SVM and Random Forest score same scores

Next Step Analysis

- Since the dataset is so simple we can achive good performance with slight tunning.
- Going forward will try this techniques in larger complex dataset and record the performance

-- Thank you by Shankesh Raju MS--