Assignment 1

FIT5145 - Introduction to Data Science

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The current notebook will cover the 1st task of assignment 1.

Task A: Investigating Population and Gender Equality in Education

Preparation

Import relevant python libraries for data wrangling and analysis

In [165]:

```
!pip install wget
!pip install motionchart
!pip install pyperclip
```

```
Requirement already satisfied: wget in /Users/maryammahmoodi/anacond
a3/lib/python3.7/site-packages (3.2)
Requirement already satisfied: motionchart in /Users/maryammahmoodi/
anaconda3/lib/python3.7/site-packages (0.3)
Requirement already satisfied: pyperclip in /Users/maryammahmoodi/an
aconda3/lib/python3.7/site-packages (1.7.0)
```

In [166]:

```
import pandas as pd
import datetime
from motionchart.motionchart import MotionChart
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from scipy.stats import linregress
from sklearn import preprocessing
from datetime import datetime, timedelta
import plotly
import plotly.plotly as py
import plotly.tools as tls
```

Importing files

Importing the CSV files into Jupyter notebook to prepare the data for further analysis

In [167]:

```
# The first step is to import the raw data

# 1. Income
in_df0 = pd.read_csv('Income.csv')

# 2. Population
pp_df0 = pd.read_csv('Population.csv')

# 3. InsuranceRate
ins_df0 = pd.read_csv('InsuranceRates.csv')

# 4. GenderEquality
ge_df0 = pd.read_csv('GenderEquality.csv')
```

In [168]:

```
# Converting the Income.csv file into a dataframe format for the analysis purpose
in_df = pd.DataFrame(in_df0)

# Highlevel view on Income Index
in_df.head()
```

Out[168]:

	Year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Austr
0	1800	603	667	715	1200	618	757	1510	514	
1	1801	603	667	716	1200	620	757	1510	514	
2	1802	603	667	717	1200	623	757	1510	514	
3	1803	603	667	718	1200	626	757	1510	514	
4	1804	603	667	719	1210	628	757	1510	514	

5 rows × 194 columns

In [169]:

```
# Converting the Population.csv file into a dataframe format for the analysis pur
pp_df = pd.DataFrame(pp_df0)

# Highlevel view on Population Index
pp_df.head()
```

Out[169]:

	Year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Au
0	1800	3280000	410000	2500000	2650	1570000	37000	534000	413000	3
1	1801	3280000	412000	2510000	2650	1570000	37000	534000	413000	3
2	1802	3280000	413000	2520000	2650	1570000	37000	534000	413000	3
3	1803	3280000	414000	2530000	2650	1570000	37000	534000	413000	3
4	1804	3280000	416000	2540000	2650	1570000	37000	534000	413000	3

5 rows × 196 columns

In [170]:

```
# Converting the Insurance.csv file into a dataframe format for the analysis purp
ins_df = pd.DataFrame(ins_df0)

# Highlevel view on Insurance Index
ins_df.head()
```

Out[170]:

	BusinessYear	StateCode	IssuerId	PlanId	Age	IndividualRate	IndividualTobac
0	2014	AK	21989	21989AK0010001	0-20	29.00	
1	2014	AK	21989	21989AK0020001	Family Option	36.95	
2	2014	AK	21989	21989AK0020001	Family Option	36.95	
3	2014	AK	21989	21989AK0010001	21	32.00	
4	2014	AK	21989	21989AK0010001	22	32.00	

In [171]:

```
# Converting the GenderEquality.csv file into a dataframe format for the analysis
ge_df1 = pd.DataFrame(ge_df0)

# Highlevel view on GenderEquality Index
ge_df1.head()
```

Out[171]:

	geo	1970	1971	1972	1973	1974	1975	1976	1977	1978	...	2006	2007	200
0	Afghanistan	15.4	15.8	15.4	15.6	15.9	16.1	16.4	16.6	16.2	...	21.5	21.9	22.
1	Albania	87.4	87.9	88.3	88.9	89.2	89.7	90.2	90.6	91.0	...	100.0	101.0	101.
2	Algeria	90.0	90.3	90.2	90.5	90.4	90.4	90.4	90.6	90.3	...	87.6	88.0	88.
3	Andorra	97.0	97.4	97.8	98.1	98.4	98.8	99.1	99.5	99.8	...	105.0	105.0	105.
4	Angola	51.3	51.4	51.9	52.3	52.8	53.2	53.4	53.8	54.3	...	68.5	68.9	69.

5 rows × 47 columns

Data wrangling

The extracted data need to be wrangled in order to be prepared for analysis.

- Make sure all data are structured and formatted aligned with the requirement of analysis.

Transpose

- GenderEquality dataframe is transposed thus countries will be placed each column.
- Transposing dataframes will replace the items on x axis with the items on y axis.

In [172]:

```
# Transposing the GenderEquality dataframe
ge_df1 = ge_df0.transpose()

# Highlevel view on GenderEquality Index
ge_df1.head()
```

Out[172]:

	0	1	2	3	4	5	6	7	8	
geo	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Australia	Aus
1970	15.4	87.4	90	97	51.3	103	96.7	91.7	95.2	
1971	15.8	87.9	90.3	97.4	51.4	103	97.2	92.1	95.5	8
1972	15.4	88.3	90.2	97.8	51.9	104	97.5	92.5	95.7	8
1973	15.6	88.9	90.5	98.1	52.3	104	97.8	92.9	96.1	8

5 rows × 187 columns

Index reset

In this stage, resetting the index which is a function of formatting to index the columns based on 'country names'.

In [173]:

```
# The index of GenderEquality dataframe is reset.
ge_df2 = ge_df1.reset_index()

# Highlevel view on GenderEquality Index
ge_df2.head()
```

Out[173]:

	index	0	1	2	3	4	5	6	7	8
0	geo	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Australia
1	1970	15.4	87.4	90	97	51.3	103	96.7	91.7	95.2
2	1971	15.8	87.9	90.3	97.4	51.4	103	97.2	92.1	95.5
3	1972	15.4	88.3	90.2	97.8	51.9	104	97.5	92.5	95.7
4	1973	15.6	88.9	90.5	98.1	52.3	104	97.8	92.9	96.1

5 rows × 188 columns

Rename using .iloc function and re-index

- The iloc indexer is used for location based on indexing by position.

In [174]:

```
# GenderEquality data need to be 'located' and 'renamed' to convey correct meanin
headers = ge_df2.iloc[0]

# Based on the selection, the column header is renamed
new_df = pd.DataFrame(ge_df2.values[1:], columns = headers)
ge_df = new_df.rename(columns ={'geo': 'Year'})

# Highlevel view on GenderEquality Index
ge_df.head()
```

Out[174]:

	Year	Afghanistan	Albania	Algeria	Andorra	Angola	Antigua and Barbuda	Argentina	Armenia	Austr
0	1970	15.4	87.4	90	97	51.3	103	96.7	91.7	(
1	1971	15.8	87.9	90.3	97.4	51.4	103	97.2	92.1	(
2	1972	15.4	88.3	90.2	97.8	51.9	104	97.5	92.5	(
3	1973	15.6	88.9	90.5	98.1	52.3	104	97.8	92.9	(
4	1974	15.9	89.2	90.4	98.4	52.8	104	98.3	93.5	(

5 rows × 188 columns

A1. Investigating the Gender Equality Data

- The plot below shows the gender ratio(women% men) in schools for Australia and China and United States overtime.

