Applicant: Gary Bair

Package Requirements:

In [32]:
```
import numpy as np
import pandas as pd
import matplotlib as plt
import seaborn as sns
import statsmodels.api as sm
import re
import nltk
from nltk.corpus import stopwords
```

1. Regression Modeling

For this exercise, we are interested in better understanding the shapes of iris flowers. Specifically, we are interested in whether the petal length and sepal length are related. We will use the “iris” data set which is available in both R and Python (and also attached as a csv, “Iris_Data.csv”) which includes the petal and sepal lengths and widths and the species of iris to which each example belongs.

In [3]:
```
iris_df = pd.read_csv('Iris_Data.csv')
iris_df.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   Labels         150 non-null    int64
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
```

a) How many irises belong to each species?

In [4]:
```
iris_df.Labels.value_counts()
```

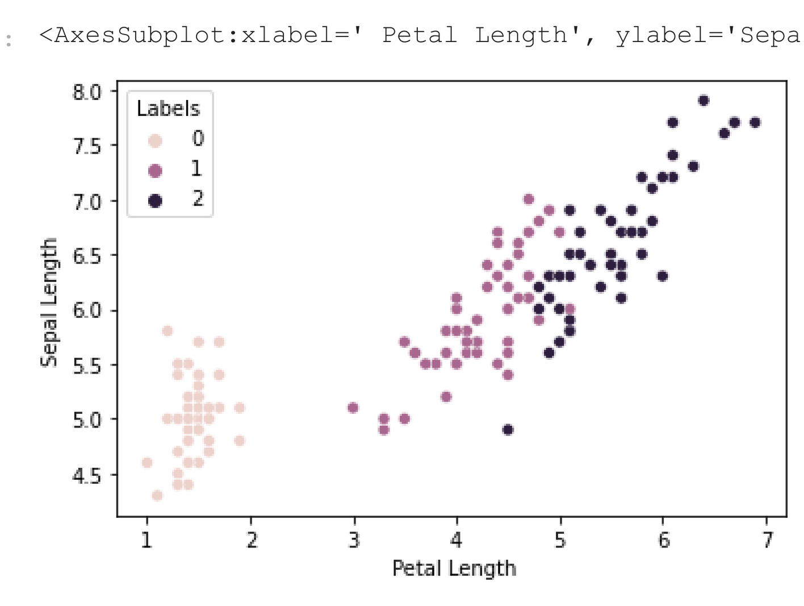
Out[4]:
```
0    50
1    50
2    50
Name: Labels, dtype: int64
```

50 records are observed for each species.

b) Make a scatterplot of petal length vs sepal length. Color the dots according to species. Document your observations (2-3 sentences)

In [6]:
```
sns.scatterplot(data = iris_df,
                x = ' Petal Length',
                y = 'Sepal Length',
                hue = 'Labels')
```

Out[6]:
```
<AxesSubplot:xlabel=' Petal Length', ylabel='Sepal Length'>
```



Two distinct clusters can be observed in the scatterplot. The larger cluster appears to note a positive linear relationship between petal length and sepal length and the second smaller cluster may not observe the same degree of relation.

c) Fit a regression model predicting sepal length based on petal length, petal width and sepal width (you do not need to test any of the regression assumptions).

In [9]:
```
X = iris_df[[' Petal Length', 'Petal Width', 'Sepal Width']]
X = sm.add_constant(X)

y = iris_df['Sepal Length']

mod = sm.OLS(y, X)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Sepal Length   R-squared:                       0.859
Model:                            OLS   Adj. R-squared:                  0.856
Method:                 Least Squares   F-statistic:                     297.0
Date:                Sat, 12 Feb 2022   Prob (F-statistic):           6.28e-62
Time:                        22:01:22   Log-Likelihood:                -37.000
No. Observations:                 150   AIC:                             82.00
Df Residuals:                     146   BIC:                             94.04
Df Model:                           3
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             1.8451      0.250      7.368      0.000       1.350       2.340
 Petal Length     0.7111      0.057     12.560      0.000       0.599       0.823
Petal Width      -0.5626      0.127     -4.426      0.000      -0.814      -0.311
Sepal Width       0.6549      0.067      9.823      0.000       0.523       0.787
==============================================================================
Omnibus:                        0.265   Durbin-Watson:                   2.053
Prob(Omnibus):                  0.876   Jarque-Bera (JB):                0.432
Skew:                           0.003   Prob(JB):                        0.806
Kurtosis:                       2.737   Cond. No.                         54.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

d) Describe the results of your regression, focusing on the relationship between sepal length and petal length.

The regression summary indicates that each predictor in the analysis is statistically significant. If we are to focus on the relationship between sepal length and petal length, our regression predicts that for each unit increase in petal length is predicted to yield an increase in sepal length of .7111.

e) Extra Credit: Fit a regression model predicting sepal length based on petal length, petal width, sepal width and species (you do not need to test for any of the “classical” regression assumptions). This is the same as part c but also with species as a predictor. Describe the results.

In [13]:
```
X = iris_df[[' Petal Length', 'Petal Width', 'Sepal Width']]

species_dummies = pd.get_dummies(iris_df['Labels'], drop_first = True)

