Implementation of Regression Model to confirm if there is a relationship between the two sets of columns, (1) “age” and “bmi” and (2) “age” and “charges” from the given data, using Python in jupyter notebook.

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Subject/Class: CMPS 451 Artificial Intelligence.

```
#Step 1:- Import the required libraries
#Numpy for statistical computations
#Matplotlib to plot the graph
#make_blobs from sklearn.datasets
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#from sklearn.datasets import make_blobs
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
#!pip install tensorflow
import tensorflow as tf

#load data from csv file
data_path = 'insurance.csv'

# create pandas dataframe
df = pd.read_csv(data_path)

# remove spaces on the column
df.columns = df.columns.str.lstrip()
df.columns = df.columns.str.rstrip()

# print out sample dataset
print("Total records:",len(df))
df.shape
df.head()
```

```
Total records: 1338
```

Out[86]:

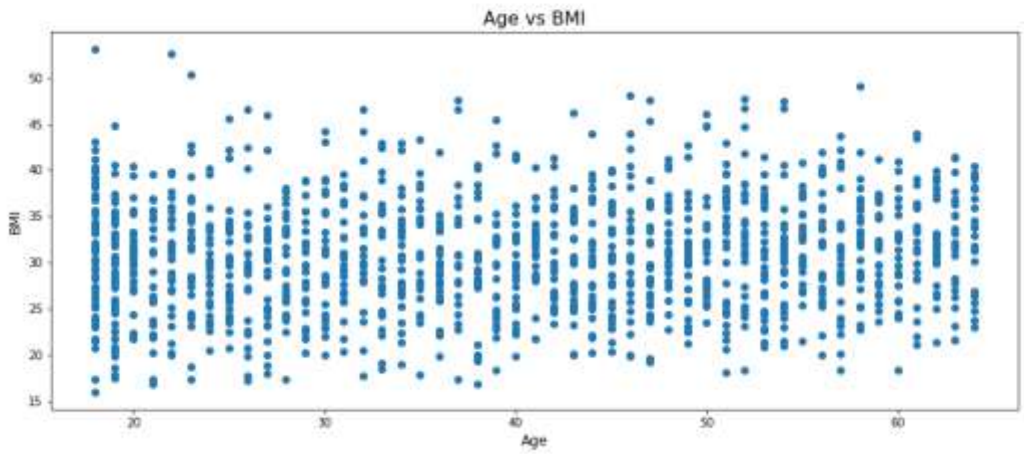
	age	sex	bmi	children	smoker	region	charges

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

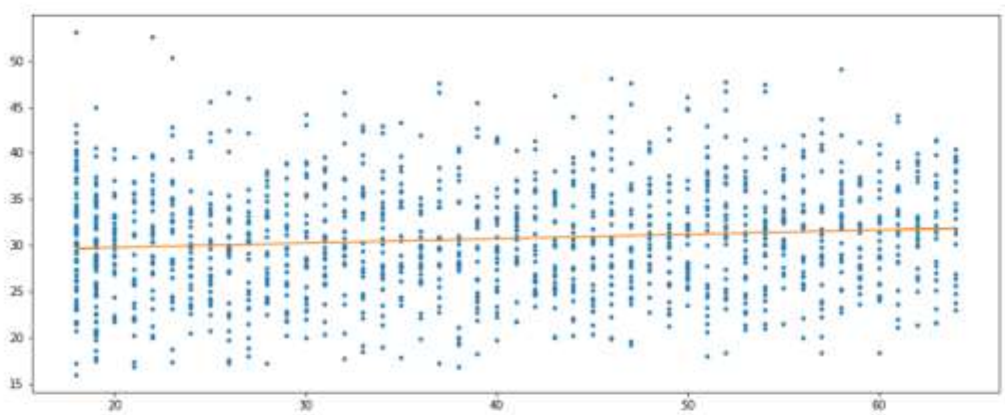
```
# filter the columns by only the required_columns
required_cols = ['age', 'bmi', 'charges']
df = df[required_cols]
df.head()
# check number of nan values in dataframe
df.isna().sum()
```

```
age        0
bmi        0
charges    0
dtype: int64
```

```
#to check relation plot scatter plot
plt.scatter('age', 'bmi', data=df);
plt.title('Age vs BMI', fontsize=16)
plt.xlabel('Age', fontsize=12)
plt.ylabel('BMI', fontsize=12)
plt.savefig("AgeVsBMI.png")
plt.show()
```