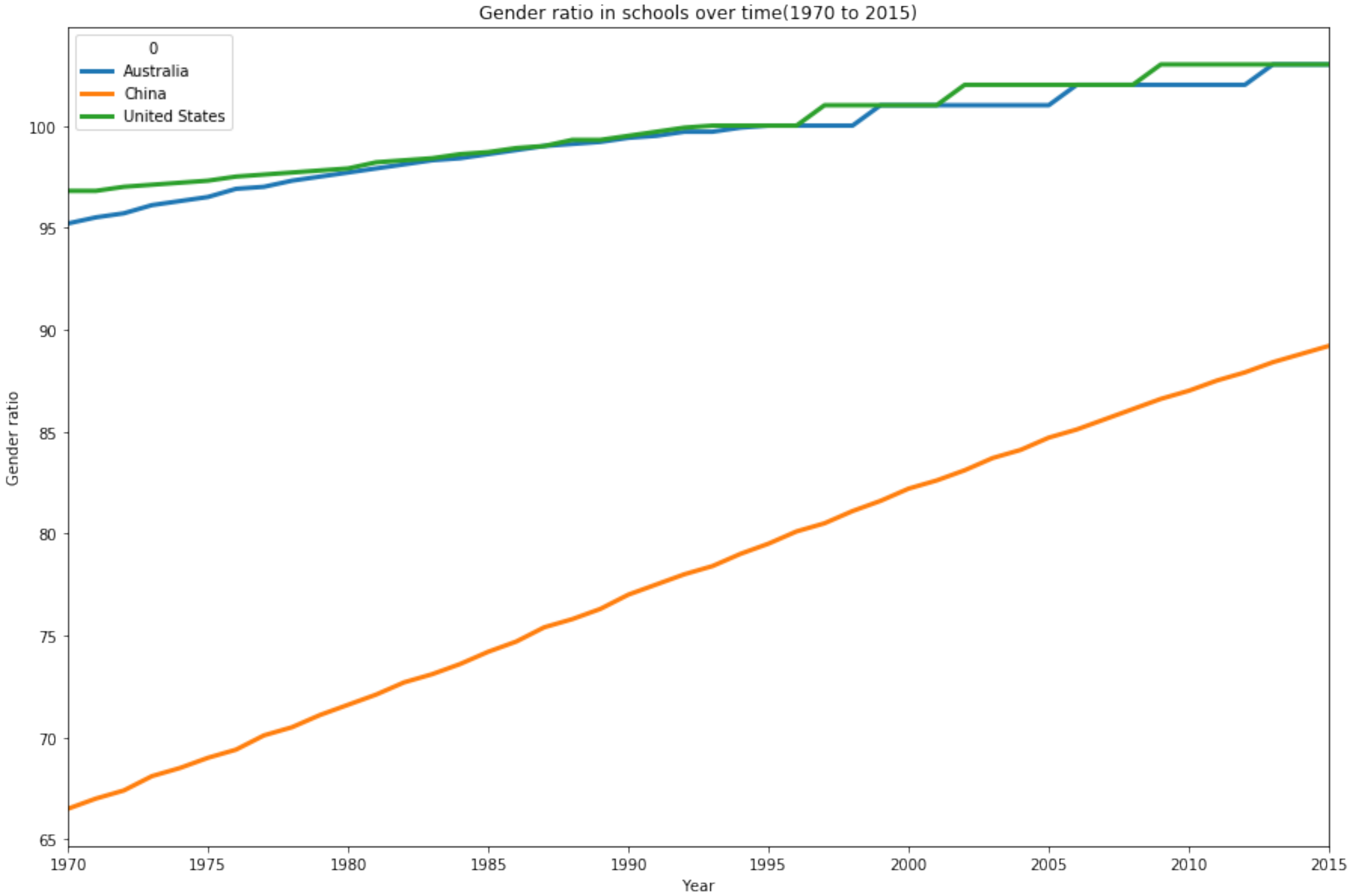
i. From the given data set, it is found that in the given time period the maximum and minimum values for the gender ratio is 103 and 95.2.

In [175]:

```
# Selected 3 countries to ceate the plot box
ge_only = ge_df[['Year','Australia','China', 'United States']]
```

In [176]:

```
# Creat the plot box
ge_only.plot(x= 'Year', lw= 3, title ='Gender ratio in schools over time(1970 to
plt.xlabel('Year')
plt.ylabel('Gender ratio')
plt.show()
```



In [177]:

```
# Maximum valus for gender ratio in Australia over time period
ge_AU_only = ge_df[['Year','Australia']]

print(ge_AU_only[ge_only.Australia == ge_AU_only.Australia.max()])
```

```
0   Year  Australia
43  2013        103
44  2014        103
45  2015        103
```

The result above state that the maximum ratio(women % men) in school for Australia is 103.

In [178]:

```
# Minimum valus for gender ratio in Australia over time period
print(ge_AU_only[ge_only.Australia == ge_AU_only.Australia.min()])
```

```
0  Year  Australia
0  1970       95.2
```

The result above state that the minimum ratio(women % men) in school for Australia is 95.2.

ii. From the analysis of the above plots it can be stated that, the USA and Australia had the similar trend in the growth of the gender ratio in the school compare to China according to the data available in the file. From the above plots, it is evident that there is sudden and increased growth in the geneder ratio from the year 2000 that continued until 2015.

In [179]:

```
 # Maximum valus for gender ratio in Australia, China and United State over time
ge_only = ge_df[['Year','Australia','China', 'United States']]

print(ge_only[ge_only.Australia == ge_only.Australia.max()])
print(ge_only[ge_only.Australia == ge_only.Australia.min()])
```

```
0   Year Australia China United States
43  2013       103  88.4           103
44  2014       103  88.8           103
45  2015       103  89.2           103
0  Year Australia China United States
0  1970      95.2  66.5          96.8
```

Task A2. Visualising the Relationship over Time

Prepration of Motion Chart

For the visulalisation skills, is required to make some adjustment to show visualise data as much as posible accurate and well designed.

In [180]:

```
# Categorising the data for a better view and better understanding on the data st
gender = ge_df.melt(id_vars=['Year'], var_name='Country', value_name= 'GenderRati
income = in_df.melt(id_vars=['Year'], var_name='Country', value_name= 'Income')
population = pp_df.melt(id_vars=['Year'], var_name='Country', value_name= 'popula
```

In [181]:

```
gender.dtypes
```

Out[181]:

```
Year           object
Country        object
GenderRatio    object
dtype: object
```

In [182]:

```
# Convert the year from 'object' to 'int' for letting us to merge with other tabl
gender [['Year']] = gender [['Year']].astype('int')
```

In [183]:

```
# merge two tables population and income by outjoin

merge1 = pd.merge(population, income, on=['Year', 'Country'], how='outer')
merge1.head()
```

Out[183]:

	Year	Country	population	Income
0	1800	Afghanistan	3280000	603.0
1	1801	Afghanistan	3280000	603.0
2	1802	Afghanistan	3280000	603.0
3	1803	Afghanistan	3280000	603.0
4	1804	Afghanistan	3280000	603.0

In [184]:

```
# Join the prevoius table by outjoin with gender table
merge = pd.merge(merge1, gender, on=['Year', 'Country'], how='outer')
merge.head()
```

Out[184]:

	Year	Country	population	Income	GenderRatio
0	1800	Afghanistan	3280000	603.0	NaN
1	1801	Afghanistan	3280000	603.0	NaN
2	1802	Afghanistan	3280000	603.0	NaN
3	1803	Afghanistan	3280000	603.0	NaN
4	1804	Afghanistan	3280000	603.0	NaN

In [185]:

```
# Drop all NaN values
consolidated_df = merge.dropna(0)
```

In [186]:

```
consolidated_df.head()
```

Out[186]:

	Year	Country	population	Income	GenderRatio
170	1970	Afghanistan	11100000	1180.0	15.4
171	1971	Afghanistan	11400000	1100.0	15.8
172	1972	Afghanistan	11700000	1050.0	15.4
173	1973	Afghanistan	12000000	1150.0	15.6
174	1974	Afghanistan	12300000	1180.0	15.9

In [187]:

```
%%html
<style>
.output_wrapper, .output {
    height:auto !important;
    max-height:1000px;  /* your desired max-height here */
}
.output_scroll {
    box-shadow:none !important;
    webkit-box-shadow:none !important;
}
</style>
```