X = pd.concat([X, species_dummies], axis = 1)
X = sm.add_constant(X)

y = iris_df['Sepal Length']

mod = sm.OLS(y, X)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Sepal Length   R-squared:                       0.868
Model:                            OLS   Adj. R-squared:                  0.863
Method:                 Least Squares   F-statistic:                     188.8
Date:                Sat, 12 Feb 2022   Prob (F-statistic):           2.22e-61
Time:                        22:47:26   Log-Likelihood:                -32.367
No. Observations:                 150   AIC:                             76.73
Df Residuals:                     144   BIC:                             94.80
Df Model:                           5
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             2.1586      0.279      7.726      0.000       1.606       2.711
 Petal Length     0.8288      0.068     12.136      0.000       0.694       0.964
Petal Width      -0.3221      0.151     -2.129      0.035      -0.621      -0.023
Sepal Width       0.5011      0.086      5.816      0.000       0.331       0.671
1                -0.7141      0.240     -2.974      0.003      -1.189      -0.239
2                -1.0096      0.334     -3.022      0.003      -1.670      -0.349
==============================================================================
Omnibus:                        0.398   Durbin-Watson:                   1.962
Prob(Omnibus):                  0.820   Jarque-Bera (JB):                0.554
Skew:                          -0.064   Prob(JB):                        0.758
Kurtosis:                       2.732   Cond. No.                         94.2
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Adding species technically increases the performance of the model as denoted in the adjusted R-squared however the increase is so minimal that it may not generalize well.

2. Implementing an Edit-Distance Algorithm

Write a program to calculate a variant of the Hamming distance with two key modifications to the standard algorithm. In information theory, the Hamming distance is a measure of the distance between two text strings. This is calculated by adding one to the Hamming distance for each character that is different between the two strings. For example, “kitten" and “mitten" have a Hamming distance of 1. See https://en.wikipedia.org/wiki/Hamming_distance for more information. Modifications to the standard Hamming distance algorithm for the purposes of this exercise include:

1. Add .5 to the Hamming distance if a capital letter is switched for a lower case letter unless it is in the first position.
   Examples include:
   - "Kitten" and "kitten" have a distance of 0
   - "kitten" and "KiTten" have a Hamming distance of .5.
   - "Puppy" and "POppy" have a distance of 1.5 (1 for the different letter, additional .5 for the different capitalization).

1. Consider S and Z (and s and z) to be the same letter. For example, "analyze" has a distance of 0 from "analyse".

Test cases with expected outputs:

First Word	Second Word	Distance Score
make	Mage	1
MaiSY	MaiZy	.5
Eagle	Eager	2
Sentences work too	Sentences wAke too	3.5

In [16]:
```
def adj_hamming_distance(string1, string2):
    distance = 0
    ### Algorthim assumes strings are same length
    string_len = len(string1)
    for i in range(string_len):
        ### Testing for correct character
        if string1[i].lower() == 's' and string2[i].lower() == 'z':
            pass ### special case that does not increase Hamming score
        elif string1[i].lower() == 'z' and string2[i].lower() == 's':
            pass ### special case that does not increase Hamming score
        elif string1[i].lower() != string2[i].lower():
            distance += 1
        else:
            pass
        ### Testing for correct capitalization
        if i == 0:
            pass ### special case that does not increase Hamming score
        elif string1[i] == string1[i].lower() and string2[i] == string2[i].lower():
            pass ### cases are the same - lower
        elif string1[i] == string1[i].upper() and string2[i] == string2[i].upper():
            pass ### cases are the same - upper
        else:
            distance += .5
    return distance
```

Use the program you wrote to score the following strings:

a) "data Science" to "Data Sciency"

In [17]:
```
adj_hamming_distance("data Science", "Data Sciency")
```

Out[17]:
```
1
```

b) "organizing" to "orGanising"

In [18]:
```
adj_hamming_distance("organizing", "orGanising")
```

Out[18]:
```
0.5
```

c) "AGPRklafsdyweIllIIgEnXuTggzF" to "AgpRkliFZdiweIllIIgENXUTygSF")

In [19]:
```
adj_hamming_distance("AGPRklafsdyweIllIIgEnXuTggzF", "AgpRkliFZdiweIllIIgENXUTygSF")
```

Out[19]:
```
6.5
```

Then:

a) Describe a scenario (3-4 sentences) where implementing the standard Hamming distance algorithm would be applicable.

Given that Hamming distance is computed to determine the similiarity of two equal length strings, the standard algorthim is commonly used for error detection and correction of data tranmistted over computer networks. This solution only works as the code transmitted is binary and does not have potential for miscapialziaztions or characters beside '0' and '1'.