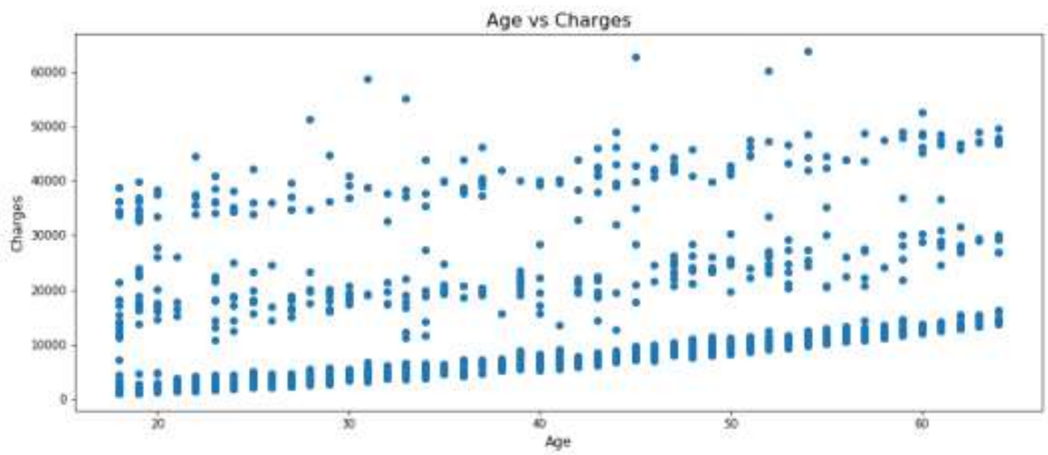

```
from numpy.polynomial.polynomial import polyfit
# Fit with polyfit
# Sample data
x = df['age']
y = df['bmi']
b, m = polyfit(x,y , 1)
plt.plot(x, y, '.')
plt.plot(x, b + m * x, '-')
plt.savefig("AgeVsBMIFt.png")
plt.show()
```



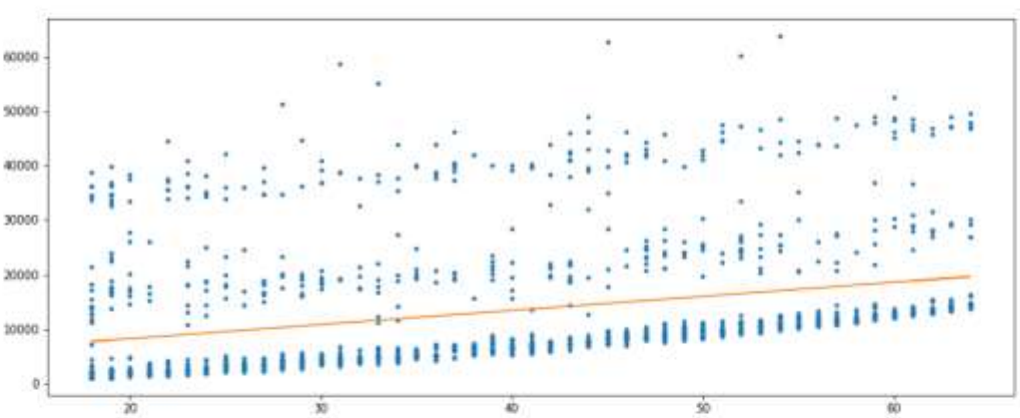
The above plots proves no relation between Age and BMI (slope is zero)

```
plt.scatter('age', 'charges', data=df);
plt.title('Age vs Charges', fontsize=16)
```

```
plt.xlabel('Age', fontsize=12)
plt.ylabel('Charges', fontsize=12)
plt.savefig("AgeVsCharges.png")
plt.show()
```




```
from numpy.polynomial.polynomial import polyfit
# Fit with polyfit
# Sample data
x = df['age']
y = df['charges']
#sns.regplot(x=x, y=y)
b, m = polyfit(x,y , 1)
plt.plot(x, y, '.')
plt.plot(x, b + m * x, '-')
plt.savefig("AgeVsChargesFt.png")
plt.show()
```



The above plots proves weak relation between Age and Charges.

calculate the Pearson's correlation between two variables

The positive correlation between the two variables is strong, if it surpasses the 0.5 threshold and approaches 1.0

```
from scipy.stats import pearsonr
corr, _ = pearsonr(df['age'], df['bmi'])
print('Pearsons correlation between Age and BMI: %.3f' % corr)
corr, _ = pearsonr(df['age'], df['charges'])
print('Pearsons correlation between Age and Charges: %.3f' % corr)
```

```
Pearsons correlation between Age and BMI: 0.109
Pearsons correlation between Age and Charges: 0.299
```

If you are unsure of the distribution and possible relationships between two variables, the Spearman correlation coefficient is a good tool to use.

```
from scipy.stats import spearmanr
corr, pvalue = spearmanr(df['age'], df['bmi'])
print('Spearman’s correlation between Age and BMI: %.3f' % corr)
#print(f"P-value: {pvalue}")
corr, pvalue = spearmanr(df['age'], df['charges'])
print('Spearman’s correlation between Age and Charges: %.3f' % corr)
#print(f"P-value: {pvalue}")
```

```
Spearman’s correlation between Age and BMI: 0.108
Spearman’s correlation between Age and Charges: 0.534
```

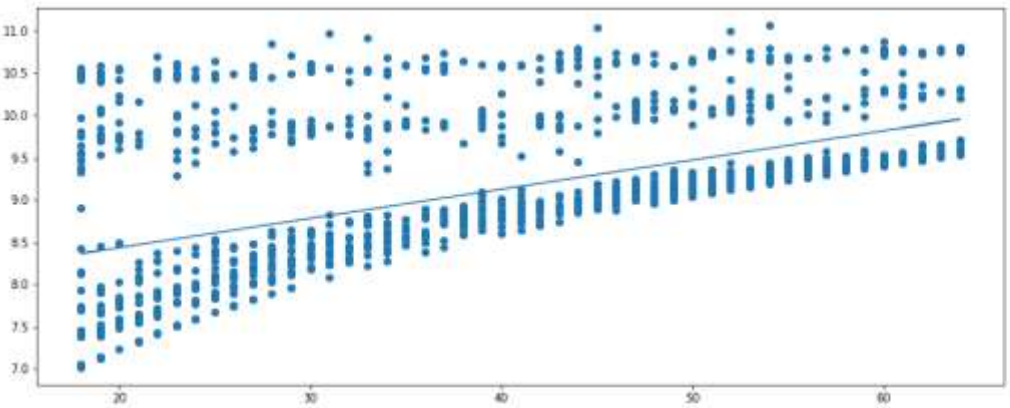
Better than pearsons but not that strong.

What if we use log transformation on Charges

```
x = df['age']
y = df['charges']
slope, intercept = np.polyfit(x, np.log(y), 1)

plt.figure()
plt.scatter(x, np.log(y))
plt.plot(x, (slope*x)+intercept)
plt.savefig("AgeVsLogChargesFt.png")
```

```
plt.show()
```




```
from scipy.stats import spearmanr
corr, pvalue = spearmanr(df['age'], df['charges'])
print('Spearman’s correlation between Age and charges: %.3f' % corr)
#print(f"P-value: {pvalue}")
corr, pvalue = spearmanr(df['age'], np.log(df['charges']))
print('Spearman’s correlation between Age and Log Charges: %.3f' % corr)
#print(f"P-value: {pvalue}")
```

```
Spearman’s correlation between Age and charges: 0.534
Spearman’s correlation between Age and Log Charges: 0.534
```

Ordinary least squares (OLS) regression is an optimization strategy used in linear regression models

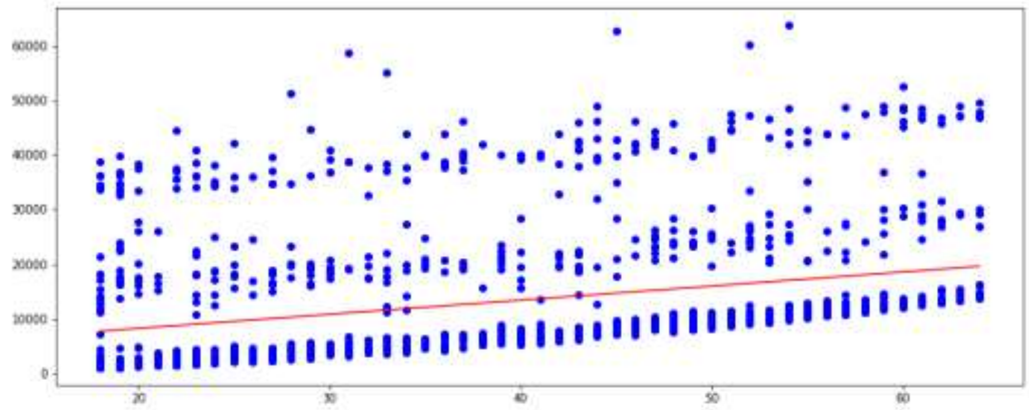
that finds a straight line that fits as close as possible to the data points, in order to help estimate the relationship between a dependent variable and one or more independent variables

```
import statsmodels.api as sm
import numpy as np
import matplotlib.pyplot as plt
x = df['age']
y = df['charges']
results = sm.OLS(y,sm.add_constant(x)).fit()
print(results.params)
print(results.summary())


mn=np.min(x)
mx=np.max(x)
```

```
x1=np.linspace(mn,mx,500)
y1=results.params[1]*x1+results.params[0]
plt.plot(x,y,'ob')
plt.plot(x1,y1,'-r')
plt.savefig("OLSRegAgeVsChargesFt.png")
plt.show()
```

```
const    3165.885006
age       257.722619
dtype: float64
                            OLS Regression Results
==============================================================================
====
Dep. Variable:                charges   R-squared:                       0
.089
Model:                            OLS   Adj. R-squared:                  0
.089
Method:                 Least Squares   F-statistic:                     1
31.2
Date:                Mon, 07 Apr 2025   Prob (F-statistic):           4.89
e-29
Time:                        14:20:24   Log-Likelihood:                -14
415.
No. Observations:                1338   AIC:                         2.883
e+04
Df Residuals:                    1336   BIC:                         2.884
e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const       3165.8850    937.149      3.378      0.001    1327.440    5004
.330
age          257.7226     22.502     11.453      0.000     213.579     301
.866
==============================================================================
====
Omnibus:                      399.600   Durbin-Watson:                   2
.033
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              864
.239
Skew:                           1.733   Prob(JB):                    2.15e
-188
Kurtosis:                       4.869   Cond. No.
124.
==============================================================================
```



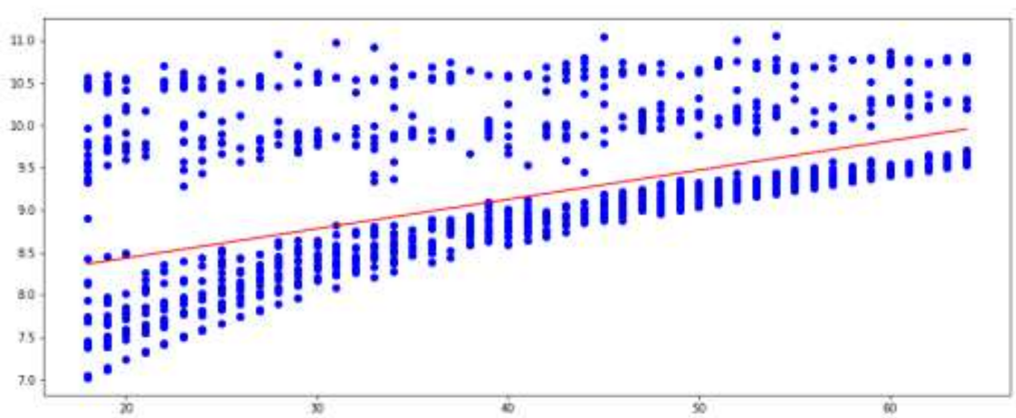
Ordinary least squares (OLS) regression using log transformation on Charges

```
import statsmodels.api as sm
import numpy as np
import matplotlib.pyplot as plt
x = df['age']
y =  np.log(df['charges'])
results = sm.OLS(y,sm.add_constant(x)).fit()
print(results.params)
print(results.summary())


mn=np.min(x)
mx=np.max(x)
x1=np.linspace(mn,mx,500)
y1=results.params[1]*x1+results.params[0]
plt.plot(x,y,'ob')
plt.plot(x1,y1,'-r')
plt.savefig("OLSRegAgeVsLogChargesFt.png")
plt.show()
```

```
const    7.744247
age      0.034545
dtype: float64
                            OLS Regression Results
==========================================================================
====
Dep. Variable:                charges   R-squared:                       0
.279
Model:                            OLS   Adj. R-squared:                  0
.278
Method:                 Least Squares   F-statistic:                     5
16.0
```

```
Date:                    Mon, 07 Apr 2025   Prob (F-statistic):              7.48
e-97
Time:                            16:04:14   Log-Likelihood:                   -15
67.3
No. Observations:                    1338   AIC:                                3
139.
Df Residuals:                        1336   BIC:                                3
149.
Df Model:                               1
Covariance Type:                nonrobust
==========================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
--------------------------------------------------------------------------
----
const          7.7442      0.063    122.272      0.000       7.620       7
.868
age            0.0345      0.002     22.715      0.000       0.032       0
.038
==========================================================================
====
Omnibus:                      179.280   Durbin-Watson:                      2
.029
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                 256
.341
Skew:                           1.067   Prob(JB):                        2.17
e-56
Kurtosis:                       3.206   Cond. No.
124.
==========================================================================
====
```



R-squared is 0.089 when charges are used as is, becomes R-squared 0.279 when log transformation is used on charges

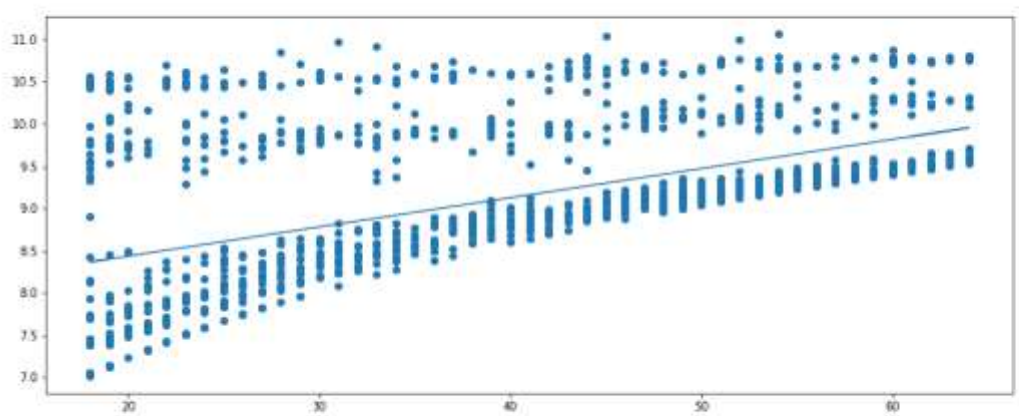
```
import matplotlib.pyplot as plt
from scipy import stats

x = df['age']
y =  np.log(df['charges'])
slope, intercept, r, p, std_err = stats.linregress(x, y)

def modelYval(x):
  return slope * x + intercept

mymodel = list(map(modelYval, x))
print("slope:",slope)
print("intercept:",intercept)
print("r:",r)
print("p:",p)
print("std_err:",std_err)
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.savefig("LinRegAgeVsLogChargesFt.png")
plt.show()
```

```
slope: 0.03454513080663117
intercept: 7.744246908060742
r: 0.5278340489394343
p: 7.477385218968553e-97
std_err: 0.0015207983609832536
```



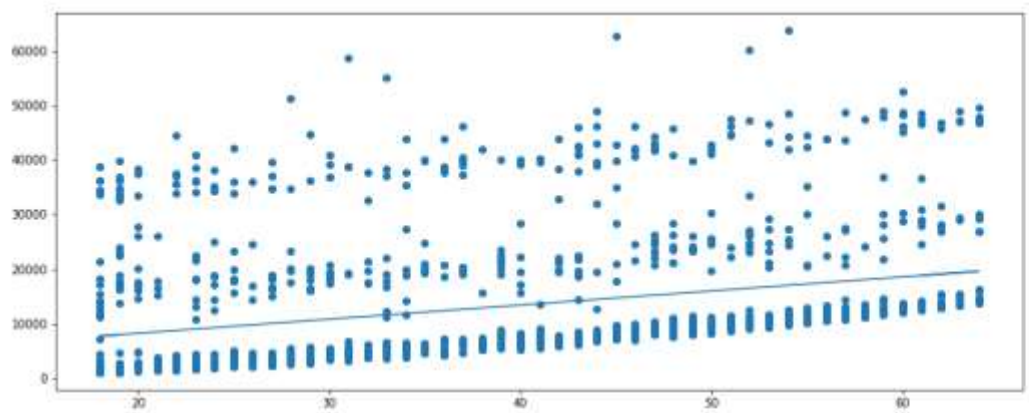

```
import matplotlib.pyplot as plt
from scipy import stats

x = df['age']
y =  df['charges']
slope, intercept, r, p, std_err = stats.linregress(x, y)
```

```
def modelYval(x):
  return slope * x + intercept

mymodel = list(map(modelYval, x))
print("slope:",slope)
print("intercept:",intercept)
print("r:",r)
print("p:",p)
print("std_err:",std_err)
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.savefig("LinRegAgeVsLogChargesFt.png")
plt.show()
```

```
slope: 257.7226186668956
intercept: 3165.885006063023
r: 0.29900819333064776
p: 4.886693331718281e-29
std_err: 22.5023892867703
```



Conclusion: from above regression analysis we can conclude that there is no relation between Age and BMI, but there is some weak relation between Age and charges.