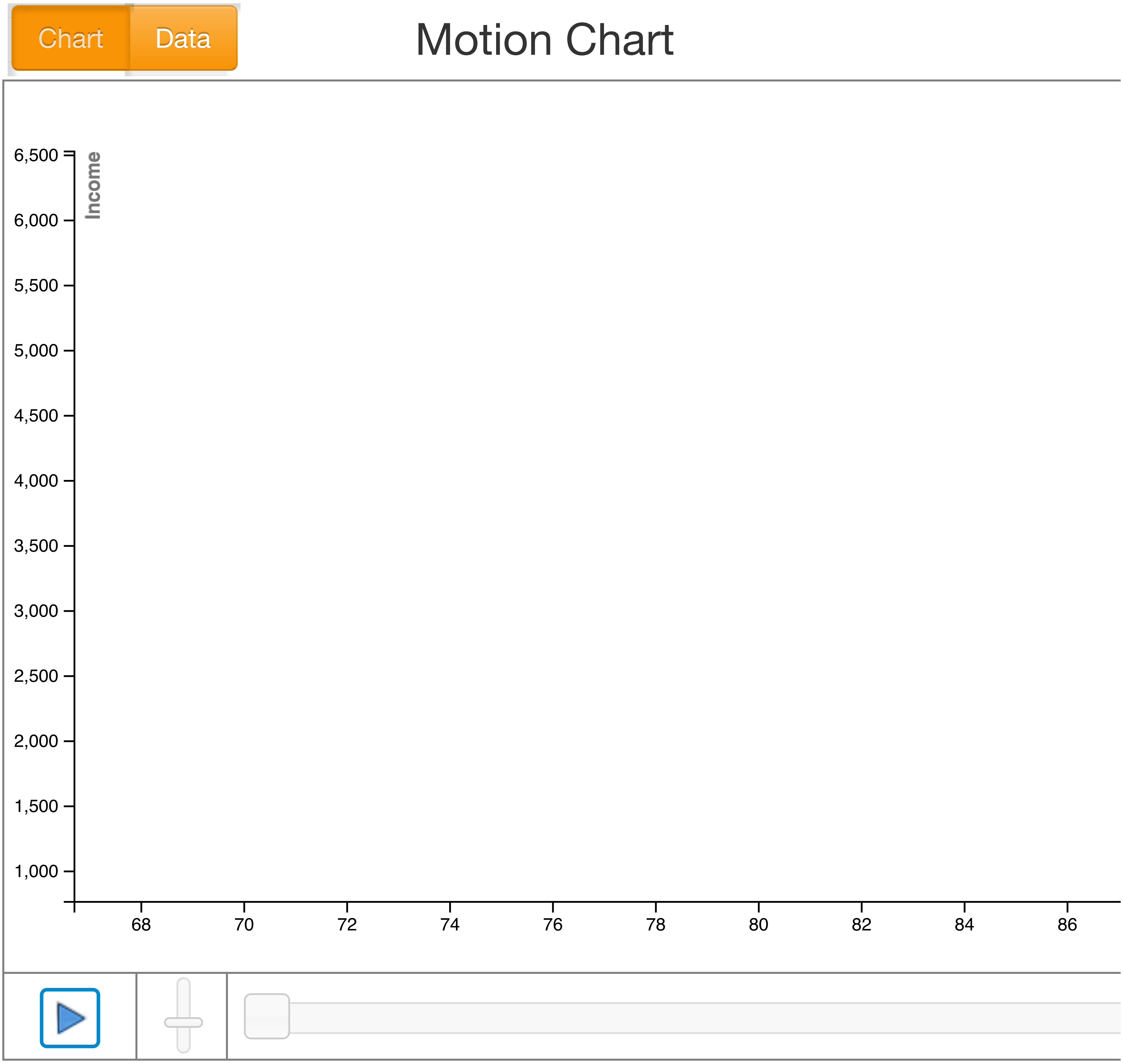
Creation of MotionChart

At this point, our dataframe is ready to place as the input in the motionchart. For the result, the code below will consume the data based on the data and provide the MotionChart.

i. The MotionChart below represent the correlation between Income and Gender ratio in different countries during 1970 to 2015. The Gender ratio is on x-axis and y-axis represent the Income. Year is selected as the index of the MotionChart also color of the circles differentiates the countries while circle size provide a population for each country.

In [188]:

```
# The code below defined by column "Year" of the final dataframe. GenderRatio and
mChart = MotionChart(df = consolidated_df, key ='Year', x ='GenderRatio', y ='Inc
                     size = 'population', category ='Country')
mChart.to_notebook()
```



By look at the Motion Chart coould say that:

In 1970 China has the most population and gender ratio is in the middle by growing population income and gender ratio show slow growth until 2015 but some countries like Qatar, Saudi Arabia, Qatar and United Arab Emirates had lots of up and down in Income during this period.

i. Yaman adn Afghanistan are the two countries generally have the lowest gender ratio in schools over this period.

ii. Select Cape Verde and Bolivia for this part.

In [189]:

```
# Select only capeVerde and bolivia countries from consolidated table

capeVerde = consolidated_df[consolidated_df.Country =='Cape Verde']
bolivia = consolidated_df[consolidated_df.Country =='Bolivia']

# Then concatenate the two selected countries by concat code then converted to pa
compareCountry = pd.concat([capeVerde, bolivia])
```

In [190]:

```
capeVerde.head()
```

Out[190]:

	Year	Country	population	Income	GenderRatio
6959	1970	Cape Verde	270000	959.0	66.7
6960	1971	Cape Verde	273000	872.0	67.2
6961	1972	Cape Verde	274000	820.0	67.9
6962	1973	Cape Verde	273000	803.0	68.3
6963	1974	Cape Verde	272000	772.0	68.8

In [191]:

```
bolivia.head()
```

Out[191]:

	Year	Country	population	Income	GenderRatio
4550	1970	Bolivia	4510000	3660.0	67.7
4551	1971	Bolivia	4600000	3700.0	68.2
4552	1972	Bolivia	4700000	3800.0	68.6
4553	1973	Bolivia	4800000	3960.0	69.3
4554	1974	Bolivia	4900000	4070.0	69.7

In [192]:

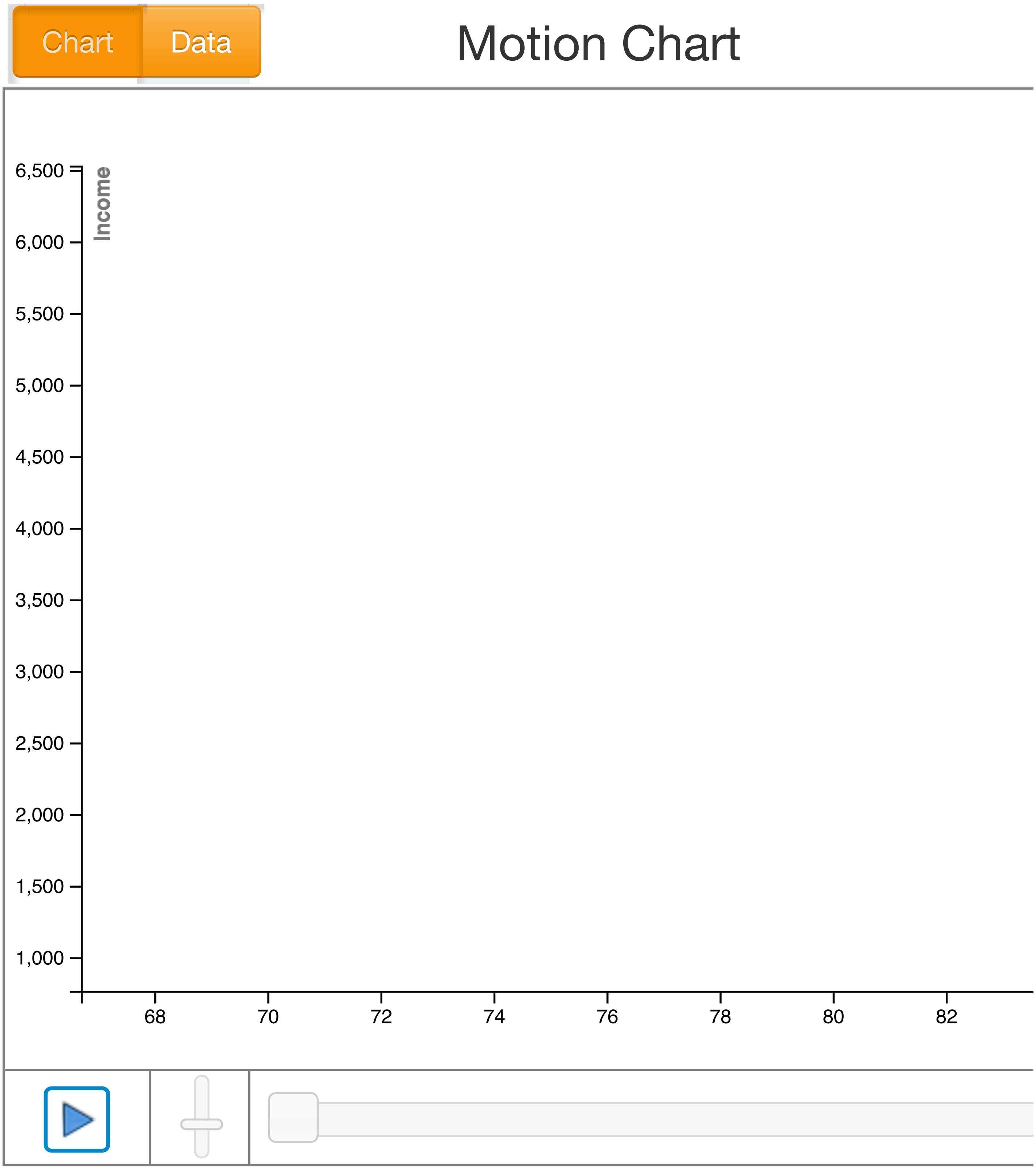
```
compareCountry
```

Out[192]:

	Year	Country	population	Income	GenderRatio
6959	1970	Cape Verde	270000	959.0	66.7
6960	1971	Cape Verde	273000	872.0	67.2
6961	1972	Cape Verde	274000	820.0	67.9
6962	1973	Cape Verde	273000	803.0	68.3
6963	1974	Cape Verde	272000	772.0	68.8
6964	1975	Cape Verde	272000	787.0	69.2
6965	1976	Cape Verde	274000	775.0	69.5
6966	1977	Cape Verde	276000	766.0	70.2
6967	1978	Cape Verde	279000	832.0	70.7
6968	1979	Cape Verde	282000	906.0	71.3
6969	1980	Cape Verde	287000	1220.0	71.7
6970	1981	Cape Verde	292000	1300.0	72.1
6971	1982	Cape Verde	297000	1310.0	72.7
6972	1983	Cape Verde	303000	1400.0	73
6973	1984	Cape Verde	309000	1420.0	73.4
6974	1985	Cape Verde	315000	1510.0	74
6975	1986	Cape Verde	320000	1510.0	74.6
6976	1987	Cape Verde	325000	1580.0	74.9
6977	1988	Cape Verde	330000	1590.0	75.5
6978	1989	Cape Verde	335000	1640.0	76
6979	1990	Cape Verde	342000	1660.0	76.6
6980	1991	Cape Verde	350000	1640.0	77
6981	1992	Cape Verde	359000	1780.0	77.6
6982	1993	Cape Verde	369000	1880.0	78.1
6983	1994	Cape Verde	379000	2180.0	78.6
6984	1995	Cape Verde	389000	2420.0	79
6985	1996	Cape Verde	399000	2630.0	79.5
6986	1997	Cape Verde	408000	2860.0	80.1
6987	1998	Cape Verde	417000	3150.0	80.7
6988	1999	Cape Verde	426000	3430.0	81.1
...	...	...	...	...	...
4566	1986	Bolivia	6340000	3500.0	76.5
4567	1987	Bolivia	6460000	3520.0	77.1
4568	1988	Bolivia	6590000	3580.0	77.6

In [193]:

```
# Creat MotionChart
mChart = MotionChart(df = compareCountry, key ='Year', x ='GenderRatio', y ='Inco
                     size = 'population', category ='Country')
mChart.to_notebook()
```



ii. Bolivia has more population compare to CapeVerde and from 1970-1979 CapeVerde and Bolivia had a very stable gender ratio and income rate but from 1980 CapeVerde start to increase the income and Bolivia had decrease in their income untill 2005 which these two countris had similar income , from 2007 CapeVerde income passed the Bolivia untill 2012. In 2012 CapeVerde had a income score of 5990 and GenderRatio 86.9 however in Bolivia the income score was 5790 and GenderRatio 90.3 but in 2013 Bolivia start to pass the CapeVerde.

iii. It is to be identified that gender ratio dose not have always positive relationship to the income as we could see that CapeVerde between 1970 to 1979 had a low income and low ratio but suddenly in 1980 start to improve their income and gender ratio until 2102 which CapeVerde passed the Bolivia by income score of 5990 about 200 more than Bolivia.

iv. From the analysis of the other attributes in the dataset we found that from the year 1995, most of the countries had increased gender ratio. Out of the different countries we found that the United States has the highest increase in the growth of the Gender ratio along with the income.

Task B: Exploratory Analysis on Big Data

Taske B1:

In [194]:

```
# Only show the unique year in column BusinessYear.

uniqueYears = ins_df['BusinessYear'].unique()
print('i. The data covers ' +  str(len(uniqueYears)) +
      ' years and they are ' + str(uniqueYears[0])+
      ' , '+ str(uniqueYears[1])+
      ' and ' + str(uniqueYears[2])+ '.')
```

```
i. The data covers 3 years and they are 2014 , 2015 and 2016.
```

In [195]:

```
ins_df.head()
```

Out[195]:

	BusinessYear	StateCode	IssuerId	PlanId	Age	IndividualRate	IndividualToba
0	2014	AK	21989	21989AK0010001	0-20	29.00	
1	2014	AK	21989	21989AK0020001	Family Option	36.95	
2	2014	AK	21989	21989AK0020001	Family Option	36.95	
3	2014	AK	21989	21989AK0010001	21	32.00	
4	2014	AK	21989	21989AK0010001	22	32.00	

In [196]:

```
# Remove all famliy option from Age column.

insClean_df = ins_df[ins_df.Age !='Family Option']
```

In [197]:

```
insClean_df.head()
```

Out[197]:

	BusinessYear	StateCode	IssuerId	PlanId	Age	IndividualRate	IndividualTobacc
0	2014	AK	21989	21989AK0010001	0-20	29.0	
3	2014	AK	21989	21989AK0010001	21	32.0	
4	2014	AK	21989	21989AK0010001	22	32.0	
7	2014	AK	21989	21989AK0010001	23	32.0	
8	2014	AK	21989	21989AK0010001	24	32.0	

ii. the code below possible unique values for Age:

In [198]:

```
# Possible unique values for Age
ageValues = insClean_df['Age']. unique()
ageValues
```

Out[198]:

```
array(['0-20', '21', '22', '23', '24', '25', '26', '27', '28', '29',
'30',
       '31', '32', '33', '34', '35', '36', '37', '38', '39', '40', '
41',
       '42', '43', '44', '45', '46', '47', '48', '49', '50', '51', '
52',
       '53', '54', '55', '56', '57', '58', '59', '60', '61', '62', '
63',
       '64', '65 and over'], dtype=object)
```

In [199]:

```
print( 'The data has '+ str(len(ageValues)) + ' age groups and they are:\n')

for i in range(0, len(ageValues)):
    print (ageValues[i])
```

```
The data has 46 age groups and they are:

0-20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65 and over
```

In [200]:

```
# use describe function to find the average, maximum and minimum values for the m
insClean_df['IndividualRate'].describe()
```

Out[200]:

```
count    1.265350e+07
mean     4.111194e+03
std      6.132124e+04
min      0.000000e+00
25%      2.945000e+01
50%      2.926600e+02
75%      4.799400e+02
max      9.999990e+05
Name: IndividualRate, dtype: float64
```

In [201]:

```
print('The average monthly insurance premium cost for an individual is ' + str(ro
print('The maximum monthly insurance premium cost for an individual is ' + str(ro
print('The minimum monthly insurance premium cost for an individual is ' + str(ro
```

```
The average monthly insurance premium cost for an individual is 4111
.19 dollars.
The maximum monthly insurance premium cost for an individual is 9999
99.0 dollars.
The minimum monthly insurance premium cost for an individual is 0.0
dollars.
```

ii. The average, maximum and minimum value for the premium cost is 4111.19, 999999 and 0. This values are not reasonable as this result may lead to the conclusion that some people who responded for this dataset may not have any insurance as their payment for the same is 0. Again the statistics shows that mean value for the insurance cost is half of the maximum cost paid by someone which indicates that the uneven distribution of wealth.

Task B2

In [202]:

```
insClean_df.head()
```

Out[202]:

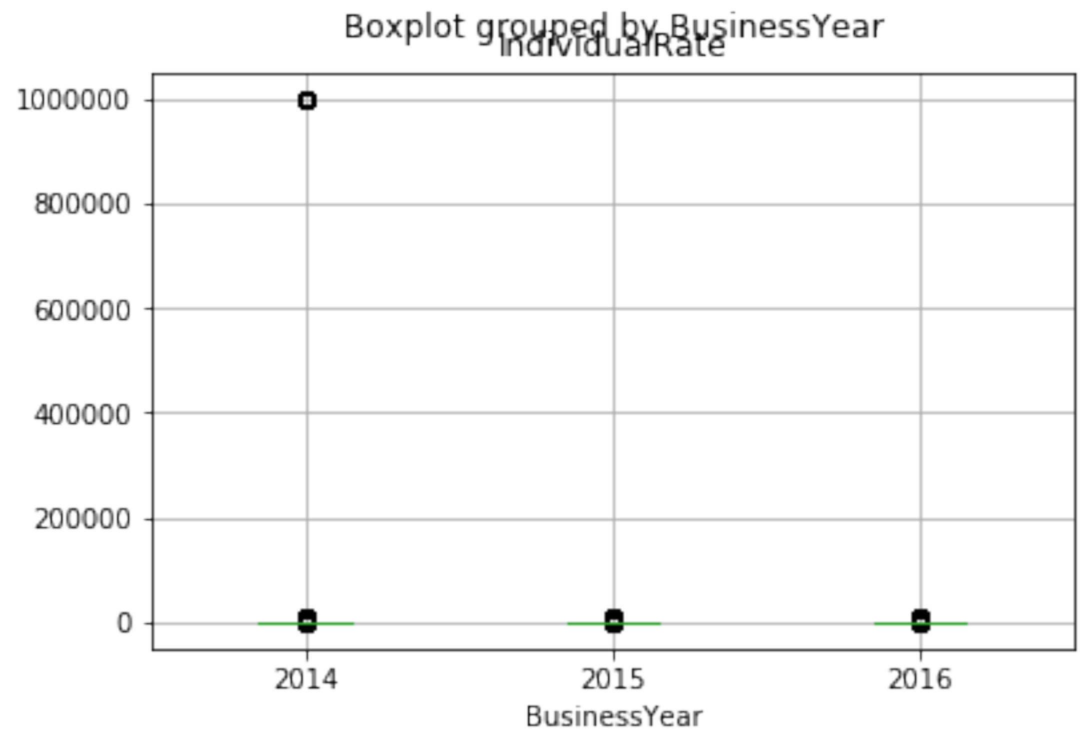
	BusinessYear	StateCode	IssuerId	PlanId	Age	IndividualRate	IndividualTobacc
0	2014	AK	21989	21989AK0010001	0-20	29.0	
3	2014	AK	21989	21989AK0010001	21	32.0	
4	2014	AK	21989	21989AK0010001	22	32.0	
7	2014	AK	21989	21989AK0010001	23	32.0	
8	2014	AK	21989	21989AK0010001	24	32.0	

In [203]:

```
# Boxplot of insurance costs versus year and age

insClean_df.boxplot(column = 'IndividualRate', by = 'BusinessYear')
```

Out[203]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a20958400>
```

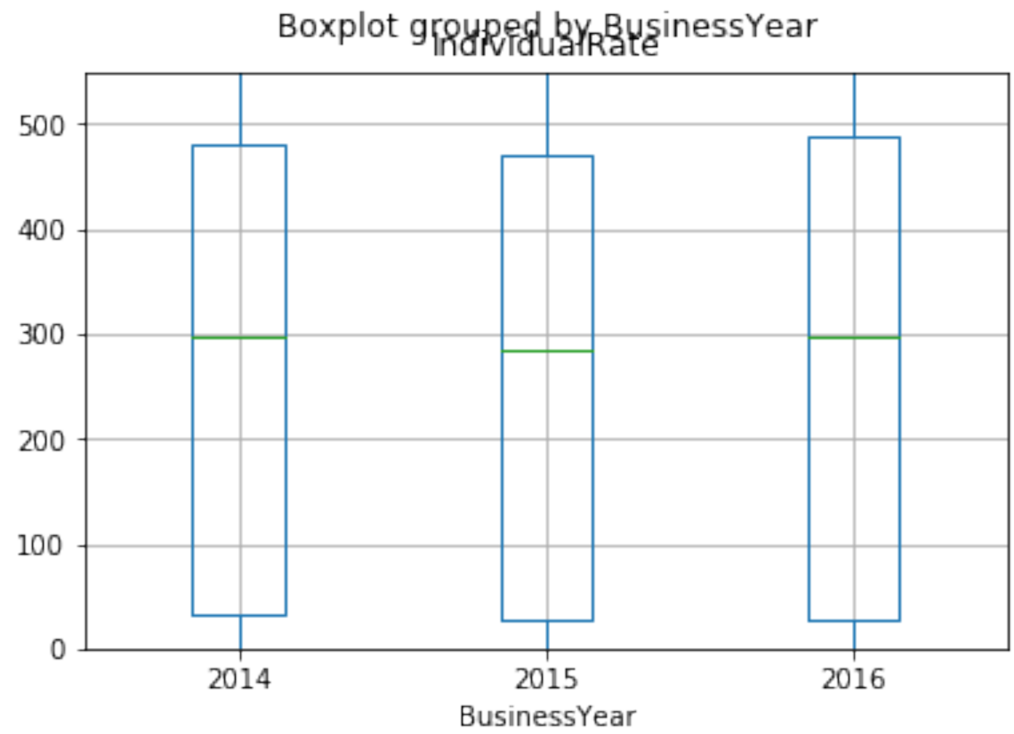


In [204]:

```
insClean_df.boxplot(column = 'IndividualRate', by = 'BusinessYear')

# limit the y axis to better see the datas.
plt.ylim(0, 550)
```

Out[204]:

```
(0, 550)
```



Over 2014 to 2016 median line shows in 2014 is about 300 dollars and in little bit dropped but in 2016 the returned to 300 dollars, then could say that not much changed during 2014 to 2016 and almost been the same.

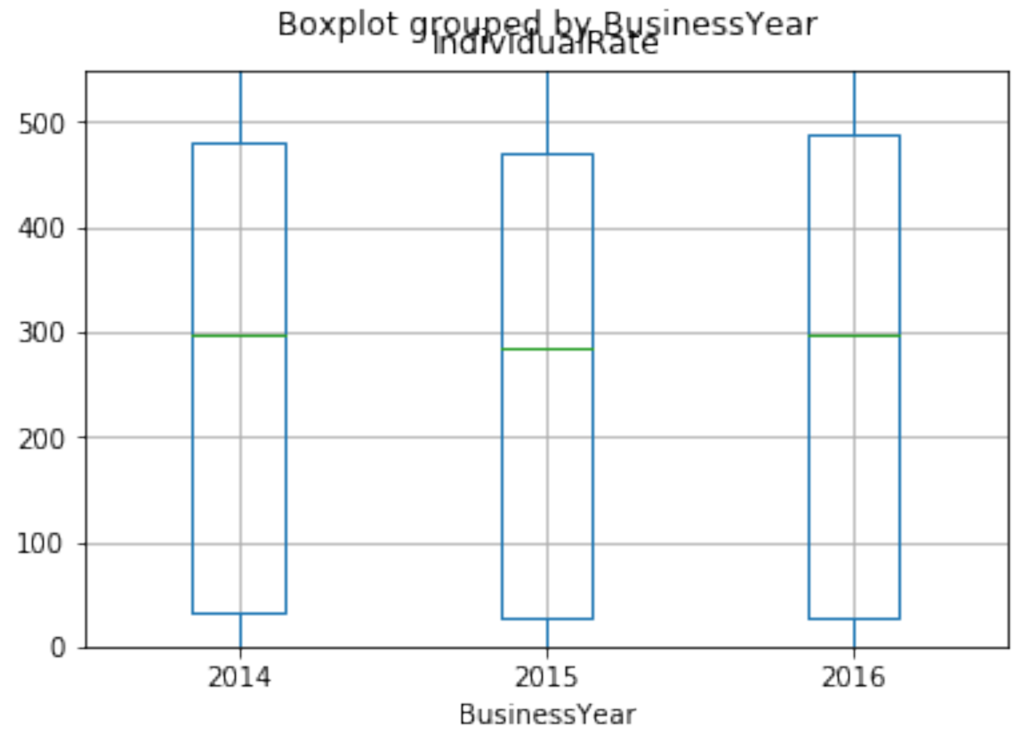
In [205]:

```
# deleting outlieres for 2014
filt = -((insClean_df['BusinessYear'] == '2014') & (insClean_df['IndividualRate']
insClean_df = insClean_df[filt]

# deleting outlieres for 2015
filt = -((insClean_df['BusinessYear'] == '2015') & (insClean_df['IndividualRate']
insClean_df = insClean_df[filt]

# deleting outlieres for 2016
filt = -((insClean_df['BusinessYear'] == '2016') & (insClean_df['IndividualRate']
insClean_df = insClean_df[filt]

insClean_df.boxplot(column = 'IndividualRate', by = 'BusinessYear')
plt.ylim(0, 550)
```

```
/Users/maryammahmoodi/anaconda3/lib/python3.7/site-packages/pandas/c
ore/ops.py:1649: FutureWarning:

elementwise comparison failed; returning scalar instead, but in the
future will perform elementwise comparison
```

Out[205]:

```
(0, 550)
```

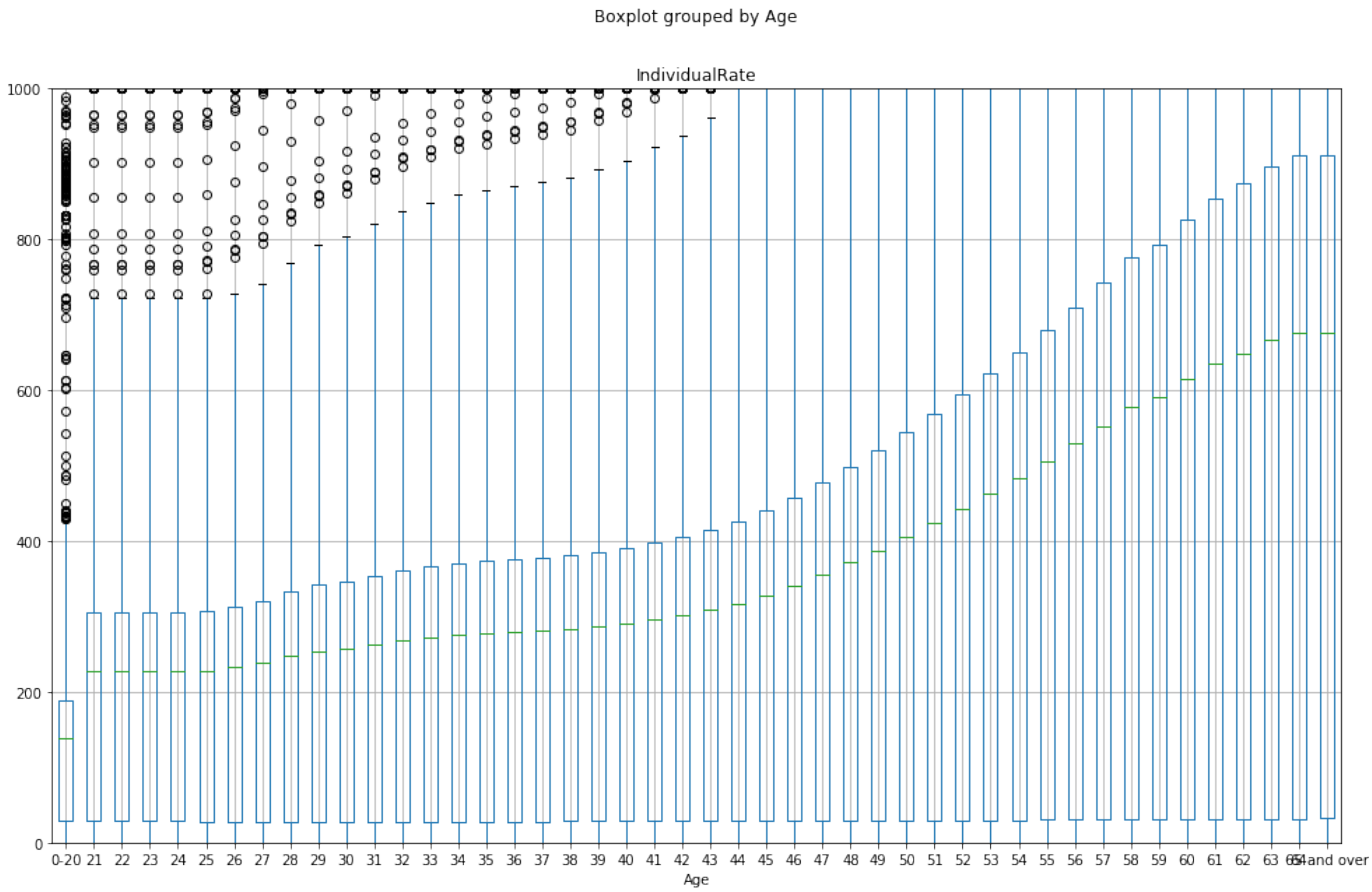


In [206]:

```
# Create the boxplot
insClean_df.boxplot(column = 'IndividualRate', by = 'Age', figsize = (16, 10 ))
plt.ylim(0, 1000)
```

Out[206]:

```
(0, 1000)
```



The insurance cost is increases as the age increases. by look at the boxplot could say that the elder people paing about $200 more than younger people.

Task C

In [207]:

```
import pandas as pd
import random
from sklearn.model_selection import train_test_split # split the dataset into tra
from sklearn.model_selection import GridSearchCV #cross validation to get more ac
from dateutil.parser import parse
from sklearn.metrics import accuracy_score as acc # to see how this model have pe
import matplotlib.pyplot as plt
import numpy as np
```

Importing files

Data for this task is extracted based on the CSV file from here (https://www.kaggle.com/jsphyg/weather-dataset-rattle-package#weatherAUS.csv) into Jupyter notebook to prepare the data for further analysis.

The row data imported into this notebook in belongs only to Australia.

In [208]:

```
# The first step is to import the raw data file from ......
weather_data = pd.read_csv('weatherAUS.csv')
# shape shows the number of rows and columns for this data
weather_data.shape
```

Out[208]:

```
(142193, 24)
```

In [209]:

```
# Highlevel view on weather_data Index
weather_data.head()
```

Out[209]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wind(
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	

5 rows × 24 columns

In [210]:

```
# down size the data
weather_data = weather_data.sample(n=10000)
weather_data.shape
```

Out[210]:

```
(10000, 24)
```

In [211]:

```
# This is a big data need to choose only random samples
weather_data = weather_data.sample(n=10000, random_state = 500)
weather_data.shape
```

Out[211]:

```
(10000, 24)
```

Data Wrangling

In [212]:

```
# Shows information about this data like unique rows and type of the data include
weather_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 4936 to 47950
Data columns (total 24 columns):
Date                10000 non-null object
Location            10000 non-null object
MinTemp             9953 non-null float64
MaxTemp             9980 non-null float64
Rainfall            9902 non-null float64
Evaporation         5716 non-null float64
Sunshine            5198 non-null float64
WindGustDir         9367 non-null object
WindGustSpeed       9370 non-null float64
WindDir9am          9277 non-null object
WindDir3pm          9727 non-null object
WindSpeed9am        9895 non-null float64
WindSpeed3pm        9806 non-null float64
Humidity9am         9866 non-null float64
Humidity3pm         9749 non-null float64
Pressure9am         9017 non-null float64
Pressure3pm         9022 non-null float64
Cloud9am            6215 non-null float64
Cloud3pm            6021 non-null float64
Temp9am             9922 non-null float64
Temp3pm             9801 non-null float64
RainToday           9902 non-null object
RISK_MM             10000 non-null float64
RainTomorrow        10000 non-null object
dtypes: float64(17), object(7)
memory usage: 1.9+ MB
```

In [213]:

```
# Describtion about the data
weather_data.describe()
```

Out[213]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	Wi
count	9953.000000	9980.000000	9902.000000	5716.000000	5198.000000	9370.000000	
mean	12.181242	23.281924	2.316754	5.539416	7.577857	40.178122	
std	6.418530	7.166898	8.017115	4.481752	3.831092	13.660998	
min	-7.200000	-3.100000	0.000000	0.000000	0.000000	9.000000	
25%	7.600000	17.900000	0.000000	2.600000	4.600000	31.000000	
50%	12.000000	22.600000	0.000000	4.600000	8.400000	39.000000	
75%	16.800000	28.300000	0.800000	7.400000	10.700000	48.000000	
max	29.700000	46.500000	168.400000	77.300000	14.000000	122.000000	

In [214]:

```
weather_data.head()
```

Out[214]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGus
4936	2014-08-31	BadgerysCreek	9.7	21.9	0.0	NaN	NaN	
83074	2012-05-24	Brisbane	14.1	23.8	0.0	3.0	3.5	N
2342	2015-08-22	Albury	7.9	20.7	1.4	NaN	NaN	
133078	2009-06-07	AliceSprings	4.6	17.5	0.0	4.0	10.3	S
133510	2010-08-13	AliceSprings	1.4	23.9	0.0	4.0	11.1	N

5 rows × 24 columns

In [215]:

```
# drop all NaN rows and save on over the weather_data file
weather_data.dropna(axis = 0, inplace = True)
weather_data.shape
```

Out[215]:

```
(3976, 24)
```

In [216]:

```
# check to see don't have any Nan in rows
weather_data.head()
```

Out[216]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDi
133078	2009-06-07	AliceSprings	4.6	17.5	0.0	4.0	10.3	SSV
133510	2010-08-13	AliceSprings	1.4	23.9	0.0	4.0	11.1	NNV
116593	2014-06-08	PerthAirport	14.4	20.0	0.0	3.0	0.0	NNI
39721	2011-10-02	Williamtown	10.4	15.9	22.0	18.0	0.0	SSI
134025	2012-02-09	AliceSprings	13.2	34.6	0.0	11.4	12.9	SSV

5 rows × 24 columns

In [217]:

```
# Deeply look at the date
for col in weather_data.columns:
    print(col, weather_data[col].nunique(), weather_data[col].dtype, sep = ' :: '
```

```
Date :: 2247 :: object
Location :: 26 :: object
MinTemp :: 305 :: float64
MaxTemp :: 332 :: float64
Rainfall :: 180 :: float64
Evaporation :: 128 :: float64
Sunshine :: 141 :: float64
WindGustDir :: 16 :: object
WindGustSpeed :: 51 :: float64
WindDir9am :: 16 :: object
WindDir3pm :: 16 :: object
WindSpeed9am :: 31 :: float64
WindSpeed3pm :: 30 :: float64
Humidity9am :: 97 :: float64
Humidity3pm :: 100 :: float64
Pressure9am :: 378 :: float64
Pressure3pm :: 369 :: float64
Cloud9am :: 9 :: float64
Cloud3pm :: 9 :: float64
Temp9am :: 316 :: float64
Temp3pm :: 334 :: float64
RainToday :: 2 :: object
RISK_MM :: 189 :: float64
RainTomorrow :: 2 :: object
```

In [218]:

```
print(weather_data.columns)
```

```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evapor
ation',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'Wi
ndDir3pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9a
m',
       'Temp3pm', 'RainToday', 'RISK_MM', 'RainTomorrow'],
      dtype='object')
```

At this point need to drop some columns which I am not interested to have them. Such as Location, Date, ... because these are categorical objects and **logistic regression** doesn't deal with categorical variable only takes numerical variable.

Drop unwanted features

In [219]:

```
# drop categorical columns
weather_data.drop(['Location', 'Date', 'RISK_MM', 'RainToday', 'WindGustDir', 'Wi
weather_data.head()
```

Out[219]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9an
133078	4.6	17.5	0.0	4.0	10.3	33.0	9.(
133510	1.4	23.9	0.0	4.0	11.1	44.0	17.(
116593	14.4	20.0	0.0	3.0	0.0	37.0	17.(
39721	10.4	15.9	22.0	18.0	0.0	61.0	31.(
134025	13.2	34.6	0.0	11.4	12.9	52.0	17.(

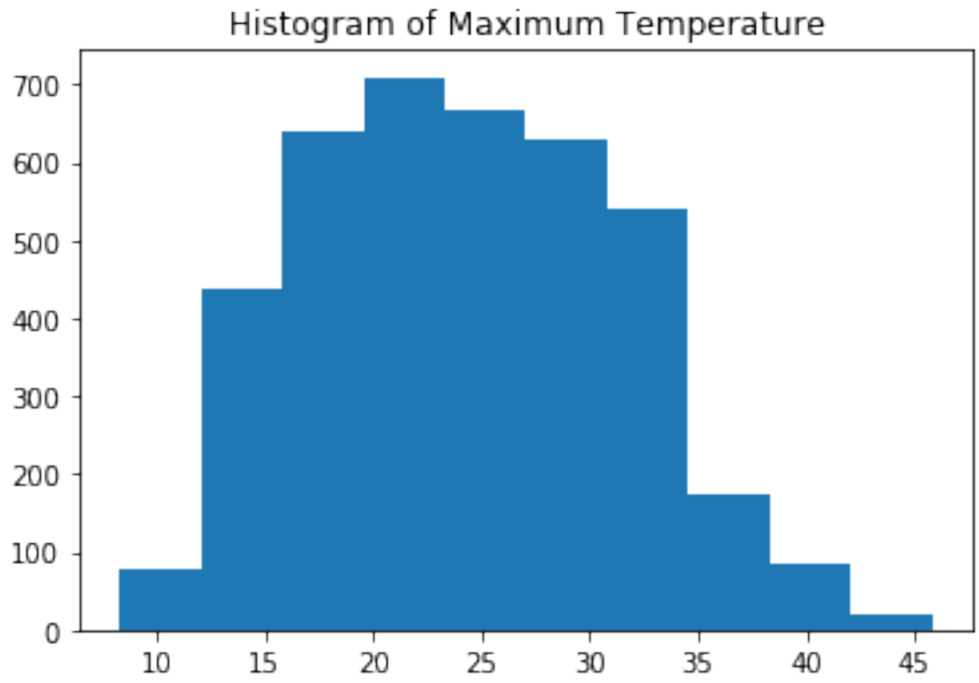
Creat feature matrix and target vector

In [220]:

```
# split the file into two files as:

# 1- creat predictor file
Maxtemp = weather_data['MaxTemp']
# 2- creat target file
Rainfall = weather_data['RainTomorrow']
```

In [221]:

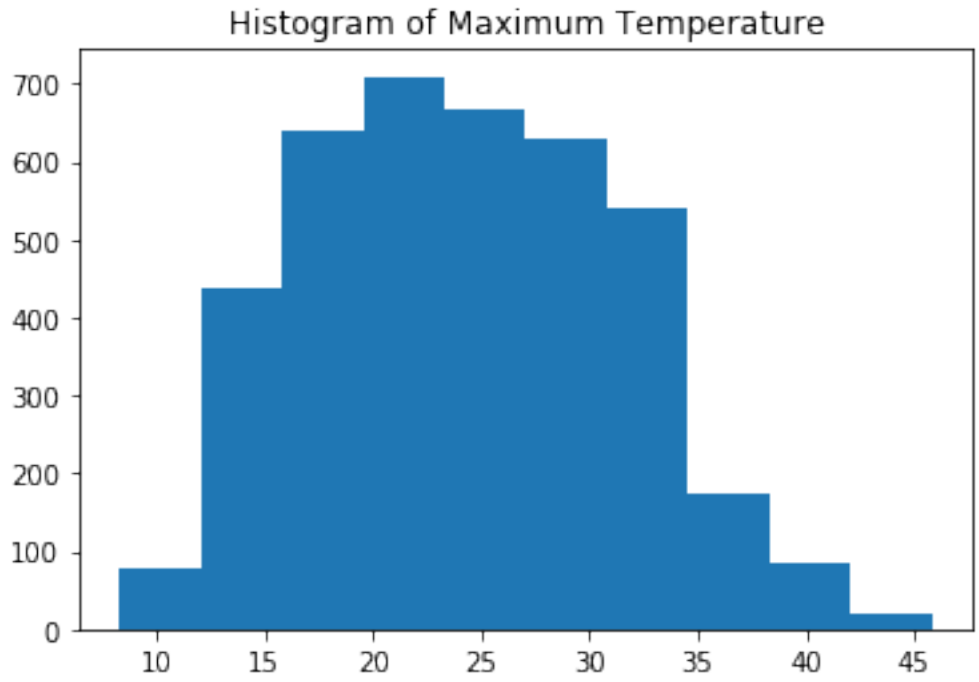
```
# Create histogram to show Maximum Temperature
plt.hist(Maxtemp)
plt.title("Histogram of Maximum Temperature")
plt.show()
```



Histogram above shows the maximum temperature which we can have ranintomorrow is around 20C.

In [222]:

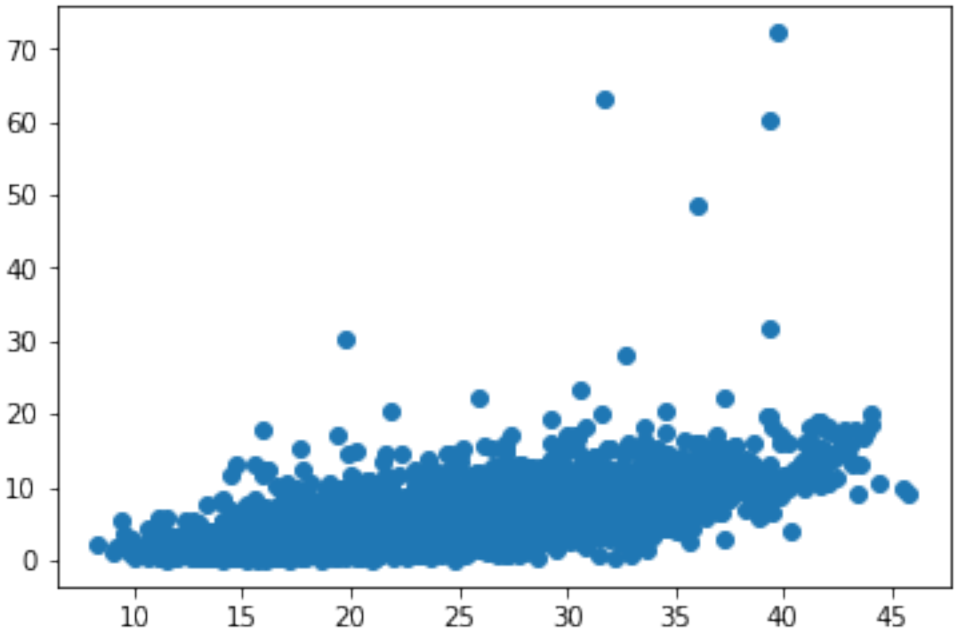
```
Mintemp = weather_data['MaxTemp']
Rainfall = weather_data['Evaporation']

# Create histogram to show Maximum Temperature
plt.hist(Maxtemp)
plt.title("Histogram of Maximum Temperature")
plt.show()
```



Histogram above shows the maximum temperature which we can have evaporation is more than 20C.

In [223]:

```
plt.scatter(Maxtemp, Rainfall)
plt.show()
```



The scatter plot above shows that the corelation between the maximum temperature and rain fall, the possibility to get rain tomorrow is high when the temperature is more than 32C. It is linear positive ralationship.

In [224]:

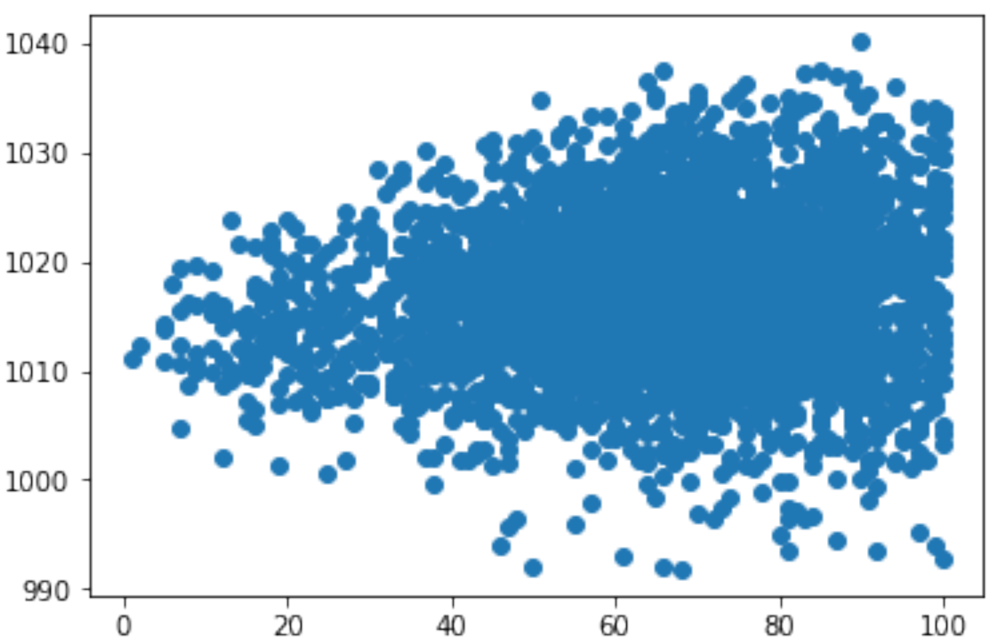
```
Humidity9am = weather_data['Humidity9am']
Pressure9am = weather_data["Pressure9am"]
```

In [225]:

```
# Create scatter plot to show Humidity
plt.scatter(Humidity9am, Pressure9am)
```

Out[225]:

```
<matplotlib.collections.PathCollection at 0x1a31503748>
```



The scatter plot above shows that the corelation between the Humidity9am and ressure9am in Australia. This plot shows in low humidity still have atmospheric pressure but by increase the humidity between 40 to 100 the presure will increase very slowly too.

Prediction

In [226]:

```
# create predictor file ( Numerical)
X = weather_data.drop('RainTomorrow', axis = 1)
# create target file ( Categorical)
y = weather_data['RainTomorrow']
```

In [227]:

```
# Split predict and target with same constant
x_train, x_test, y_train, y_test = train_test_split(X, y, random_state = 500)
```

In [228]:

```
# predict train
x_train.shape
```

Out[228]:

```
(2982, 16)
```

In [229]:

```
# target train
y_train.shape
```

Out[229]:

```
(2982,)
```

In [230]:

```
# predict test
x_test.shape
```

Out[230]:

```
(994, 16)
```

In [231]:

```
# target test
y_test.shape
```

Out[231]:

```
(994,)
```

Model- Logistic Regression

For prediction I used Logistic Regression from the library which called **sklearn.linear_model**

In [232]:

```
from sklearn.linear_model import LogisticRegression
```

In [233]:

```
# lr is a short name for LogisticRegression
model_lr = LogisticRegression()
```

For optimal accuracy need to use parameter grid. Inside logistic regression there are lots of parameters has been buit in which we use two of them as a "penalty" and "c" that can optimise the values and bring the accuracy high.

In [234]:

```
# optimisation of the model by taking two parameters of the model
param_grid = {'penalty':['l1', 'l2'],
              'C':[.1, .01, .001, .0001]}
```

In [235]:

```
# cross validation used to take the accuracy up and give us more confidence for g
# cv = 5 means cross validation has been repeated 5 times to get more accurate re
# verbos performing is lock somewhere during performing, we need to see the best
model_lr_gs = GridSearchCV(model_lr, param_grid=param_grid, n_jobs=-1, cv=5, verb
```

In [236]:

```
# Fitting is for folds 5 times for each of 8 candidates, totalling 40 fits to get
model_lr_gs.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent w
orkers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:    4.8s finish
ed
/Users/maryammahmoodi/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/logistic.py:433: FutureWarning:

Default solver will be changed to 'lbfgs' in 0.22. Specify a solver
to silence this warning.
```

Out[236]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=F
alse, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn
',
          tol=0.0001, verbose=0, warm_start=False),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid={'penalty': ['l1', 'l2'], 'C': [0.1, 0.01, 0.001,
0.0001]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn
',
       scoring=None, verbose=3)
```

In [242]:

```
# shows the best parameters which I can have
model_lr_gs.best_params_
```

Out[242]:

```
{'C': 0.01, 'penalty': 'l2'}
```

In [243]:

```
# shows the accuracy
model_lr_gs.best_score_
```

Out[243]:

```
0.8514419852448022
```

In [244]:

```
# predict function for validation part (x_test =997 record) which could not seen
lr_prediction = model_lr_gs.predict(x_test)
# rain tomorrow prediction file
lr_prediction
```

Out[244]:

```
array(['Yes', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
'No',
       'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No', 'No'
,
       'No', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No', 'No', 'N
o',
       'No', 'Yes', 'No', 'Yes', 'No', 'Yes', 'No', 'No', 'No', 'No'
,
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
'Yes',
       'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No',
'No',
       'Yes', 'Yes', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No'
,
       'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'No', 'No', 'No',
'No',
       'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No',
'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'Yes', 'No',
'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', '
No',
       'Yes', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No',
'No',
       'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes',
       'Yes', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No',
'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', '
No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes', 'No',
'No',
       'Yes', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'Yes', 'No', 'Ye
s',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'Yes', 'No', 'No',
'No',
       'Yes', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No', 'Yes'
,
       'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No',
'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', '
No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
'No',
       'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'No', 'No', 'No',
'No',
       'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', 'No', '
No',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'No', 'Yes', 'No', 'No',
'No',
       'No', 'No', 'No', 'No', 'Yes', 'No', 'No', 'No', 'Yes', 'No',
'No',
       'No', 'No', 'No', 'No', 'No', 'Yes', 'Yes', 'No', 'No', 'Yes'
```

,

In [245]:

```
# find accuracy from logestic regresion model
accuracy = acc(y_test,lr_prediction)
```

In [246]:

```
print("The accuracy of the logestic regression model is " + str(round((accuracy *
```

```
The accuracy of the logestic regression model is 84.9%.
```

In [ ]:

```

```