```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn import linear_model
```

```
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

Assignment5

Ground Cricket Chirps

In *The Song of Insects* (1948) by George W. Pierce, Pierce mechanically measured the frequency (the number of wing vibrations per second) of chirps (or pulses of sound) made by a striped ground cricket, at various ground temperatures. Since crickets are ectotherms (cold-blooded), the rate of their physiological processes and their overall metabolism are influenced by temperature. Consequently, there is reason to believe that temperature would have a profound effect on aspects of their behavior, such as chirp frequency.

In general, it was found that crickets did not sing at temperatures colder than 60º F. or warmer than 100º F.

```
ground_cricket_data = {"ChirpsperSecond": [20.0, 16.0, 19.8, 18.4, 17.1, 15.5, 14.7,
                                            15.7, 15.4, 16.3, 15.0, 17.2, 16.0, 17.0,
                                            14.4],
                       "GroundTemperature": [88.6, 71.6, 93.3, 84.3, 80.6, 75.2, 69.7,
                                             71.6, 69.4, 83.3, 79.6, 82.6, 80.6, 83.5,
                                             76.3]}
df = pd.DataFrame(ground_cricket_data)
```

Tasks

1. Find the linear regression equation for this data.
2. Chart the original data and the equation on the chart.
3. Find the equation's R^2 score (use the `.score` method) to determine whether the equation is a good fit for this data. (0.8 and greater is considered a strong correlation.)
4. Extrapolate data: If the ground temperature reached 95, then at what approximate rate would you expect the crickets to be chirping?
5. Interpolate data: With a listening device, you discovered that on a particular morning the crickets were chirping at a rate of 18 chirps per second. What was the approximate ground temperature that morning?

```
df
```

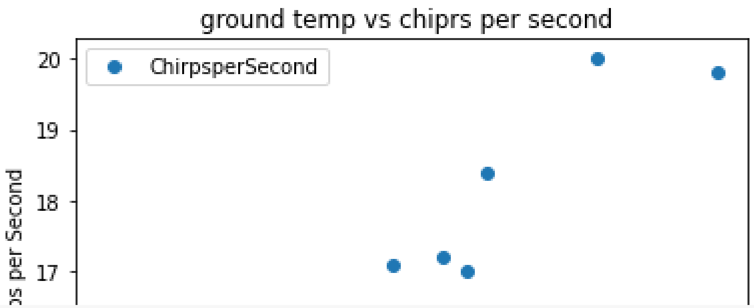
	ChirpsperSecond	GroundTemperature
0	20.0	88.6
1	16.0	71.6

```
df.describe().style.background_gradient()
```

	ChirpsperSecond	GroundTemperature
count	15.000000	15.000000
mean	16.566667	79.346667
std	1.712837	7.020467
min	14.400000	69.400000
25%	15.450000	73.400000
50%	16.000000	80.600000
75%	17.150000	83.400000
max	20.000000	93.300000

12	16.0	80.6

```
#visual
df.plot(x='GroundTemperature',y='ChirpsperSecond',style="o")
plt.title("ground temp vs chiprs per second ")
plt.xlabel("Ground Temp")
plt.ylabel('Chirps per Second')
plt.show()
```




```
df['GroundTemperature']=df['GroundTemperature'].to_frame()
df['GroundTemperature']
```

```
0     88.6
1     71.6
2     93.3
3     84.3
4     80.6
5     75.2
6     69.7
7     71.6
8     69.4
9     83.3
10    79.6
11    82.6
12    80.6
13    83.5
14    76.3
Name: GroundTemperature, dtype: float64
```

```
df['ChirpsperSecond']=df['ChirpsperSecond'].to_frame()
df['ChirpsperSecond']
```

```
0     20.0
1     16.0
2     19.8
3     18.4
4     17.1
5     15.5
6     14.7
```

```
7     15.7
8     15.4
9     16.3
10    15.0
11    17.2
12    16.0
13    17.0
14    14.4
Name: ChirpsperSecond, dtype: float64
```

Modelling

```
x = df['GroundTemperature']
x = x.to_frame()
y = df['ChirpsperSecond']
```

```
linreg=linear_model.LinearRegression()
linreg.fit(x,y)
```

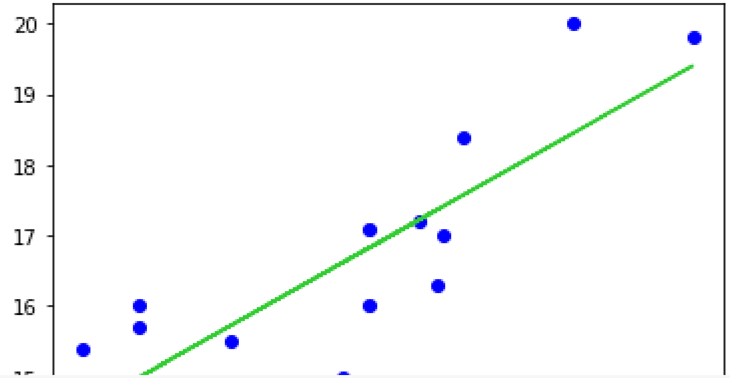
```
LinearRegression()
```

```
print('intercept',linreg.intercept_)
print('coff',linreg.coef_)
```

```
intercept 0.45931464523595267
coff [0.20299973]
```

```
plt.scatter(x,y,color='blue')
plt.plot(x,linreg.predict(x),color='limegreen')
```

```
[<matplotlib.lines.Line2D at 0x7f55e7aa2050>]
```




```
print('R2 Score : ',linreg.score(x,y))
```

```
R2 Score :  0.6922946529146998
```

Extrapolate

```
i=float(input())
p=linreg.predict([[i]])
z=int(p.round())
print("If the ground temperature reached ",str(i)," then approximatly we can expect the crickets to be chirping at ", str(z)," chirps
```

```
90
If the ground temperature reached  90.0  then approximatly we can expect the crickets to be chirping at  19  chirps per sec.
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feature names, but LinearRegress
  "X does not have valid feature names, but"
```

Intrapolate

```
m=float(input())
```

```
c=(m-linreg.intercept_)/(linreg.coef_)
o=int(c.round())
print("If the crickets were chirping at a rate of ",str(m)," chirps per second. then the approximate ground temperature that morning
```

```
12
If the crickets were chirping at a rate of  12.0  chirps per second. then the approximate ground temperature that morning would
```

Assignment6

Brain vs. Body Weight

In the file `brain_body.txt`, the average brain and body weight for a number of mammal species are recorded. Load this data into a Pandas data frame.

Tasks

1. Find the linear regression equation for this data for brain weight to body weight.
2. Chart the original data and the equation on the chart.
3. Find the equation's R^2 score (use the `.score` method) to determine whether the equation is a good fit for this data. (0.8 and greater is considered a strong correlation.)

```
df = pd.read_fwf("brain_body.txt")
print(df.shape)
df.head()
```

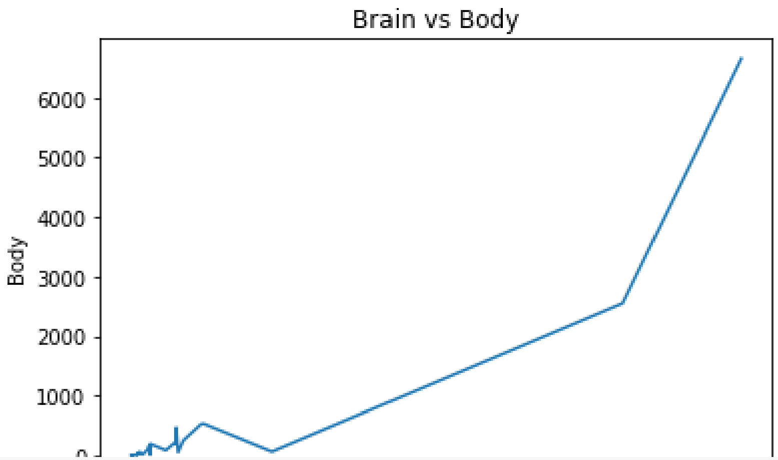
```
(62, 2)
```

	Brain	Body
0	3.385	44.5
1	0.480	15.5
2	1.350	8.1
3	465.000	423.0

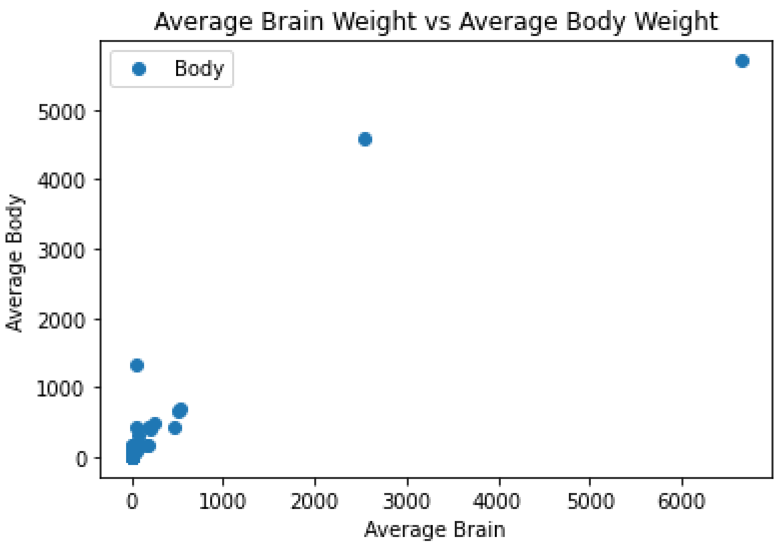
```
df.describe().style.background_gradient()
```

	Brain	Body
count	62.000000	62.000000
mean	198.789984	283.134194
std	899.158011	930.278942
min	0.005000	0.140000
25%	0.600000	4.250000
50%	3.342500	17.250000
75%	48.202500	166.000000
max	6654.000000	5712.000000

```
df.groupby('Body')['Brain'].mean().plot()
plt.title('Brain vs Body')
plt.xlabel("Brain")
plt.ylabel("Body")
plt.show()
```




```
df.plot(x='Brain',y='Body', style="o")
plt.title('Average Brain Weight vs Average Body Weight')
plt.xlabel('Average Brain')
plt.ylabel('Average Body')
plt.show()
```




```
df.corr()
```

	Brain	Body
Brain	1.000000	0.934164
Body	0.934164	1.000000

```
x=df['Brain']
x=x.to_frame()
y=df['Body']


linreg = linear_model.LinearRegression()
linreg.fit(x, y)

print('intercept:', linreg.intercept_)
print('coefficient:', linreg.coef_)
print('R2 Score : ', linreg.score(x, y))
```

```
intercept: 91.00439620740687
coefficient: [0.96649637]
R2 Score :  0.8726620843043331
```

```
plt.scatter(x, y, color='green')
plt.plot(x, linreg.predict(x), color='orange', linewidth=2)
```

```
[<matplotlib.lines.Line2D at 0x7f55e7377890>]
```

Assignment7

Salary Discrimination

The file `salary.txt` contains data for 52 tenure-track professors at a small Midwestern college. This data was used in legal proceedings in the 1980s about discrimination against women in salary.

The data in the file, by column:

1. Sex. 1 for female, 0 for male.
2. Rank. 1 for assistant professor, 2 for associate professor, 3 for full professor.
3. Year. Number of years in current rank.
4. Degree. Highest degree. 1 for doctorate, 0 for master's.
5. YSdeg. Years since highest degree was earned.
6. Salary. Salary/year in dollars.

Tasks

1. Find the linear regression equation for this data using columns 1-5 to column 6.
2. Find the selection of columns with the best R^2 score.
3. Report whether sex is a factor in salary.

```
df = pd.read_fwf("salary.txt", header=None,
                 names=["Sex", "Rank", "Year", "Degree", "YSdeg", "Salary"])
print(df.shape)
df.head()
```

```
(52, 6)
```

	Sex	Rank	Year	Degree	YSdeg	Salary
0	0	3	25	1	35	36350
1	0	3	13	1	22	35350
2	0	3	10	1	23	28200
3	1	3	7	1	27	26775
4	0	3	19	0	30	33696

```
df.describe().style.background_gradient()
```

	Sex	Rank	Year	Degree	YSdeg	Salary
count	52.000000	52.000000	52.000000	52.000000	52.000000	52.000000
mean	0.269231	2.038462	7.480769	0.653846	16.115385	23797.653846
std	0.447888	0.862316	5.507536	0.480384	10.222340	5917.289154
min	0.000000	1.000000	0.000000	0.000000	1.000000	15000.000000
25%	0.000000	1.000000	3.000000	0.000000	6.750000	18246.750000
50%	0.000000	2.000000	7.000000	1.000000	15.500000	23719.000000
75%	1.000000	3.000000	11.000000	1.000000	23.250000	27258.500000
max	1.000000	3.000000	25.000000	1.000000	35.000000	38045.000000

IQR Method

- Finding of Interquartile Range And Lower Limit And Upper Limit Method

```
def outlier_presence(df):
```

```
def outlier_presence(df):
  for i in df.keys():
    Q1 = df[i].quantile(0.25)
    Q3 = df[i].quantile(0.75)
    IQR = Q3-Q1
    lower_limit = Q1 - 1.5*IQR
····upper_limit·=·Q3·+·1.5*IQR
····print("Interquartile·Range·of·"·+·i·+·"·is",·IQR)
····print("Lower·Limit·",·lower_limit)
····print("Upper·Limit·",·upper_limit)
····outliers·=·df[(df[i]<lower_limit)|(df[i]>upper_limit)]
    if outliers.shape[0] != 0:
      print("Outlier is Presented In",i )
      print("\n")
    else:
      print("Outlier is Not Presented In",i )
      print("\n")

outlier_presence(df)
```

```
Interquartile Range of Sex is 1.0
Lower Limit  -1.5
Upper Limit  2.5
Outlier is Not Presented In Sex


Interquartile Range of Rank is 2.0
Lower Limit  -2.0
Upper Limit  6.0
Outlier is Not Presented In Rank


Interquartile Range of Year is 8.0
Lower Limit  -9.0
Upper Limit  23.0
Outlier is Presented In Year


Interquartile Range of Degree is 1.0
```

```
Lower Limit  -1.5
Upper Limit  2.5
Outlier is Not Presented In Degree


Interquartile Range of YSdeg is 16.5
Lower Limit  -18.0
Upper Limit  48.0
Outlier is Not Presented In YSdeg


Interquartile Range of Salary is 9011.75
Lower Limit  4729.125
Upper Limit  40776.125
Outlier is Not Presented In Salary
```

```
def Outlier_Data_Points(df):
  for i in df.keys():
    Q1 = df[i].quantile(0.25)
    Q3 = df[i].quantile(0.75)
    IQR = Q3-Q1
    lower_limit = Q1 - 1.5*IQR
    upper_limit = Q3 + 1.5*IQR
    outliers = df[(df[i]<lower_limit)|(df[i]>upper_limit)] # Here We Find The All outliers In Given Data set
    if outliers.shape[0] != 0:
      print("Outlier is Presented In " + i + " is")
      for j in outliers[i]:
        print(j)
      print("\n")
    else:
      print("No Outlier is Presented In",i )
Outlier_Data_Points(df)
```

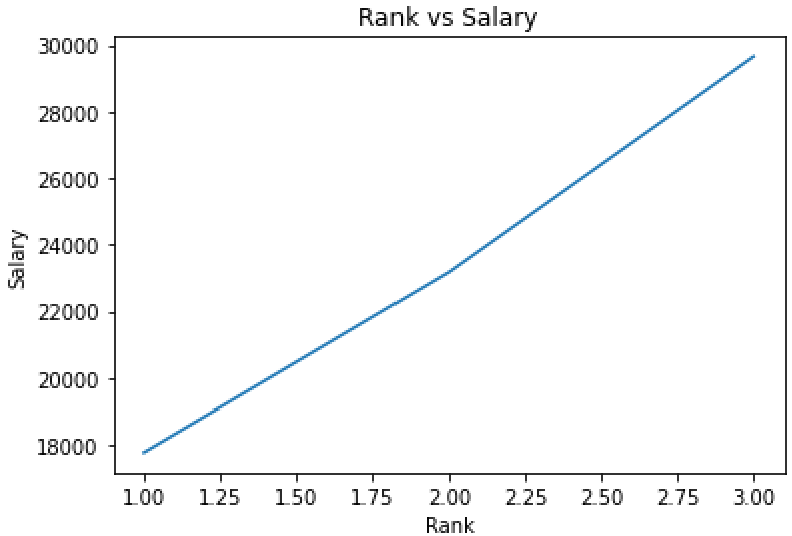
```
No Outlier is Presented In Sex
No Outlier is Presented In Rank
Outlier is Presented In Year is
25
```

```
No Outlier is Presented In Degree
No Outlier is Presented In YSdeg
No Outlier is Presented In Salary
```

- Finding The Relationship Between ("Sex", "Rank", "Year", "Degree", "YSdeg") To "Salary"

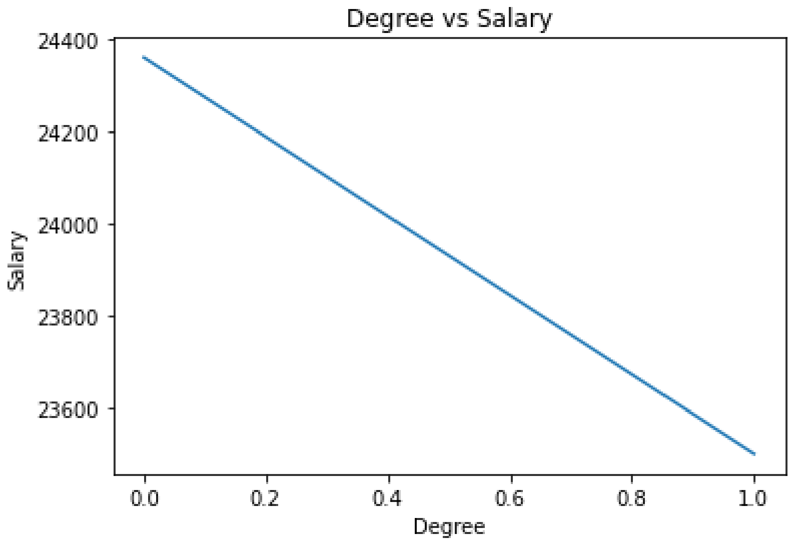
```
df.groupby('Sex')['Salary'].mean().plot()
plt.title('Sex vs Salary')
plt.xlabel('Sex')
plt.ylabel('Salary')
plt.show()

df[['Sex', 'Salary']].corr()
```

```
df.groupby('Rank')['Salary'].mean().plot()
plt.title('Rank vs Salary')
plt.xlabel('Rank')
plt.ylabel('Salary')
plt.show()

df[['Rank', 'Salary']].corr()
```



	Rank	Salary
Rank	1.000000	0.867488
Salary	0.867488	1.000000

```
df.groupby('Degree')['Salary'].mean().plot()
plt.title('Degree vs Salary')
plt.xlabel('Degree')
plt.ylabel('Salary')
plt.show()

df[['Degree', 'Salary']].corr()
```



	Degree	Salary
Degree	1.000000	-0.069726
Salary	-0.069726	1.000000

Testing and Training and Model Creation

```
from sklearn.model_selection import train_test_split
X = df.loc[:, ["Sex", "Rank", "Year", "Degree", "YSdeg"]].values
y = df.loc[:, 'Salary'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state = 7)
```

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train,y_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train_scaled, y_train)

y_pred = regressor.predict(X_test_scaled)
y_pred
```

```
array([28887.02952781, 29426.57400482, 23074.53644172, 28540.36845393,
       25457.22218901, 21555.98100223, 18962.5998726 , 21372.19690045,
       29866.04049028, 30373.83764927, 16107.69878742, 22869.45858675,
       16429.97095763, 26138.34988493, 15599.90162843, 18976.31516693])
```

```
Predicted = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
Predicted
```

	Actual	Predicted
0	27959	28887.029528
1	25500	29426.574005
2	22450	23074.536442
3	29342	28540.368454

```
df_coff = pd.DataFrame(regressor.coef_ , ['Sex', 'Rank', 'Year', 'Degree', 'YSdeg'], columns= ['Cofficient'])
df_coff
```

	Cofficient
Sex	929.457566
Rank	5310.095498
Year	3112.935207
Degree	-715.662197
YSdeg	-1907.195112

12	16700	16429.970958

```
print(regressor.intercept_)
print('R2 SCORE : ', metrics.r2_score(y_test,y_pred))
```

```
23947.555555555555
R2 SCORE :  0.7801347152885464
```

```
def Selc_Col(df):
  for i in df.keys():
    if i != 'Salary':
      X = df.loc[:, [i]].values
      y = df.loc[:, 'Salary'].values
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state = 7)
      scaler = StandardScaler()
      scaler.fit(X_train,y_train)
```

```
      X_train_scaled = scaler.transform(X_train)
      X_test_scaled = scaler.transform(X_test)
      regressor = LinearRegression()
      regressor.fit(X_train_scaled, y_train)
      y_pred = regressor.predict(X_test_scaled)
      print('R2- SCORE of ' + i + ' is: ', metrics.r2_score(y_test,y_pred))
Selc_Col(df)
```

```
R2- SCORE of Sex is:  -0.012233465811496869
R2- SCORE of Rank is:  0.6723218219021224
R2- SCORE of Year is:  0.39359646731694975
R2- SCORE of Degree is:  -0.05577210942642963
R2- SCORE of YSdeg is:  0.3561736731232156
```

Here Sex Is Not a Factor for Salary Prediction Because It Have Low Cofficient Value And Low Score

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