ASSIGNMENT 6

Data Analytics 3

1. Implement Simple Naive Bayes classification algorithm using Python/R on iris.csv dataset.
2. Compute confusion matrix to find TP,FP,TN,FN, Accuracy, Error Rate, Precision, Recall on the given dataset.

> Importing Libraries and Loading Dataset

In [1]:

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

In [2]:

```
df = pd.read_csv("Iris.csv")
```

In [3]:
```
df
```

Out[3]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

> Data Preprocessing

In [4]:
```
#first 5 rows
df.head()
```

Out[4]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [5]:
```
#checks total size(rows*columns)
df.size
```
Out[5]:
```
900
```
In [6]:
```
#checks dimensions of the dataframe
df.shape
```
Out[6]:
```
(150, 6)
```
In [7]:
```
#checks the columns present
df.columns
```
Out[7]:
```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWid
thCm',
       'Species'],
      dtype='object')
```
In [8]:
```
#checks initial statistics
df.describe()
```
Out[8]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

In [9]:
```
#prints information of the dataset
df.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [10]:
```
#checks datatype of each column
df.dtypes
```

Out[10]:
```
Id                 int64
SepalLengthCm    float64
SepalWidthCm     float64
PetalLengthCm    float64
PetalWidthCm     float64
Species           object
dtype: object
```

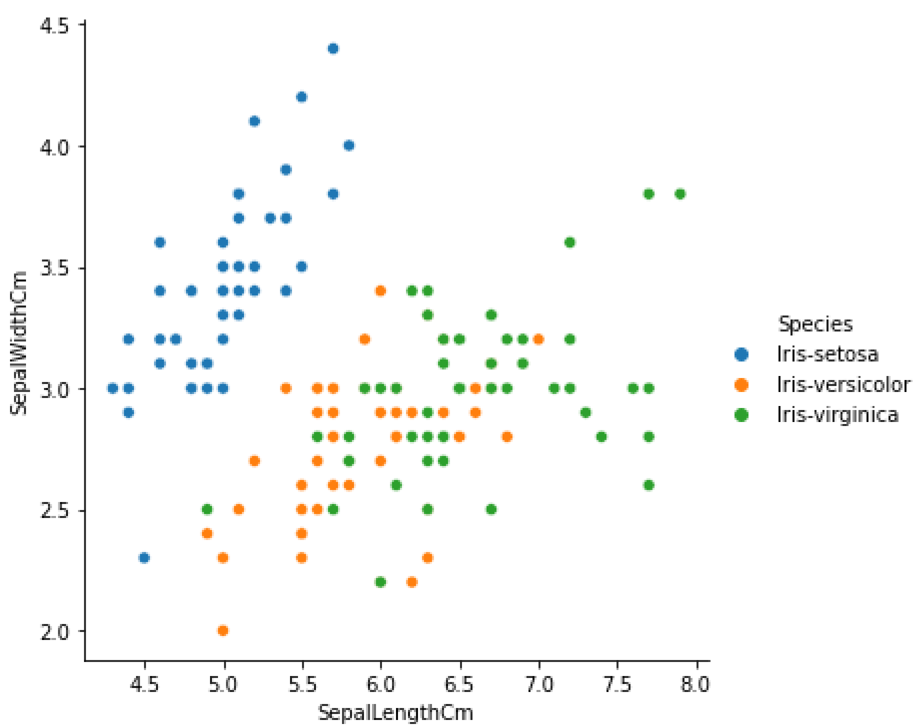
> Data Visualizations

Relplots in seaborn are scatterplot-based visualizations that depict the relationship between variables, accommodating numeric and categorical data, while allowing for additional dimensions and faceting to explore various subgroups or conditions. They provide a concise way to analyze correlations, patterns, and trends in data.

In [11]:
```
sns.relplot(df['SepalLengthCm'],df['SepalWidthCm'],hue=df['Species'])
```

```
C:\Users\Shravani Sajekar\anaconda3\lib\site-packages\seaborn\_decorator
s.py:36: FutureWarning: Pass the following variables as keyword args: x,
y. From version 0.12, the only valid positional argument will be `data`,
and passing other arguments without an explicit keyword will result in a
n error or misinterpretation.
  warnings.warn(
```

Out[11]:
```
<seaborn.axisgrid.FacetGrid at 0x250e2cc1550>
```

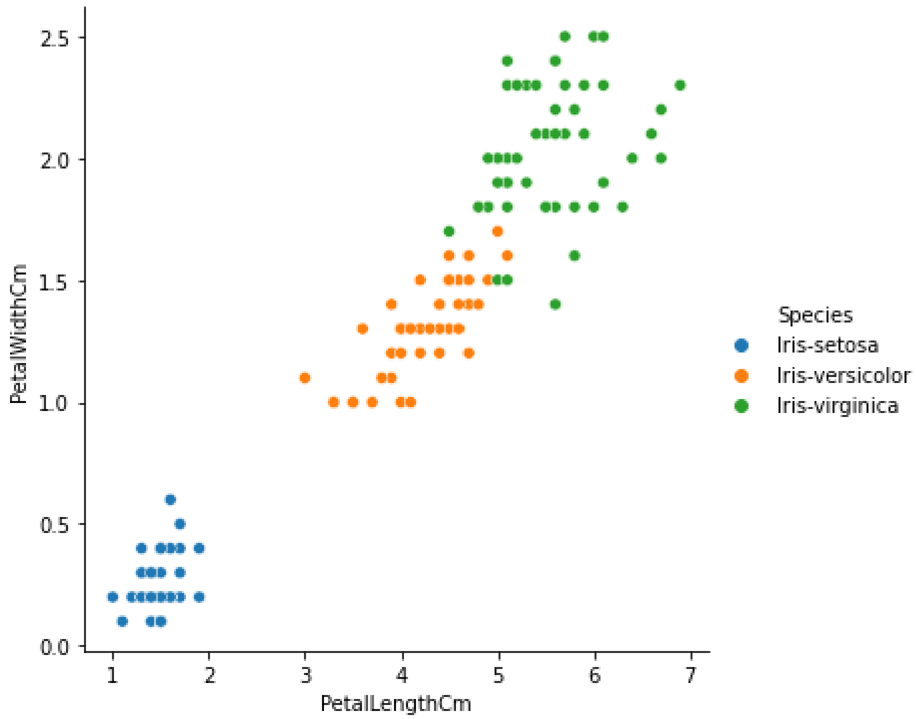


In [12]:

```
sns.relplot(df['PetalLengthCm'],df['PetalWidthCm'],hue=df['Species'])
```

```
C:\Users\Shravani Sajekar\anaconda3\lib\site-packages\seaborn\_decorator
s.py:36: FutureWarning: Pass the following variables as keyword args: x,
y. From version 0.12, the only valid positional argument will be `data`,
and passing other arguments without an explicit keyword will result in a
n error or misinterpretation.
  warnings.warn(
```

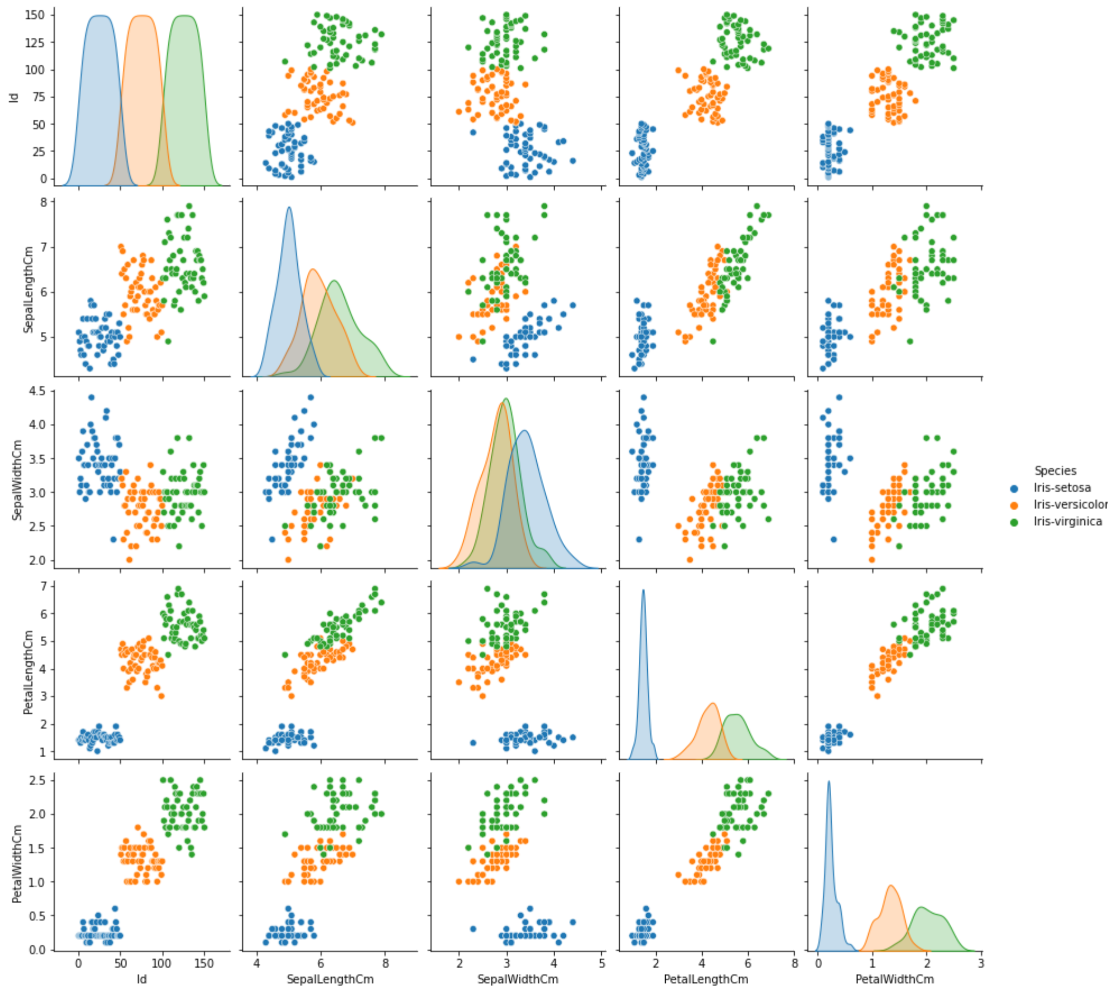
Out[12]: <seaborn.axisgrid.FacetGrid at 0x250e685a460>



Pair Plots are a really simple way to visualize relationships between each variable. It produces a matrix of relationships between each variable in your data for an instant examination of our data. pair plot gives scatter plot of different features. pair plot for iris data set.

In [13]:
```python
sns.pairplot(df,hue='Species')
```

Out[13]:
```
<seaborn.axisgrid.PairGrid at 0x250e7e27820>
```



Boxplot is a standardized way of displaying the distribution of data based on a five number summary (“minimum”, first quartile (Q1), median, third quartile (Q3), and “maximum”). It can tell you about your outliers and what their values are. It can also tell you if your data is symmetrical, how tightly your data is grouped, and if and how your data is skewed.

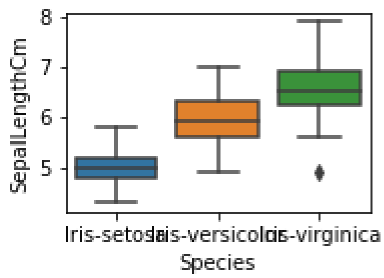
In [14]:
```python
plt.figure(figsize=(15,10))
```

Out[14]:
```
<Figure size 1080x720 with 0 Axes>