3. Data Cleaning

Perform some data cleaning using the provided file, “patent_drawing.csv”. “Patent_drawing.csv” contains a list of patents and a short description of each drawing included with a patent grant. For example, patent number 0233365 (https://patents.google.com/patent/US20030233365A1/en) has 16 images. For each image, there is a brief description of the drawings. The description is included in the “text” field in patent_drawing.csv.

In [56]:
```
patent_df = pd.read_csv('patent_drawing data.csv')
patent_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8156 entries, 0 to 8155
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   uuid        8156 non-null   object
 1   patent_id   8156 non-null   object
 2   text        8156 non-null   object
dtypes: object(3)
memory usage: 191.3+ KB
```

In [57]:
```
patent_df.head()
```

Out[57]:

	uuid	patent_id	text
0	urfl2ulyjgez01g5selfflnz7	4491930	A better understanding of the invention may be...
1	nqdxwthotlcted3d961ao373x	4490979	A better understanding of the invention will b...
2	9mwinm7as0p0j3245tdxhfuiz	4491969	A better understanding of the invention will b...
3	l1n6w0ofqic6yow2t7qwmvqry	4490948	A better understanding of the present inventio...
4	86bndneq4omf3mfxi60dzr5mx	4491426	A better understanding of the present inventio...

In [70]:
```
def clean_text(text):
    return re.sub("(@[A-Za-z0-9]+)|([^0-9A-Za-z \t])|(\w+:\/\/\S+)", " ", text).split()

def join_text(text_list):
    return ' '.join(text_list)
```

In [71]:
```
stop = stopwords.words('english')
```

In [72]:
```
patent_df['clean_text'] = patent_df['text'].str.lower()
patent_df['clean_text'] = patent_df['clean_text'].map(clean_text)
patent_df['clean_text'] = patent_df['clean_text'].apply(lambda x: [word for word in x if word not in (stop)])
patent_df['clean_text'] = patent_df['clean_text'].map(join_text)
```

In [73]:
```
patent_df.head()
```

Out[73]:

	uuid	patent_id	text	clean_text
0	urfl2ulyjgez01g5selfflnz7	4491930	A better understanding of the invention may be...	better understanding invention may obtained co...
1	nqdxwthotlcted3d961ao373x	4490979	A better understanding of the invention will b...	better understanding invention following detai...
2	9mwinm7as0p0j3245tdxhfuiz	4491969	A better understanding of the invention will b...	better understanding invention obtained follow...
3	l1n6w0ofqic6yow2t7qwmvqry	4490948	A better understanding of the present inventio...	better understanding present invention many ad...
4	86bndneq4omf3mfxi60dzr5mx	4491426	A better understanding of the present inventio...	better understanding present invention well ob...

a) How many of the field descriptions reference a perspective that is not standard (i.e. viewed from the top, bottom, front or rear)? Specifically, write code to count how many of the rows have the words "view" or "perspective" but do not include "bottom", "top", "front" or "rear" in the text field?

In [103...
```
patent_df['contains_search_term'] = patent_df['clean_text'].str.contains( "view|perspective")
patent_df['contains_exclusion_term'] = patent_df['clean_text'].str.contains("bottom|top|front|rear")
patent_df.head()
```

Out[103...

	uuid	patent_id	text	clean_text	contains_search_term	contains_exclusion_term
0	urfl2ulyjgez01g5selfflnz7	4491930	A better understanding of the invention may be...	better understanding invention may obtained co...	False	False
1	nqdxwthotlcted3d961ao373x	4490979	A better understanding of the invention will b...	better understanding invention following detai...	False	False
2	9mwinm7as0p0j3245tdxhfuiz	4491969	A better understanding of the invention will b...	better understanding invention obtained follow...	False	False
3	l1n6w0ofqic6yow2t7qwmvqry	4490948	A better understanding of the present inventio...	better understanding present invention many ad...	False	False
4	86bndneq4omf3mfxi60dzr5mx	4491426	A better understanding of the present inventio...	better understanding present invention well ob...	False	False

In [122...
```
patent_df[(patent_df['contains_search_term'] == True) & (patent_df['contains_exclusion_term'] == False)].count
```

Out[122...
```
uuid                       3665
patent_id                  3665
text                       3665
clean_text                 3665
contains_search_term       3665
contains_exclusion_term    3665
dtype: int64
```

There appears to be 3665 descriptions containing nonstandard views.

b) What is the average number of drawing descriptions per patent?

In [115...
```
patent_df.groupby(['patent_id']).count().mean()
```

Out[115...
```
uuid                       7.441606
text                       7.441606
clean_text                 7.441606
contains_search_term       7.441606
contains_exclusion_term    7.441606
dtype: float64
```

The average number of drawing descriptions per patent is 7.4416

In [ ]: