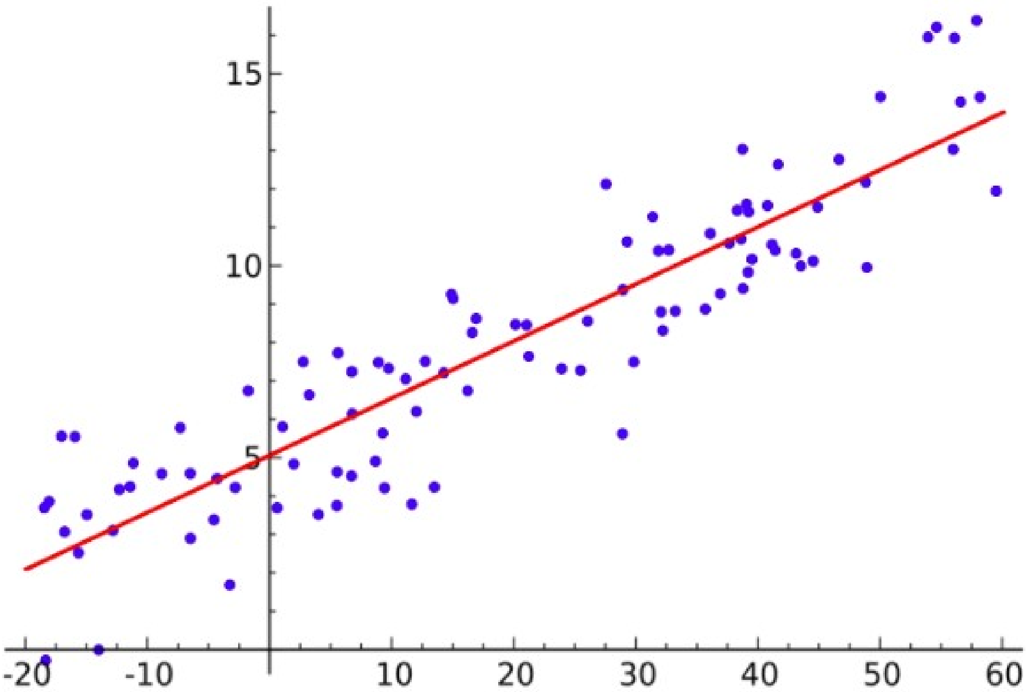
Université Abdelmalek Essaadi Faculté des Sciences et Techniques –Tanger
Département Génie Informatique

Atelier 1
« Régression »



Réalisé par :
KAISSI Houda

Objective :

l'objective principal de cet atelier est de pratiquer les deux concepts de la régression : la régression linière simple et la régression linière multiple, en traitant des données de plusieurs Data Sets.

Partie 1 (Data Visualisation):

1. En utilisant pandas essayer d'explorer les données des deux Data sets.

-Premierement on vas installer pandas et numpy
pip install pandas
pip install numpy

```
import pandas as pd
import numpy as np
files = ["Salary_Data.csv", "insurance.csv"]
```

```
column_names = [["years", "salary"], ["age", "sex", "bmi", "children", "smoker", "region", "charges"]]
```

```
for i in range(len(files)):
    if i == 0:
        print("Dataset des salaires")
    else:
        print(" Dataset d'assurance ")

    df = pd.read_csv(files[i], names=column_names[i])
    print(df.head())
```

Dataset des salaires :

```
 Dataset des salaires
              years     salary
 0  YearsExperience     Salary
 1              1.1   39343.00
 2              1.3   46205.00
 3              1.5   37731.00
 4              2.0   43525.00
```

Dataset d'assurance :

```
 Dataset d'assurance
   age     sex     bmi  children  smoker     region     charges
0  age     sex     bmi  children  smoker     region     charges
1   19  female    27.9         0     yes  southwest   16884.924
2   18    male   33.77         1      no  southeast   1725.5523
3   28    male      33         3      no  southeast    4449.462
4   33    male  22.705         0      no  northwest 21984.47061
```

2. Afficher le résumer statistique des deux Data Sets avec une interprétation des résultats obtenues.

```
column_names = [["years", "salary"], ["age", "sex", "bmi", "children", "smoker", "region", "charges"]]
```

```
for i in range(len(files)):
    if i == 0:
        print("Dataset des salaires")
    else:
        print("Dataset d'assurance")

    df = pd.read_csv(files[i], names=column_names[i])

    print("  Sans transformation des données --- ")
    print(df.describe())

    print("   Avec transformation des données --- ")
    df = df.apply(pd.to_numeric, errors='coerce')
    print(df.describe())
```

Dataset des salaires avant et aprés transformation :

```
Dataset des salaires
  Sans transformation des données ---
       years  salary
count     31      31
unique    29      31
top      3.2  Salary
freq       2       1
   Avec transformation des données ---
           years         salary
count  30.000000      30.000000
mean    5.313333   76003.000000
std     2.837888   27414.429785
min     1.100000   37731.000000
25%     3.200000   56720.750000
50%     4.700000   65237.000000
75%     7.700000  100544.750000
max    10.500000  122391.000000
```

Dataset d’assurance avant et aprés transformation :

```
Dataset d'assurance
  Sans transformation des données ---
         age   sex   bmi children smoker     region    charges
count   1339  1339  1339     1339   1339       1339       1339
unique    48     3   549        7      3          5       1338
top       18  male  32.3        0     no  southeast  1639.5631
freq      69   676    13      574   1064        364          2
   Avec transformation des données ---
                age  sex          bmi     children  smoker  region  \
count   1338.000000  0.0  1338.000000  1338.000000     0.0     0.0
mean      39.207025  NaN    30.663397     1.094918     NaN     NaN
std       14.049960  NaN     6.098187     1.205493     NaN     NaN
min       18.000000  NaN    15.960000     0.000000     NaN     NaN
25%       27.000000  NaN    26.296250     0.000000     NaN     NaN
50%       39.000000  NaN    30.400000     1.000000     NaN     NaN
75%       51.000000  NaN    34.693750     2.000000     NaN     NaN
max       64.000000  NaN    53.130000     5.000000     NaN     NaN

             charges
count    1338.000000
mean    13270.422265
std     12110.011237
min      1121.873900
25%      4740.287150
50%      9382.033000
75%     16639.912515
max     63770.428010
```

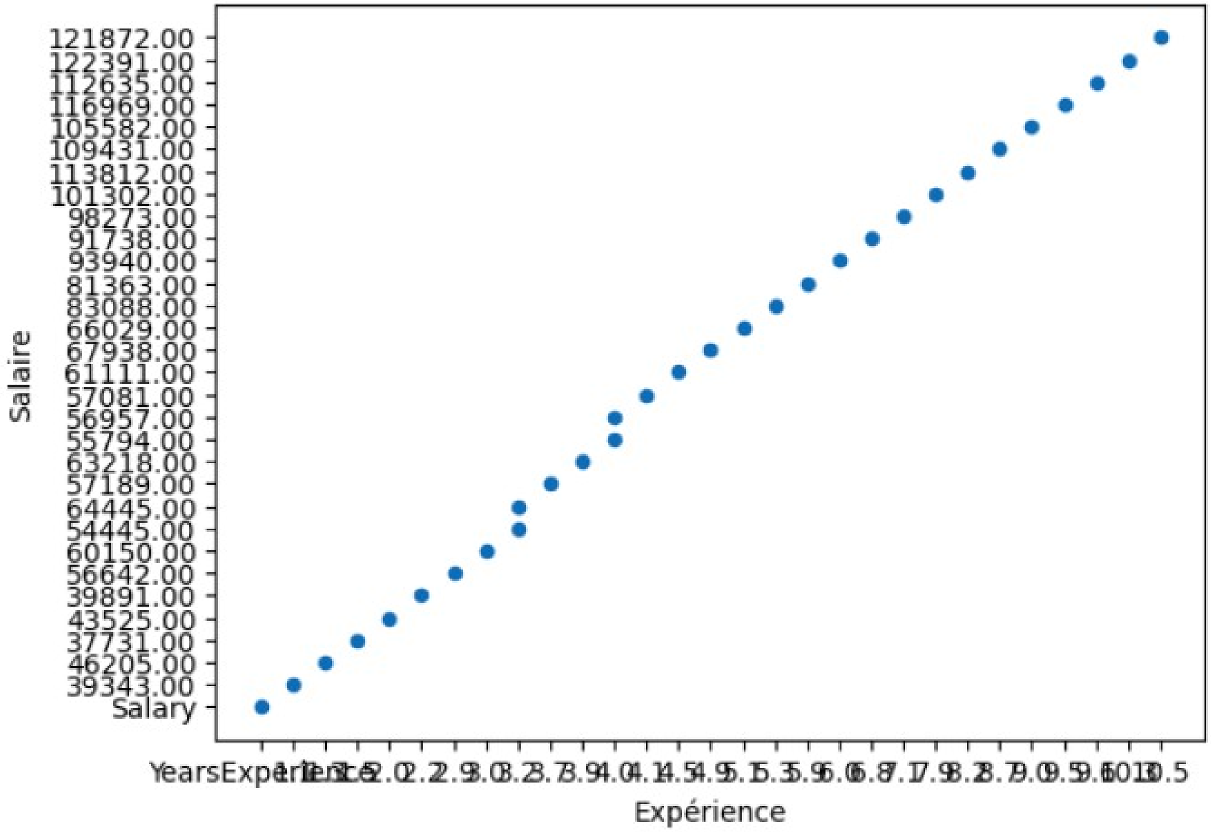
3. Afficher la nuage des points du premier data set « Expérience / Salaire » en utilisant matplotlib et pandas.

Avant on vas installer matplotlib
pip install matplotlib

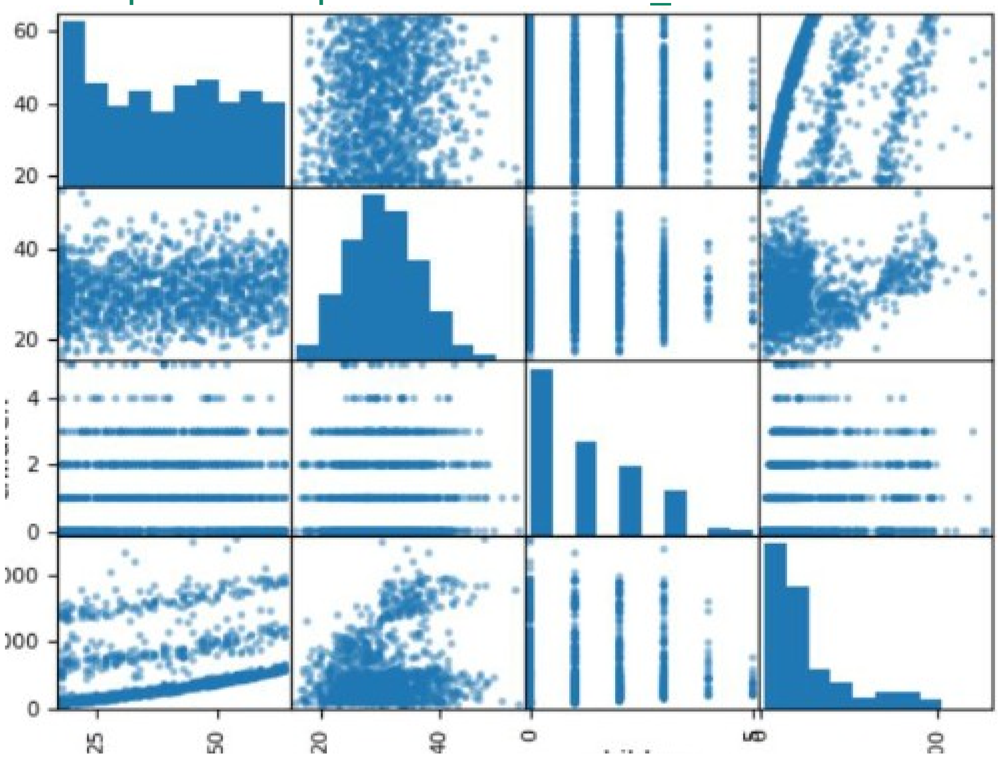
```python
import matplotlib.pyplot as plt
```

```python
df = pd.read_csv(files[0], names=column_names[0])
df = df.rename(columns={"years": "experience", "salary": "salaire"})

df.plot.scatter(x="experience", y="salaire")
plt.xlabel("Expérience")
plt.ylabel("Salaire")
plt.show()
```

Résultat :



4. Afficher les nuages des points du deuxième data set selon les propriétés « Features » en
utilisant matplotlib et pandas « scatter_matrix ».



Partie 2 « Régression Simple cas Expérience Salaire »:

1. en utilisant l'API sklearn entraîner le modèle par intermédiaire de algorithme de la régression linière.

Avant on vas installer scikit-learn

pip install -U scikit-learn

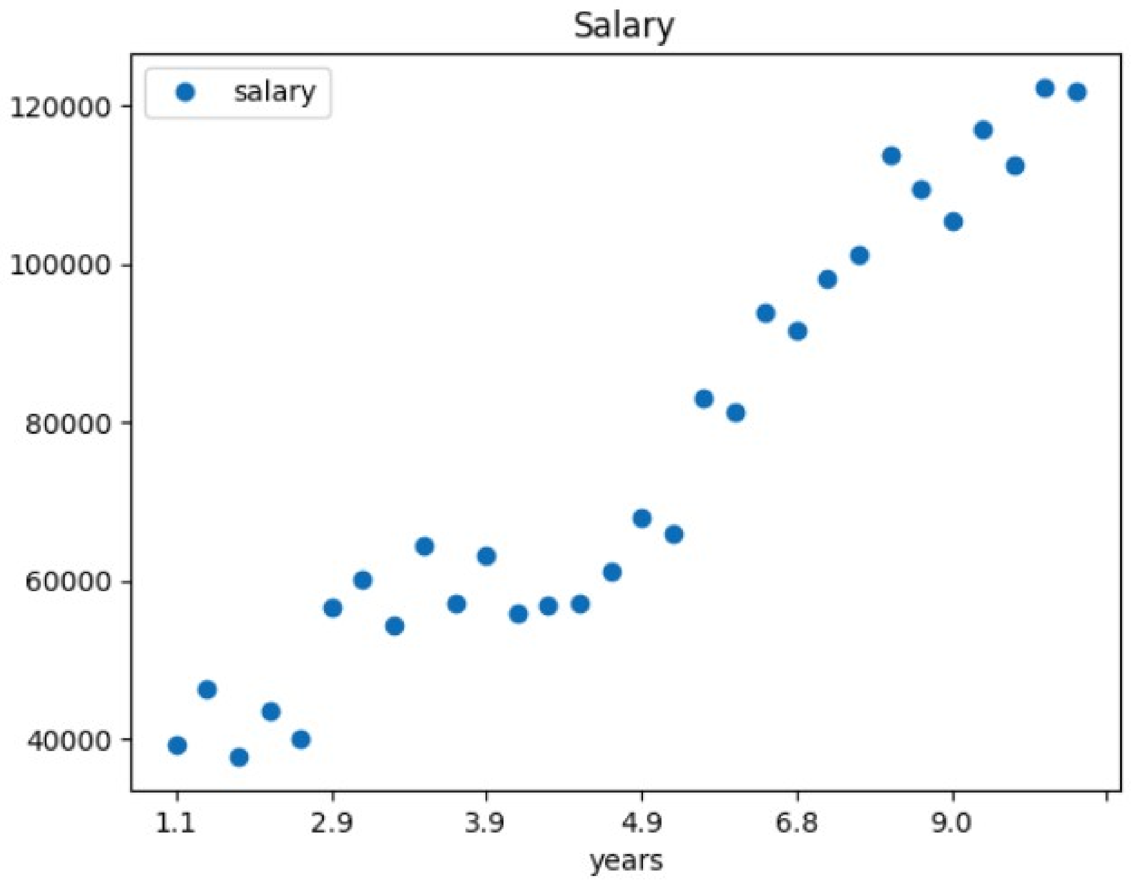
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

```
import pandas as pd
```

```
file_paths = ["Salary_Data.csv", "insurance.csv"]
```

```
import pandas as pd
import matplotlib.pyplot as plt

file_paths = ["Salary_Data.csv"]
col_names = [["years", "salary"]]

f = 0
df = pd.read_csv(file_paths[f], names=col_names[f])

# Convert 'salary' column to numeric, coercing errors to NaN
df['salary'] = pd.to_numeric(df['salary'], errors='coerce')

# Remove rows with NaN values in the 'salary' column
df = df.dropna(subset=['salary'])

print(df.describe())

x = df['years'].values.reshape(-1, 1)
y = df['salary'].values.reshape(-1, 1)

df.plot(x="years", y="salary", style="o")
plt.title("Salary")

plt.show()
```

Resultat :




```
x = df['years'].values.reshape(-1, 1)
y = df['salary'].values.reshape(-1, 1)

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_

regressor = LinearRegression()
regressor.fit(x_train, y_train)

print("b0 (intercept) = " + str(regressor.intercept_[0]))
print("b1 (coefficient) = " + str(regressor.coef_[0][0]))
```

```
b0 (intercept) = 26780.09915062818
b1 (coefficient) = 9312.575126729189
```

2. prédire les données d'un data set de test.

Actual values et predicted values :

```
y_p = regressor.predict(x_test)
result = pd.DataFrame({'Actual Values': y_test.flatten(), 'Predicted Values': y_p.flatten()})
print(result)
```

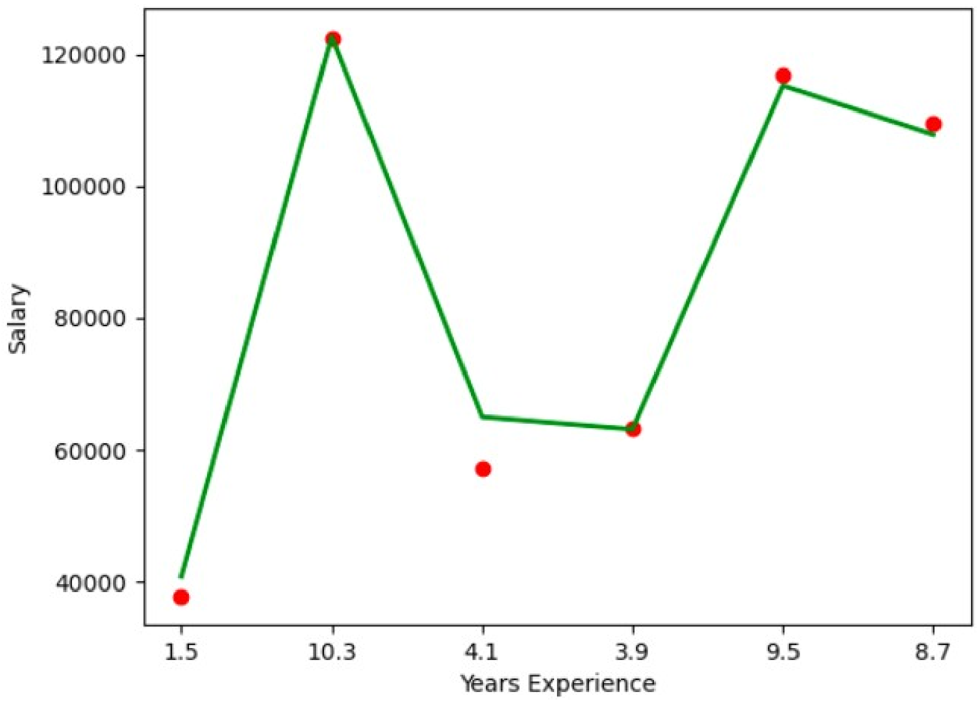
```
   Actual Values  Predicted Values
0        37731.0      40748.961841
1       122391.0     122699.622956
2        57081.0      64961.657170
3        63218.0      63099.142145
4       116969.0     115249.562855
5       109431.0     107799.502753
```

```
#3
```

3. Visualiser le résultat de la régression sous forme d’un graphe.

```
plt.scatter(x_test.flatten(), y_test.flatten(), color="red")
plt.plot(x_test.flatten(), y_p.flatten(), color="green", linewidth=2)
plt.xlabel("Years Experience")
plt.ylabel("Salary")
plt.title("Actual vs. Predicted Salary")
plt.show()
```

Resultat :



4. Évaluer le modèle en utilisant ces trois méthodes :
Mean Squared Error (MSE)

Root Mean Squared Error (RMSE)
Mean Absolute Error (MAE)

```
MAR = metrics.mean_absolute_error(y_test, y_p)
MSR = metrics.mean_squared_error(y_test, y_p)
RMSR = np.sqrt(MSR)

print("Mean Absolute Error:", MAR)
print("Mean Squared Error:", MSR)
print("Root Mean Squared Error:", RMSR)
```

Resulta :

Mean Absolute Error : 2446.1723690465055
Mean Squared Error : 12823412.298126549
Root Mean Squared Error 3580.979237321343

Interpréter le résultat de l'évaluation.

RMSE de 3581 indique que le modèle a une précision moyenne d'environ 3581 donc Estimation d'erreur est via RMSE

partie 3 « Régression multiple cas d'assurance »:

1. en utilisant l'API sklearn entraîner le modèle par intermédiaire de algorithme de la régression linière.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics

file_paths = ["./Salary_Data.csv", "./insurance.csv"]
col_names = [["years", "salary"], ["age", "sex", "bmi", "children", "smoker", "region", "charges"]]

f = 1
df = pd.read_csv(file_paths[f], names=col_names[f], skiprows=1)

print(df.describe())


x = df[['age', 'bmi', 'children']].values
y = df['charges'].values


x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)


regressor = LinearRegression()
regressor.fit(x_train, y_train)
```

```
               age          bmi     children       charges
count  1338.000000  1338.000000  1338.000000   1338.000000
mean     39.207025    30.663397     1.094918  13270.422265
std      14.049960     6.098187     1.205493  12110.011237
min      18.000000    15.960000     0.000000   1121.873900
25%      27.000000    26.296250     0.000000   4740.287150
50%      39.000000    30.400000     1.000000   9382.033000
75%      51.000000    34.693750     2.000000  16639.912515
max      64.000000    53.130000     5.000000  63770.428010
```

```
▾ LinearRegression
LinearRegression()
```

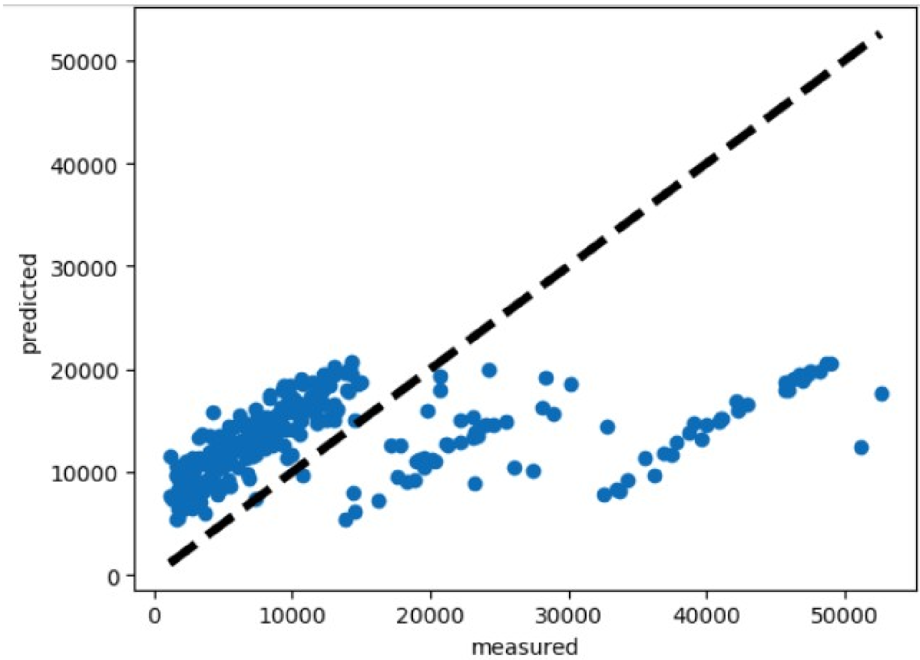
2. prédire les données d’un data set de test.

```
# y_pred = f(x_train)
y_pred = regressor.predict(x_test)
df = pd.DataFrame({'Actual': y_test.flatten(), 'Predicted': y_pred.flatten()})
print(df)
```

```
          Actual     Predicted
0     9724.53000  15837.629611
1     8547.69130  14487.653537
2    45702.02235  18706.162588
3    12950.07120  19600.798933
4     9644.25250  11334.387366
..           ...           ...
263  15019.76005  18790.825212
264   6664.68595  12876.924896
265  20709.02034  19285.274525
266  40932.42950  14945.641710
267   9500.57305  14223.551476

[268 rows x 2 columns]
```

3. Visualiser le résultat de la régression sous forme d’un graphe.

Resultat :



4. Évaluer le modèle en utilisant ces trois méthodes :

Mean Squared Error (MSE)
Root Mean Squared Error (RMSE)
Mean Absolute Error (MAE)

```
MAR = metrics.mean_absolute_error(y_test, y_pred)
MSR = metrics.mean_squared_error(y_test, y_pred)
RMSR = np.sqrt(MSR)

print("Mean Absolute Error:", MAR)
print("Mean Squared Error:", MSR)
print("Root Mean Squared Error:", RMSR)
```

```
Mean Absolute Error: 9016.00255819533
Mean Squared Error: 133189853.20376825
Root Mean Squared Error: 11540.790839616158
```

Interpréter le résultat de l'évaluation.

le modèle a une précision moyenne d'environ 9016 unités (MAE) dans la même unité que la variable cible, et la dispersion moyenne des erreurs est d'environ 11540 unités (RMSE).

partie 4 « Régression linière polynomial multiple cas de china GDP»:

1. en utilisant l'API sklearn entraîner le modèle par intermédiaire de algorithme de la régression linière et puis la régression linière polynomiale .

Linear Regression :

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error

# Load the data
df = pd.read_csv('china_gdp.csv')
print(df.describe())
# Select features and target variable
X = df[['Year']]
y = df['Value']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

# Linear Regression
linear_regressor = LinearRegression()
linear_regressor.fit(X_train, y_train)
```

Polynomial Regression :

```
# Polynomial Regression
degree = 2  # You can change the degree as needed
poly_features = PolynomialFeatures(degree=degree)
X_train_poly = poly_features.fit_transform(X_train)
X_test_poly = poly_features.transform(X_test)

poly_regressor = LinearRegression()
poly_regressor.fit(X_train_poly, y_train)
```

Resultat :

```
             Year         Value
count    55.00000  5.500000e+01
mean   1987.00000  1.437042e+12
std      16.02082  2.500085e+12
min    1960.00000  4.668518e+10
25%    1973.50000  1.395123e+11
50%    1987.00000  3.074796e+11
75%    2000.50000  1.268748e+12
max    2014.00000  1.035483e+13
```

2. prédire les données d'un data set de test pour les deux modèles .

```python
# Linear Regression
print("Linear regression")
y_pred_linear = linear_regressor.predict(X_test)
df_linear = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_linear})
print(df_linear)

# Polynomial Regression
print("polynomial regression")
y_pred_poly = poly_regressor.predict(X_test_poly)
df_poly = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_poly})
print(df_poly)
```

```
Linear regression
          Actual     Predicted
45  2.268599e+12  3.944526e+12
33  4.428746e+11  2.396492e+12
40  1.205261e+12  3.299511e+12
26  2.988058e+11  1.493472e+12
11  9.856202e+10 -4.415713e+11
2   4.668518e+10 -1.602597e+12
32  4.249341e+11  2.267489e+12
43  1.649929e+12  3.686520e+12
46  2.729784e+12  4.073529e+12
30  3.589732e+11  2.009483e+12
4   5.906225e+10 -1.344591e+12
```

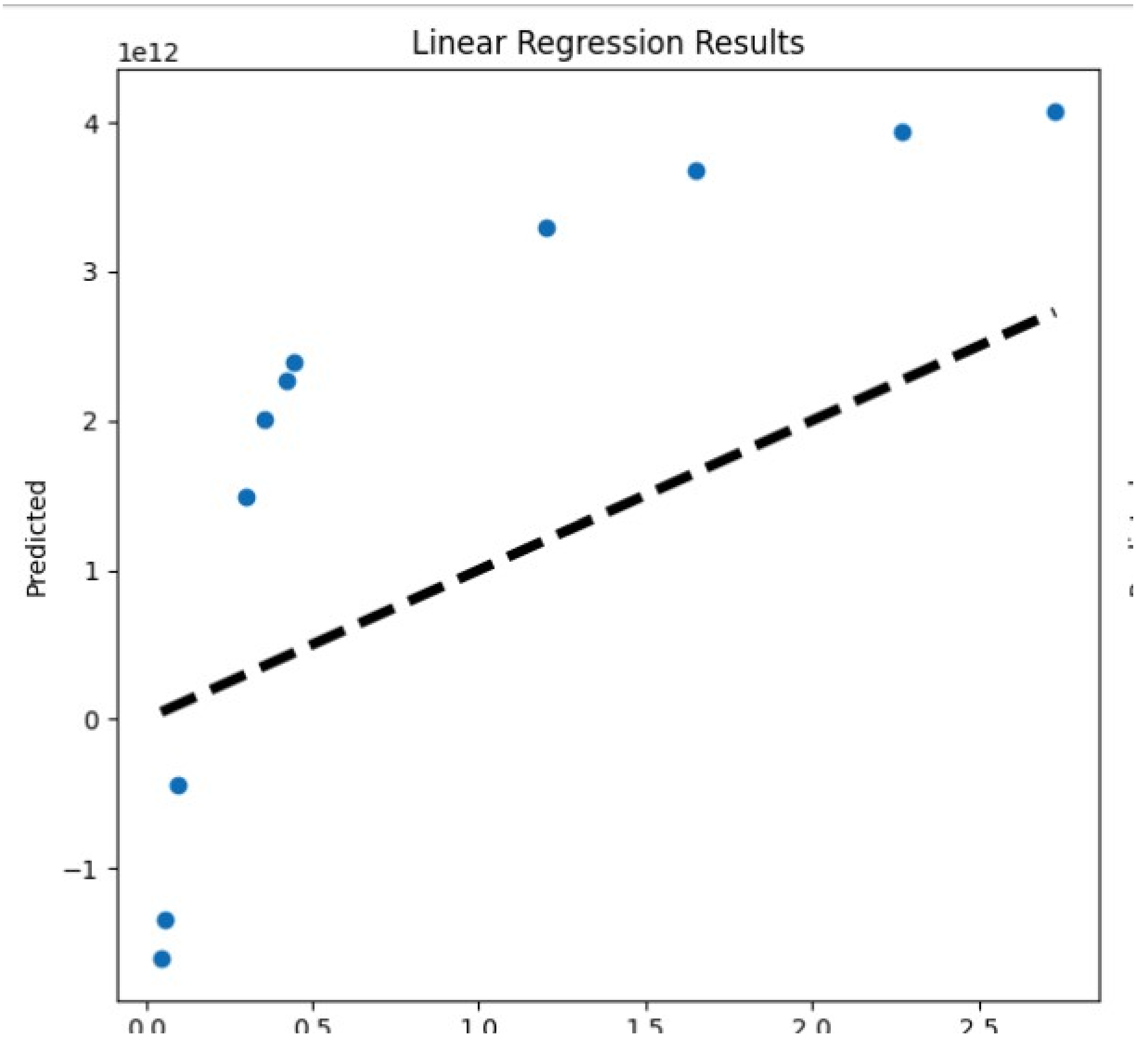
```
polynomial regression
          Actual     Predicted
45  2.268599e+12  4.210332e+12
33  4.428746e+11  9.175305e+11
40  1.205261e+12  2.612618e+12
26  2.988058e+11 -1.455611e+11
11  9.856202e+10 -2.954634e+11
2   4.668518e+10  1.007567e+12
32  4.249341e+11  7.269666e+11
43  1.649929e+12  3.532553e+12
46  2.729784e+12  4.568568e+12
30  3.589732e+11  3.845325e+11
4   5.906225e+10  6.277193e+11
```

3. Visualiser le résultat de la régression sous forme d’un graphe des deux modèles.

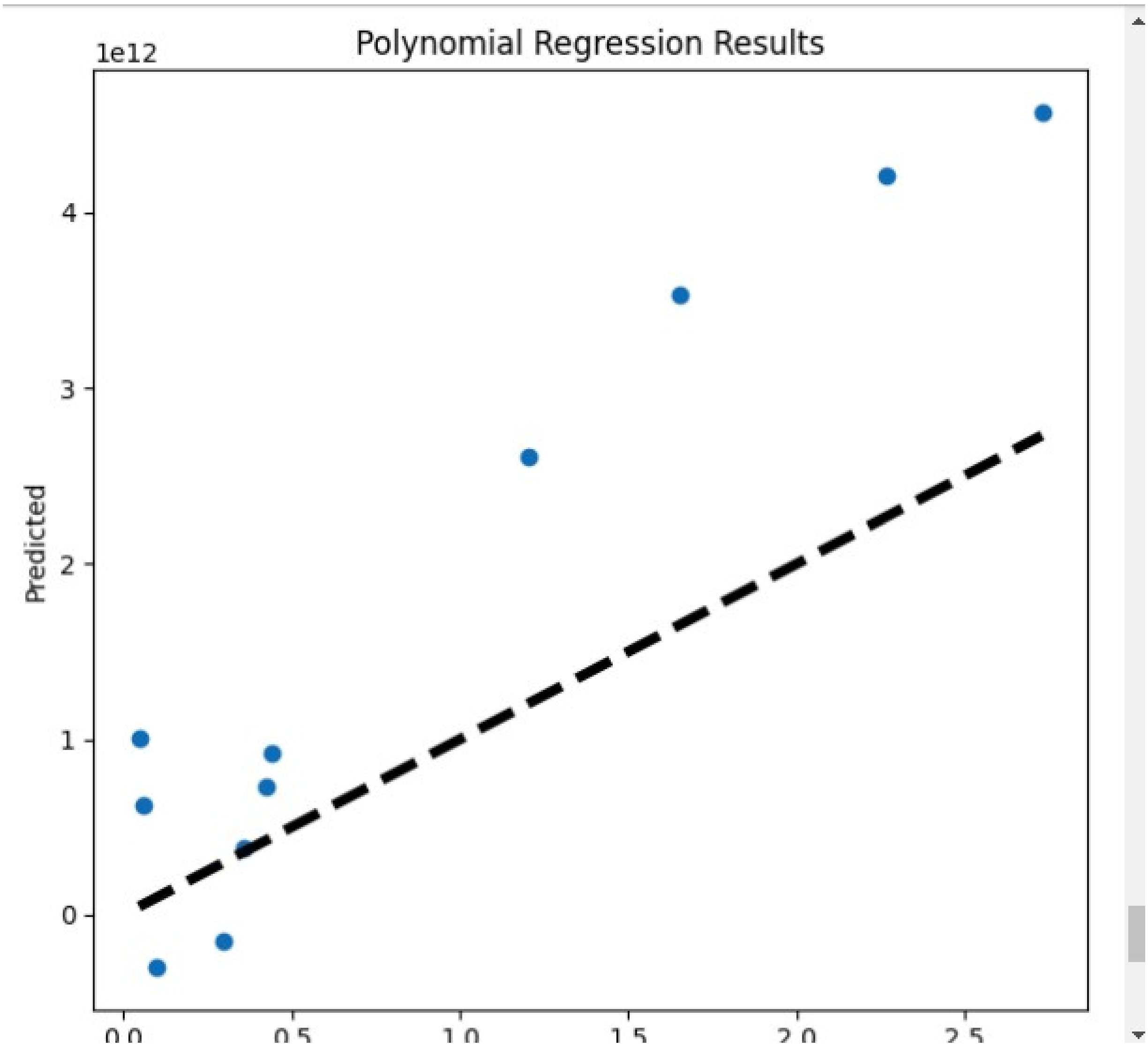
```
import matplotlib.pyplot as plt

# Linear Regression
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.scatter(y_test, y_pred_linear)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=4)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Linear Regression Results')

# Polynomial Regression
plt.subplot(1, 2, 2)
plt.scatter(y_test, y_pred_poly)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=4)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Polynomial Regression Results')

plt.tight_layout()
plt.show()
```

Resultat :

Linear Regression :



Polynomial Regression :



4. Évaluer les deux modèles en utilisant ces trois méthodes :
Mean Squared Error (MSE)
Root Mean Squared Error (RMSE)
Mean Absolute Error (MAE)

```python
from sklearn import metrics

# Linear Regression Metrics
linear_MSE = metrics.mean_squared_error(y_test, y_pred_linear)
linear_RMSE = np.sqrt(linear_MSE)
linear_MAE = metrics.mean_absolute_error(y_test, y_pred_linear)

print("Linear Regression Metrics:")
print("Mean Squared Error (MSE):", linear_MSE)
print("Root Mean Squared Error (RMSE):", linear_RMSE)
print("Mean Absolute Error (MAE):", linear_MAE)
print()

# Polynomial Regression Metrics
poly_MSE = metrics.mean_squared_error(y_test, y_pred_poly)
poly_RMSE = np.sqrt(poly_MSE)
poly_MAE = metrics.mean_absolute_error(y_test, y_pred_poly)

print("Polynomial Regression Metrics:")
print("Mean Squared Error (MSE):", poly_MSE)
print("Root Mean Squared Error (RMSE):", poly_RMSE)
print("Mean Absolute Error (MAE):", poly_MAE)
```

Resultat :

```
Linear Regression Metrics:
Mean Squared Error (MSE): 2.6811931196364024e+24
Root Mean Squared Error (RMSE): 1637434920733.1577
Mean Absolute Error (MAE): 1580448121034.8318

Polynomial Regression Metrics:
Mean Squared Error (MSE): 1.326631094098924e+24
Root Mean Squared Error (RMSE): 1151794727414.1013
Mean Absolute Error (MAE): 930970716433.7007
```

Interpréter le résultat de l'évaluation.

Linear

MAE Cela représente l'erreur absolue moyenne entre les prédictions du modèle et les valeurs réelles

La RMSE donne une indication de la dispersion des erreurs et, dans ce cas, elle est assez élevée.

polynomial

(MAE): Le modèle a une précision moyenne d'environ 931
(RMSE): La dispersion moyenne des erreurs est d'environ 1.15 trillion (1.15 x 10^12)