<Figure size 1080x720 with 0 Axes>
```

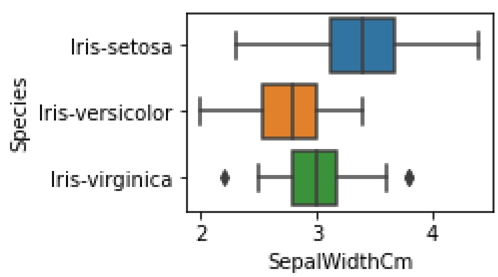
In [15]:
```python
plt.subplot(2,2,1)
sns.boxplot(x='Species',y='SepalLengthCm',data=df)
```

Out[15]: <AxesSubplot:xlabel='Species', ylabel='SepalLengthCm'>



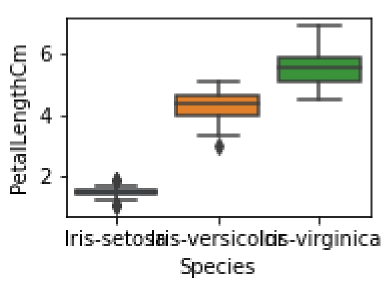
In [16]:
```python
plt.subplot(2,2,2)
sns.boxplot(x='SepalWidthCm',y='Species',data=df)
```

Out[16]: <AxesSubplot:xlabel='SepalWidthCm', ylabel='Species'>



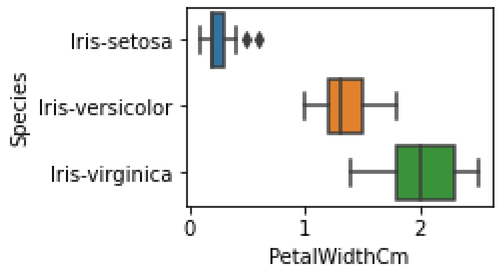
In [17]:
```python
plt.subplot(2,2,3)
sns.boxplot(x='Species',y='PetalLengthCm',data=df)
```

Out[17]: <AxesSubplot:xlabel='Species', ylabel='PetalLengthCm'>



In [18]:
```
plt.subplot(2,2,4)
sns.boxplot(x='PetalWidthCm',y='Species',data=df)
```

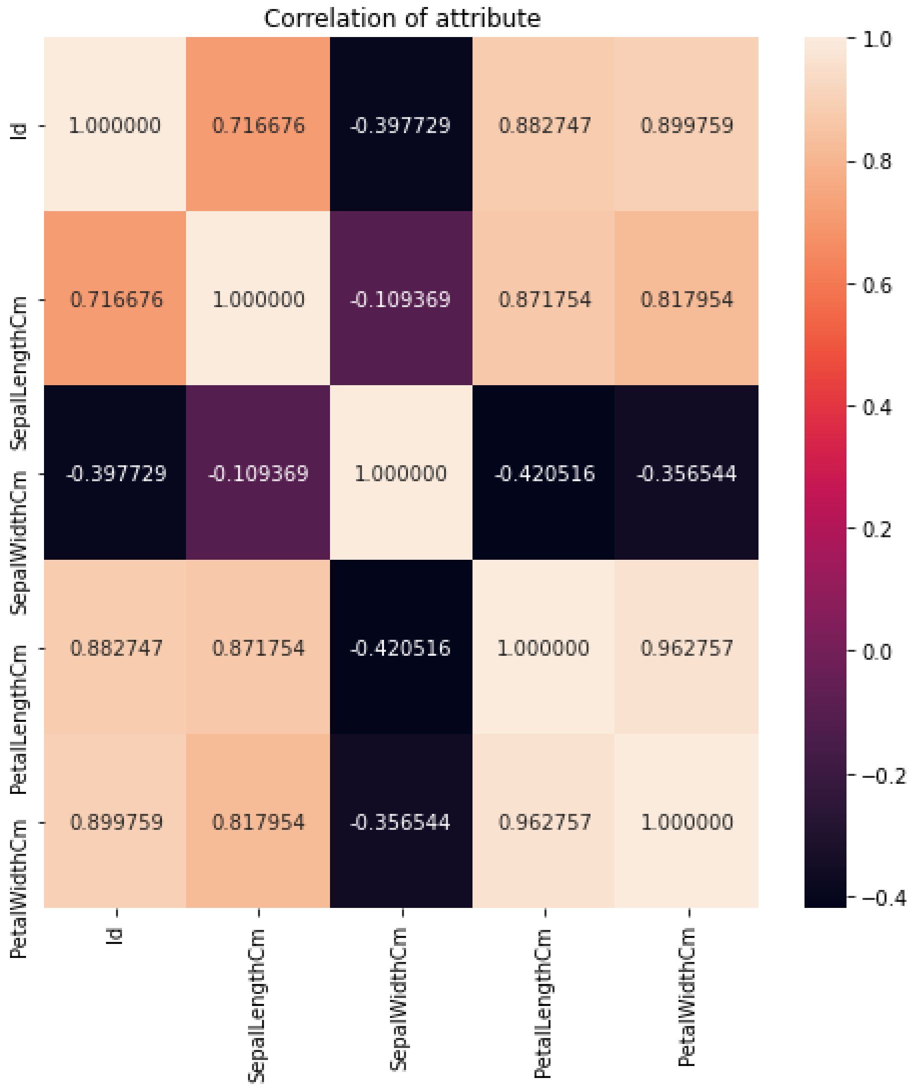
Out[18]: <AxesSubplot:xlabel='PetalWidthCm', ylabel='Species'>



Now, when we train any algorithm, the number of features and their correlation plays an important role. If there are features and many of the features are highly correlated, then training an algorithm with all the features will reduce the accuracy. Thus features selection should be done carefully. This dataset has less features but still we will see the correlation.

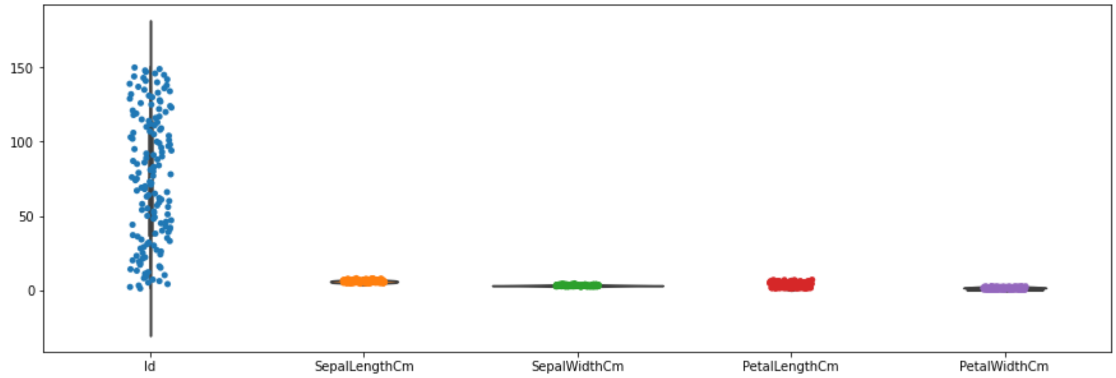
In [19]:
```
plt.subplots(figsize=(8,8))
sns.heatmap(df.corr(),annot=True,fmt='f').set_title("Correlation of attrib
```

Out[19]: Text(0.5, 1.0, 'Correlation of attribute')



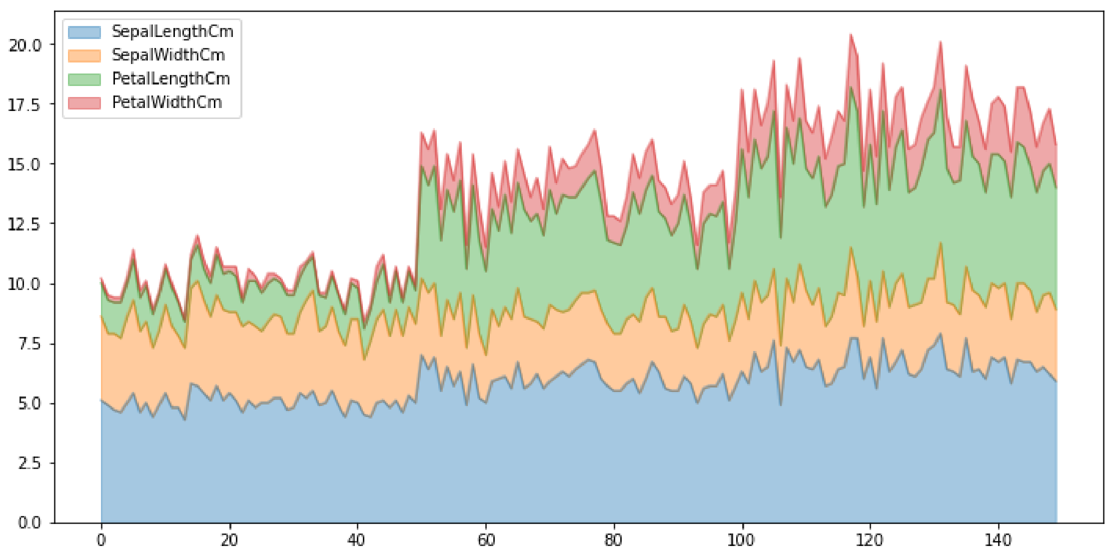
Violin Plot is a method to visualize the distribution of numerical data of different variables. It is similar to Box Plot but with a rotated plot on each side, giving more information about the density estimate on the y-axis.

In [35]:
```
plt.subplots(figsize=(15,5))
sns.violinplot(data=df)
sns.stripplot(data=df)
plt.show()
```



Area Plot gives us a visual representation of Various dimensions of Iris flower and their range in dataset.

In [37]:
```
df.plot.area(y=['SepalLengthCm','SepalWidthCm','PetalLengthCm','PetalWidtl
```



> Data Formatting

In [41]:
```
#extracting indepedent variables
x = df.iloc[:,0:4].values
```

In [42]:
```
x
```

Out[42]:
```
array([[  1. ,   5.1,   3.5,   1.4],
       [  2. ,   4.9,   3. ,   1.4],
       [  3. ,   4.7,   3.2,   1.3],
       [  4. ,   4.6,   3.1,   1.5],
       [  5. ,   5. ,   3.6,   1.4],
       [  6. ,   5.4,   3.9,   1.7],
       [  7. ,   4.6,   3.4,   1.4],
       [  8. ,   5. ,   3.4,   1.5],
       [  9. ,   4.4,   2.9,   1.4],
       [ 10. ,   4.9,   3.1,   1.5],
       [ 11. ,   5.4,   3.7,   1.5],
       [ 12. ,   4.8,   3.4,   1.6],
       [ 13. ,   4.8,   3. ,   1.4],
       [ 14. ,   4.3,   3. ,   1.1],
       [ 15. ,   5.8,   4. ,   1.2],
       [ 16. ,   5.7,   4.4,   1.5],
       [ 17. ,   5.4,   3.9,   1.3],
       [ 18. ,   5.1,   3.5,   1.4],
       [ 19. ,   5.7,   3.8,   1.7],
```

In [43]:
```
#extracting depedent variables
y = df.iloc[:,5].values
```

In [44]:

