Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

In [2]:

```
df = pd.read_csv('Iris.csv', index_col=False)
```

In [3]:

```
df.drop('Id', axis=1, inplace=True)
```

In [4]:

```
df.head()
```

Out[4]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
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

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
SepalLengthCm    150 non-null float64
SepalWidthCm     150 non-null float64
PetalLengthCm    150 non-null float64
PetalWidthCm     150 non-null float64
Species          150 non-null object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [6]:

```
df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
SepalLengthCm	150.0	5.843333	0.828066	4.3	5.1	5.80	6.4	7.9
SepalWidthCm	150.0	3.054000	0.433594	2.0	2.8	3.00	3.3	4.4
PetalLengthCm	150.0	3.758667	1.764420	1.0	1.6	4.35	5.1	6.9
PetalWidthCm	150.0	1.198667	0.763161	0.1	0.3	1.30	1.8	2.5

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

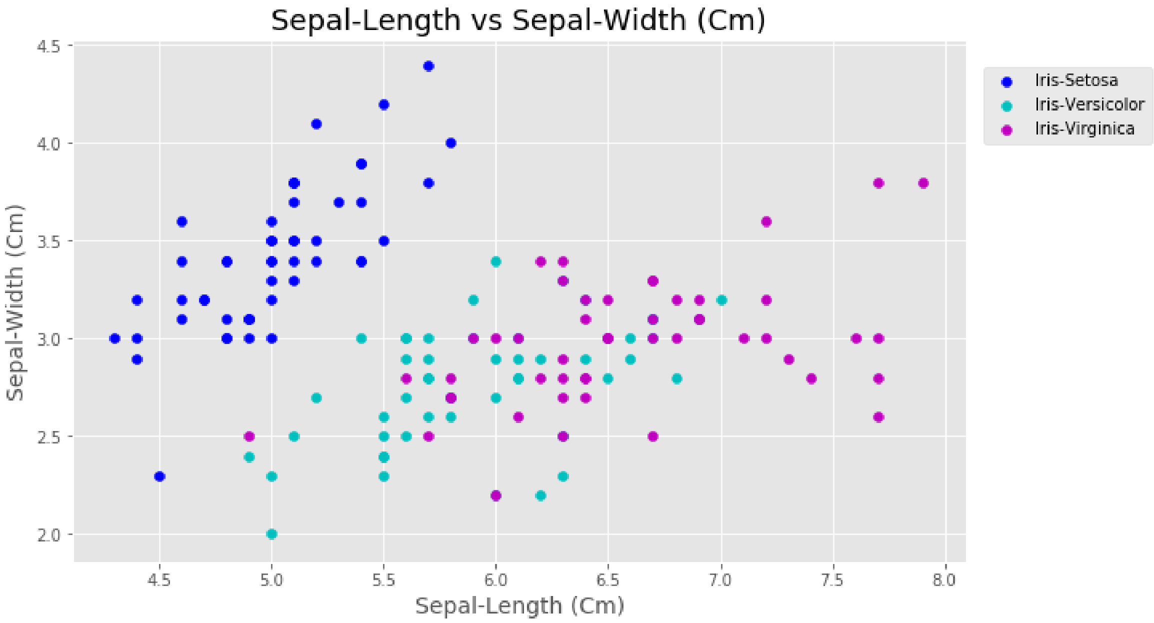
In [8]:

```
setosa = df[df.Species == 'Iris-setosa']
versicolor = df[df.Species == 'Iris-versicolor']
virginica = df[df.Species == 'Iris-virginica']
```

Visual EDA

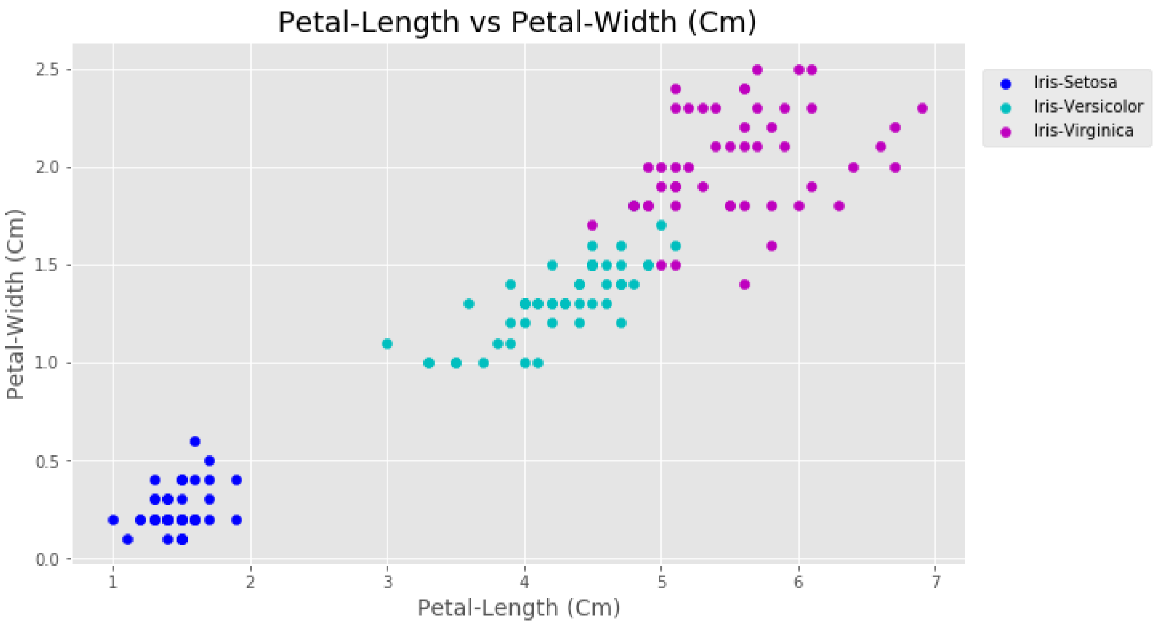
In [9]:

```
plt.figure(figsize=(10,6))
plt.style.use('ggplot')
plt.scatter(setosa['SepalLengthCm'], setosa['SepalWidthCm'], c = 'b', label = 'Iris-Setosa')
plt.scatter(versicolor['SepalLengthCm'], versicolor['SepalWidthCm'], c = 'c', label = 'Iris-Versico
lor')
plt.scatter(virginica['SepalLengthCm'], virginica['SepalWidthCm'], c = 'm', label = 'Iris-Virginica
')
plt.xlabel('Sepal-Length (Cm)', fontsize = 14)
plt.ylabel('Sepal-Width (Cm)', fontsize = 14)
plt.title('Sepal-Length vs Sepal-Width (Cm)', fontsize = 18)
plt.legend(loc = (1.02, 0.8))
plt.show()
```



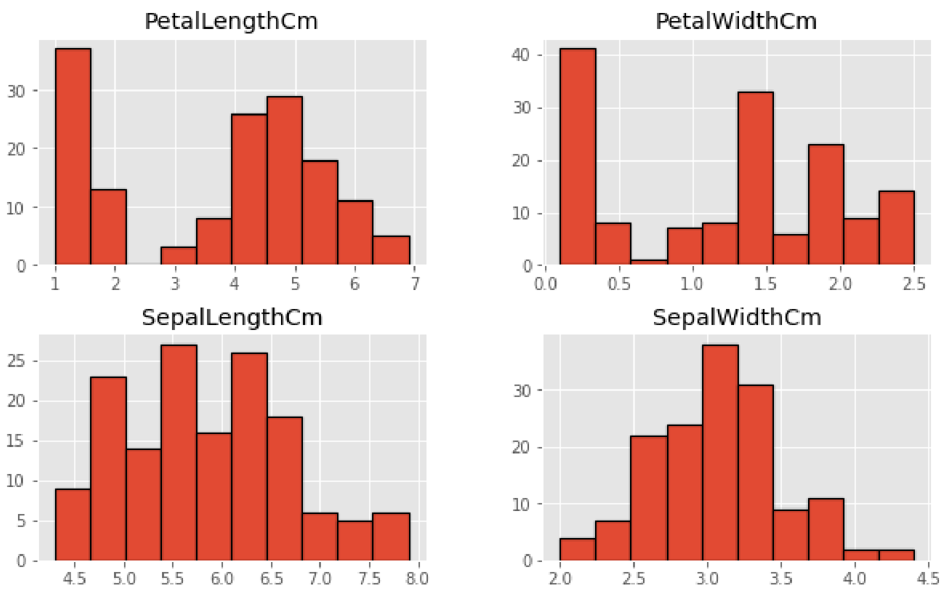
In [10]:

```
plt.figure(figsize=(10,6))
plt.style.use('ggplot')
plt.scatter(setosa['PetalLengthCm'], setosa['PetalWidthCm'], c = 'b', label = 'Iris-Setosa')
plt.scatter(versicolor['PetalLengthCm'], versicolor['PetalWidthCm'], c = 'c', label = 'Iris-Versico
lor')
plt.scatter(virginica['PetalLengthCm'], virginica['PetalWidthCm'], c = 'm', label = 'Iris-Virginica
')
plt.xlabel('Petal-Length (Cm)', fontsize = 14)
plt.ylabel('Petal-Width (Cm)', fontsize = 14)
plt.title('Petal-Length vs Petal-Width (Cm)', fontsize = 18)
plt.legend(loc = (1.02, 0.8))
plt.show()
```



In [11]:

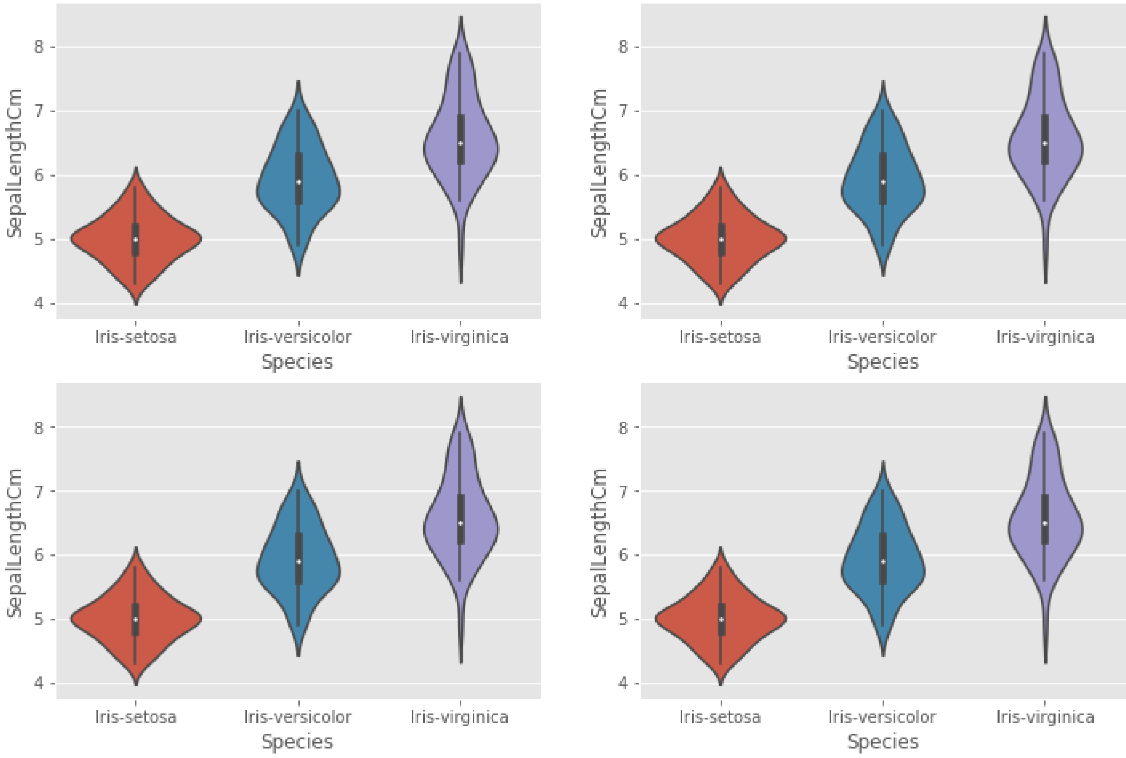
```
df.hist(edgecolor = 'black', linewidth = 1.2)
plt.gcf().set_size_inches(10, 6)
plt.show()
```



In [12]:

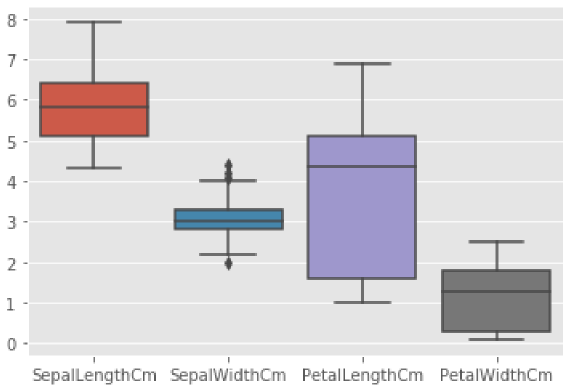
```
plt.figure(figsize=(12,8))
plt.subplot(2,2,1)
sns.violinplot(x='Species', y='SepalLengthCm', data=df)
plt.subplot(2,2,2)
sns.violinplot(x='Species', y='SepalLengthCm', data=df)
```

```
plt.subplot(2,2,3)
sns.violinplot(x='Species', y='SepalLengthCm', data=df)
plt.subplot(2,2,4)
sns.violinplot(x='Species', y='SepalLengthCm', data=df)
plt.show()
```



In [13]:

```
sns.boxplot(data=df)
plt.show()
```



In [14]:

```
df.shape
```

Out[14]:

```
(150, 5)
```

Train Test Split

In [15]:

```
X = df.drop('Species', axis = 1)
y = df['Species']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42, strat
```

```
ify = y)
```

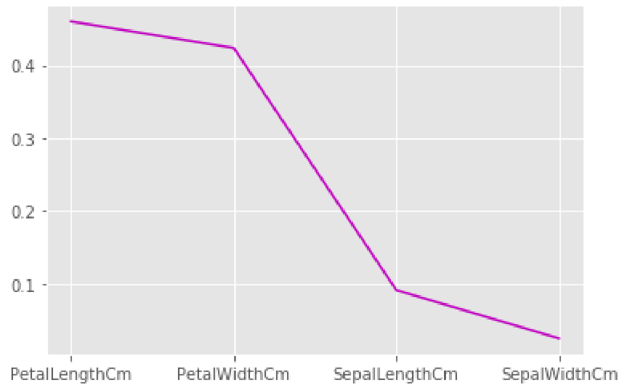
Feature Selection

In [16]:

```
plt.figure(figsize=(7,4))
sns.heatmap(df.corr(), annot = True, cmap = 'RdYlGn', square=True)
plt.yticks(rotation = 45)
plt.xticks(rotation = -45)
plt.show()
```

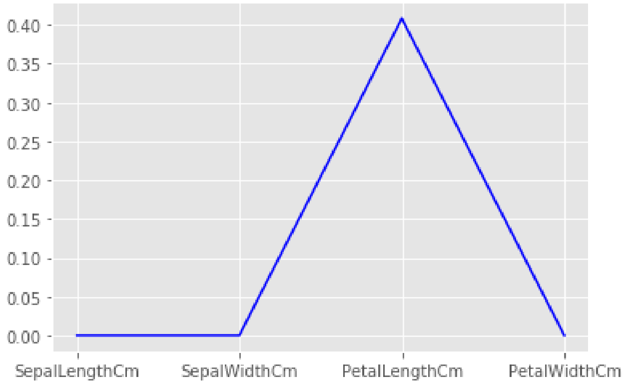
In [17]:

```
model = RandomForestClassifier(n_estimators=100, random_state=0)
model.fit(X, y)
imp_features = pd.Series(model.feature_importances_, index = X.columns).sort_values(ascending=False
)
# print(imp_features)
plt.plot(imp_features, color = 'm')
plt.show()
```



In [18]:

```
from sklearn.preprocessing import LabelEncoder
g = y.copy()
le = LabelEncoder().fit(g)
# print(le.classes_)
encoded_y = le.transform(g)
from sklearn.linear_model import Lasso
names = X.columns
lasso = Lasso(alpha=0.1)
features = lasso.fit(X, encoded_y).coef_
plt.plot(features, color = 'blue')
plt.xticks(range(len(names)), names, rotation = 0)
plt.figure(figsize=(7,4))
plt.show()
```




```
<Figure size 504x288 with 0 Axes>
```

Checking Accuracy of Each Model

In [19]:

```
accuracy = []
error = []
classifiers = ['Linear_SVC', 'Radial_SVC', 'KNN', 'Logistic_Regression', 'Decision_Tree', 'Random_F
orest']
models = [SVC(gamma='scale', kernel='linear'), SVC(gamma='auto', kernel='rbf'),
KNeighborsClassifier(n_neighbors=5),
         LogisticRegression(solver='liblinear', multi_class='auto'), DecisionTreeClassifier(), Rand
omForestClassifier(n_estimators=100)]
for i in models:
    model = i
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy.append(metrics.accuracy_score(y_pred, y_test))
    y_pred_encoded = LabelEncoder().fit_transform(y_pred)
    y_test_encoded = LabelEncoder().fit_transform(y_test)
    error.append(np.sqrt(mean_squared_error(y_test_encoded, y_pred_encoded)))
d = {'Accuracy' : accuracy, 'RMSE' : error}
score = pd.DataFrame(d, index = classifiers)
score
```

Out[19]:

	Accuracy	RMSE
Linear_SVC	1.000000	0.000000
Radial_SVC	0.977778	0.149071
KNN	0.977778	0.149071
Logistic_Regression	0.911111	0.298142
Decision_Tree	0.977778	0.149071
Random_Forest	0.911111	0.298142

Hyper-Parameter Tuning (KNN)

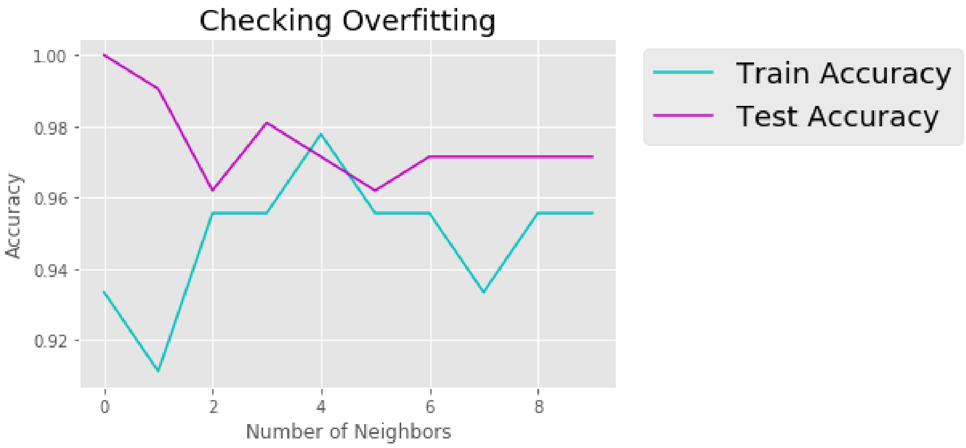
In [20]:

```
param_grid = {'n_neighbors' : np.arange(1, 51)}
knn_model = KNeighborsClassifier()
knn_cv = GridSearchCV(knn_model, param_grid, cv = 5)
knn_cv.fit(X, y)
print(knn_cv.best_params_)
print(knn_cv.best_score_)
```

```
{'n_neighbors': 6}
0.98
```

In [21]:

```
neighbors = np.arange(1, 11)
test_accuracy = np.empty(len(neighbors))
train_accuracy = np.empty(len(neighbors))
for i, k in enumerate(neighbors):
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)
    test_accuracy[i] = model.score(X_train, y_train)
    train_accuracy[i] = model.score(X_test, y_test)
plt.plot(train_accuracy, label='Train Accuracy', color = 'c')
plt.plot(test_accuracy, label='Test Accuracy', color = 'm')
plt.title('Checking Overfitting', fontsize = 18)
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.legend(fontsize=18, loc = (1.05, 0.7))
plt.figure(figsize=(12,6))
plt.show()
```




```
<Figure size 864x432 with 0 Axes>
```

Choosing Radial_SVC

In [22]:

```
model = SVC(gamma='auto', kernel='rbf')
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
print(f'Root Mean Square Error: {mean_squared_error(y_test_encoded, y_pred_encoded)}')
print(f'Model Accuracy: {round(metrics.accuracy_score(y_test, y_pred), 3) * 100}%')
```

```
Root Mean Square Error: 0.08888888888888889
Model Accuracy: 97.8%
```

Saving the Model

In [23]:

```
import joblib
#save the model
joblib.dump(model, 'iris_model.pkl')
new_model = joblib.load('iris_model.pkl')
new_model.fit(X_train, y_train)
new_model.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))
```

```
0.9777777777777777
```