```
y
```

Out[44]:

```
array(['Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-setosa', 'Iris-setosa',
       'Iris-setosa', 'Iris-setosa', 'Iris-versicolor', 'Iris-versicolo
r',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-versicolor', 'Iris-versicolor', 'Iris-versicolor',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica', 'Iris-virginica',
       'Iris-virginica', 'Iris-virginica'], dtype=object)
```

> Label Encoding

We need to use LabelEncoder to transform categorical labels into numbers. Iris-setosa

In [45]:
```python
from sklearn.preprocessing import LabelEncoder
```

In [46]:
```python
le = LabelEncoder()
```

In [47]:
```python
y = le.fit_transform(y)
```

In [48]:
```python
y
```

Out[48]:
```
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])
```

> Splitting Data into 70% training & 30% testing

x_train and x_test represent the input features used for training and evaluating the model, respectively. y_test is the corresponding set of true target variable values for the test set, and y_pred is the predicted target variable values generated by the trained model when applied to the test set.

In [49]:
```python
from sklearn.model_selection import train_test_split
```

In [50]:
```python
x_train,x_test,y_train,y_test = train_test_split(x,y,train_size=0.7,test_s
```

In [51]:

```
x_train
```

Out[51]:
```
array([[ 81. ,   5.5,   2.4,   3.8],
       [145. ,   6.7,   3.3,   5.7],
       [ 46. ,   4.8,   3. ,   1.4],
       [ 14. ,   4.3,   3. ,   1.1],
       [ 78. ,   6.7,   3. ,   5. ],
       [131. ,   7.4,   2.8,   6.1],
       [ 56. ,   5.7,   2.8,   4.5],
       [ 49. ,   5.3,   3.7,   1.5],
       [146. ,   6.7,   3. ,   5.2],
       [ 96. ,   5.7,   3. ,   4.2],
       [ 42. ,   4.5,   2.3,   1.3],
       [ 68. ,   5.8,   2.7,   4.1],
       [ 73. ,   6.3,   2.5,   4.9],
       [ 48. ,   4.6,   3.2,   1.4],
       [ 21. ,   5.4,   3.4,   1.7],
       [ 43. ,   4.4,   3.2,   1.3],
       [ 37. ,   5.5,   3.5,   1.3],
       [ 39. ,   4.4,   3. ,   1.3],
       [ 13. ,   4.8,   3. ,   1.4],
       [122. ,   5.6,   2.8,   4.9],
       [  6. ,   5.4,   3.9,   1.7],
       [121. ,   6.9,   3.2,   5.7],
       [133. ,   6.4,   2.8,   5.6],
       [109. ,   6.7,   2.5,   5.8],
       [124. ,   6.3,   2.7,   4.9],
       [123. ,   7.7,   2.8,   6.7],
       [101. ,   6.3,   3.3,   6. ],
       [ 79. ,   6. ,   2.9,   4.5],
       [140. ,   6.9,   3.1,   5.4],
       [ 90. ,   5.5,   2.5,   4. ],
       [ 98. ,   6.2,   2.9,   4.3],
       [ 19. ,   5.7,   3.8,   1.7],
       [  2. ,   4.9,   3. ,   1.4],
       [ 24. ,   5.1,   3.3,   1.7],
       [ 35. ,   4.9,   3.1,   1.5],
       [  8. ,   5. ,   3.4,   1.5],
       [ 34. ,   5.5,   4.2,   1.4],
       [142. ,   6.9,   3.1,   5.1],
       [129. ,   6.4,   2.8,   5.6],
       [ 97. ,   5.7,   2.9,   4.2],
       [ 69. ,   6.2,   2.2,   4.5],
       [ 22. ,   5.1,   3.7,   1.5],
       [102. ,   5.8,   2.7,   5.1],
       [ 82. ,   5.5,   2.4,   3.7],
       [ 76. ,   6.6,   3. ,   4.4],
       [147. ,   6.3,   2.5,   5. ],
       [ 41. ,   5. ,   3.5,   1.3],
       [ 59. ,   6.6,   2.9,   4.6],
       [ 87. ,   6.7,   3.1,   4.7],
       [106. ,   7.6,   3. ,   6.6],
       [139. ,   6. ,   3. ,   4.8],
       [143. ,   5.8,   2.7,   5.1],
       [ 99. ,   5.1,   2.5,   3. ],
       [  7. ,   4.6,   3.4,   1.4],
       [ 27. ,   5. ,   3.4,   1.6],
       [ 11. ,   5.4,   3.7,   1.5],
       [116. ,   6.4,   3.2,   5.3],
```

```
       [ 31. ,   4.8,   3.1,   1.6],
       [ 17. ,   5.4,   3.9,   1.3],
       [ 89. ,   5.6,   3. ,   4.1],
       [ 36. ,   5. ,   3.2,   1.2],
       [125. ,   6.7,   3.3,   5.7],
       [110. ,   7.2,   3.6,   6.1],
       [ 16. ,   5.7,   4.4,   1.5],
       [ 91. ,   5.5,   2.6,   4.4],
       [ 64. ,   6.1,   2.9,   4.7],
       [ 92. ,   6.1,   3. ,   4.6],
       [127. ,   6.2,   2.8,   4.8],
       [ 60. ,   5.2,   2.7,   3.9],
       [  5. ,   5. ,   3.6,   1.4],
       [105. ,   6.5,   3. ,   5.8],
       [114. ,   5.7,   2.5,   5. ],
       [ 26. ,   5. ,   3. ,   1.6],
       [ 29. ,   5.2,   3.4,   1.4],
       [ 83. ,   5.8,   2.7,   3.9],
       [117. ,   6.5,   3. ,   5.5],
       [130. ,   7.2,   3. ,   5.8],
       [ 80. ,   5.7,   2.6,   3.5],
       [ 25. ,   4.8,   3.4,   1.9],
       [ 50. ,   5. ,   3.3,   1.4],
       [ 88. ,   6.3,   2.3,   4.4],
       [ 84. ,   6. ,   2.7,   5.1],
       [ 10. ,   4.9,   3.1,   1.5],
       [ 51. ,   7. ,   3.2,   4.7],
       [ 66. ,   6.7,   3.1,   4.4],
       [ 94. ,   5. ,   2.3,   3.3],
       [ 20. ,   5.1,   3.8,   1.5],
       [ 57. ,   6.3,   3.3,   4.7],
       [ 38. ,   4.9,   3.1,   1.5],
       [ 44. ,   5. ,   3.5,   1.6],
       [ 54. ,   5.5,   2.3,   4. ],
       [ 53. ,   6.9,   3.1,   4.9],
       [ 28. ,   5.2,   3.5,   1.5],
       [ 67. ,   5.6,   3. ,   4.5],
       [ 61. ,   5. ,   2. ,   3.5],
       [ 65. ,   5.6,   2.9,   3.6],
       [144. ,   6.8,   3.2,   5.9],
       [  3. ,   4.7,   3.2,   1.3],
       [ 18. ,   5.1,   3.5,   1.4],
       [ 85. ,   5.4,   3. ,   4.5],
       [119. ,   7.7,   2.6,   6.9],
       [115. ,   5.8,   2.8,   5.1],
       [ 86. ,   6. ,   3.4,   4.5],
       [ 63. ,   6. ,   2.2,   4. ],
       [ 40. ,   5.1,   3.4,   1.5]])
```

In [52]:

```
x_train.shape
```

Out[52]: (105, 4)

In [53]:
```
x_test
```

Out[53]:
```
array([[ 93. ,   5.8,   2.6,   4. ],
       [  9. ,   4.4,   2.9,   1.4],
       [150. ,   5.9,   3. ,   5.1],
       [118. ,   7.7,   3.8,   6.7],
       [ 74. ,   6.1,   2.8,   4.7],
       [ 30. ,   4.7,   3.2,   1.6],
       [126. ,   7.2,   3.2,   6. ],
       [138. ,   6.4,   3.1,   5.5],
       [134. ,   6.3,   2.8,   5.1],
       [141. ,   6.7,   3.1,   5.6],
       [ 55. ,   6.5,   2.8,   4.6],
       [128. ,   6.1,   3. ,   4.9],
       [ 58. ,   4.9,   2.4,   3.3],
       [132. ,   7.9,   3.8,   6.4],
       [111. ,   6.5,   3.2,   5.1],
       [103. ,   7.1,   3. ,   5.9],
       [ 45. ,   5.1,   3.8,   1.9],
       [ 71. ,   5.9,   3.2,   4.8],
       [ 52. ,   6.4,   3.2,   4.5],
       [108. ,   7.3,   2.9,   6.3],
       [ 33. ,   5.2,   4.1,   1.5],
       [ 77. ,   6.8,   2.8,   4.8],
       [104. ,   6.3,   2.9,   5.6],
       [ 62. ,   5.9,   3. ,   4.2],
       [112. ,   6.4,   2.7,   5.3],
       [ 12. ,   4.8,   3.4,   1.6],
       [  1. ,   5.1,   3.5,   1.4],
       [ 95. ,   5.6,   2.7,   4.2],
       [137. ,   6.3,   3.4,   5.6],
       [ 15. ,   5.8,   4. ,   1.2],
       [ 23. ,   4.6,   3.6,   1. ],
       [113. ,   6.8,   3. ,   5.5],
       [ 70. ,   5.6,   2.5,   3.9],
       [ 72. ,   6.1,   2.8,   4. ],
       [120. ,   6. ,   2.2,   5. ],
       [ 47. ,   5.1,   3.8,   1.6],
       [149. ,   6.2,   3.4,   5.4],
       [  4. ,   4.6,   3.1,   1.5],
       [107. ,   4.9,   2.5,   4.5],
       [136. ,   7.7,   3. ,   6.1],
       [ 75. ,   6.4,   2.9,   4.3],
       [100. ,   5.7,   2.8,   4.1],
       [148. ,   6.5,   3. ,   5.2],
       [135. ,   6.1,   2.6,   5.6],
       [ 32. ,   5.4,   3.4,   1.5]])
```

In [54]:
```
x_test.shape
```

Out[54]:
```
(45, 4)
```

In [55]:
```
y_train
```

Out[55]:
```
array([1, 2, 0, 0, 1, 2, 1, 0, 2, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 2, 0, 2,
       2, 2, 2, 2, 2, 1, 2, 1, 1, 0, 0, 0, 0, 0, 0, 2, 2, 1, 1, 0, 2, 1,
       1, 2, 0, 1, 1, 2, 2, 2, 1, 0, 0, 0, 2, 0, 0, 1, 0, 2, 2, 0, 1, 1,
       1, 2, 1, 0, 2, 2, 0, 0, 1, 2, 2, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1,
       0, 0, 1, 1, 0, 1, 1, 1, 2, 0, 0, 1, 2, 2, 1, 1, 0])
```

In [56]:
```
y_train.shape
```

Out[56]:
```
(105,)
```

In [57]:
```
y_test
```

Out[57]:
```
array([1, 0, 2, 2, 1, 0, 2, 2, 2, 2, 1, 2, 1, 2, 2, 2, 0, 1, 1, 2, 0, 1,
       2, 1, 2, 0, 0, 1, 2, 0, 0, 2, 1, 1, 2, 0, 2, 0, 2, 2, 1, 1, 2, 2,
       0])
```

In [58]:
```
y_test.shape
```

Out[58]:
```
(45,)
```

> Initializing Naive Bayes Model and Training

Naive Bayes is a classification algorithm for binary (two-class) and multi-class classification problems. The technique is easiest to understand when described using binary or categorical input values.

It is called naive Bayes or idiot Bayes because the calculation of the probabilities for each hypothesis are simplified to make their calculation tractable.

In [59]:
```
from sklearn.naive_bayes import GaussianNB
```

In [60]:
```
model = GaussianNB()
```

In [61]:
```
model.fit(x_train,y_train)
```

Out[61]:
```
▾ GaussianNB
GaussianNB()
```

> Prediction

By comparing y_pred with the actual values of y_test, we can evaluate the model's performance and assess how well it generalizes to unseen data.

In [62]:
```
prediction = model.predict(x_test)
```

In [63]:
```
prediction
```

Out[63]:
```
array([1, 0, 2, 2, 1, 0, 2, 2, 2, 2, 1, 2, 1, 2, 2, 2, 0, 1, 1, 2, 0, 1,
       2, 1, 2, 0, 0, 1, 2, 0, 0, 2, 1, 1, 2, 0, 2, 0, 1, 2, 1, 1, 2, 2,
       0])
```

In [64]:
```
y_test
```

Out[64]:
```
array([1, 0, 2, 2, 1, 0, 2, 2, 2, 2, 1, 2, 1, 2, 2, 2, 0, 1, 1, 2, 0, 1,
       2, 1, 2, 0, 0, 1, 2, 0, 0, 2, 1, 1, 2, 0, 2, 0, 2, 2, 1, 1, 2, 2,
       0])
```

> Confusion Matrix

A confusion matrix is a matrix that summarizes the performance of a machine learning model on a set of test data

In [65]:
```
from sklearn.metrics import confusion_matrix
```

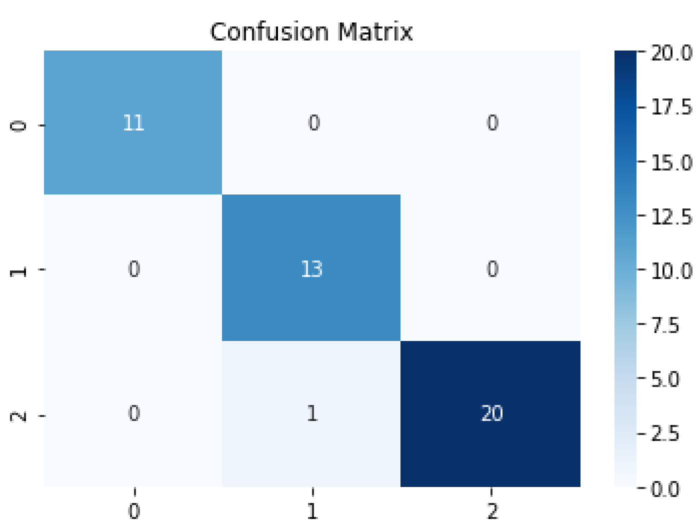
In [66]:
```
cm = confusion_matrix(y_test,prediction)
```

In [67]:
```
cm
```

Out[67]:
```
array([[11,  0,  0],
       [ 0, 13,  0],
       [ 0,  1, 20]], dtype=int64)
```

In [68]:
```
sns.heatmap(cm,annot=True,cmap='Blues').set_title("Confusion Matrix")
```

Out[68]:
```
Text(0.5, 1.0, 'Confusion Matrix')
```



> Accuracy

In [69]:
```
from sklearn.metrics import accuracy_score
```

In [70]:
```
acc = accuracy_score(y_test,prediction)
```

In [71]:
```
acc
```

Out[71]:
```
0.9777777777777777
```

In [72]:
```
#Calculate performance metrics

from sklearn.metrics import classification_report

print(classification_report(y_test,prediction))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        11
           1       0.93      1.00      0.96        13
           2       1.00      0.95      0.98        21

    accuracy                           0.98        45
   macro avg       0.98      0.98      0.98        45
weighted avg       0.98      0.98      0.98        45
```

> TP,FP,TN,FN

True positive (TP): correct positive prediction

False positive (FP): incorrect positive prediction

True negative (TN): correct negative prediction

False negative (FN): incorrect negative prediction

In [73]:
```
tp = cm[0,[0]]
fp = cm[0,[1]]
fn = cm[1,[0]]
tn = cm[1,[1]]
```

In [74]:
```
print("TRUE POSITIVE : ",tp)
print("FALSE POSITIVE : ",fp)
print("FALSE NEGATIVE : ",fn)
print("TRUE NEGATIVE : ",tn)
```

```
TRUE POSITIVE :  [11]
FALSE POSITIVE :  [0]
FALSE NEGATIVE :  [0]
TRUE NEGATIVE :  [13]
```

> Accuracy(using cm)

Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset.

In [75]:
```
accuracy = (tp+tn)/(tp+fp+tn+fn)
```

In [76]:
```
print("ACCURACY :",accuracy*100)
```

```
ACCURACY : [100.]
```

> Error Rate

Error rate is calculated as the number of all incorrect predictions divided by the total number of the dataset.

In [77]:
```
error_rate = (fp+fn)/(tp+fp+tn+fn)
```

In [78]:
```
print("ERROR RATE :",error_rate*100)
```

```
ERROR RATE : [0.]
```

> Precision

Precision is calculated as the number of correct positive predictions divided by the total number of positive predictions.

In [79]:
```
precision = (tp)/(tp+fp)
```

In [80]:
```
print("PRECISION :",precision*100)
```

```
PRECISION : [100.]
```

> Recall

Recall indicates the proportion of correctly identified positive instances out of all the actual positive instances.

In [81]:
```
recall = (tp)/(tp+fn)
```

In [82]:
```
print("RECALL :",recall*100)
```

```
RECALL : [100.]
```

> Specify

Specificity is calculated as the number of correct negative predictions divided by the total number of negatives.

In [83]:
```
specify = (tn)/(tn+fp)
```

In [84]:
```
print("SPECIFY :",specify*100)
```

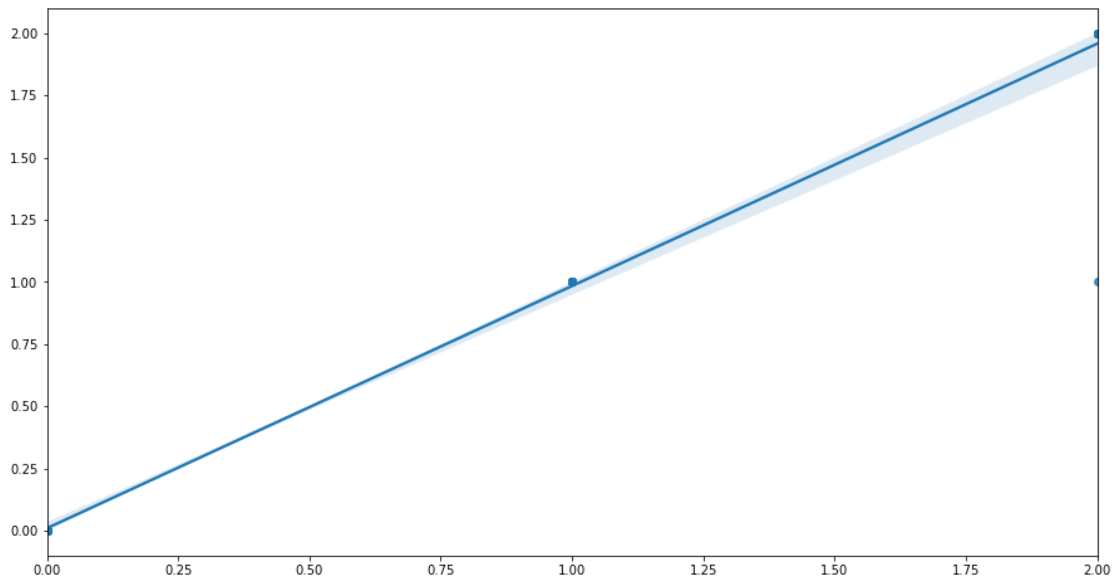
```
SPECIFY : [100.]
```

In [85]:

```
plt.figure(figsize=(15,8))
sns.regplot(y_test,prediction)
```

```
C:\Users\Shravani Sajekar\anaconda3\lib\site-packages\seaborn\_decorator
s.py:36: FutureWarning: Pass the following variables as keyword args: x,
y. From version 0.12, the only valid positional argument will be `data`,
and passing other arguments without an explicit keyword will result in a
n error or misinterpretation.
  warnings.warn(
```

Out[85]: <AxesSubplot:>



In [ ]: