Estimate the China gdp based on sigmod function

November 15, 2022

The aim of this experiment is to compute the GDP of China using the sigmoid function and compare the results with a polynomial regression model. The data set for this experiment can be downloaded form this link

Tools To work with this experiment, multiple libraries and frameworks need to be installed. The following is a list of them.

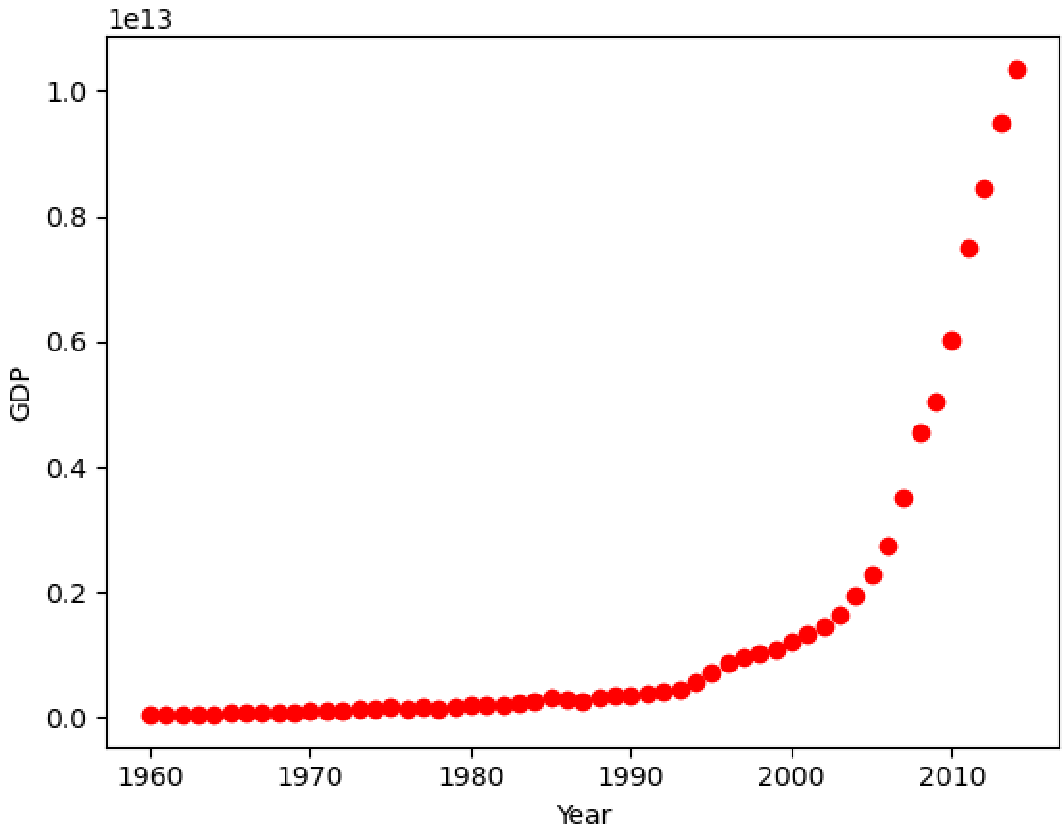
- Pandas
- Numpy
- Matplotlib
- scikit-learn

  Note: If the slope (intercept) is less than 0.7 or the line is curvy, then the system needs a non-linear model. The data used contains only one independent variable, the year, and one target variable, the GDP value.

Let us first sketch the relationship between the year and the value. and according to the slope, the function will select

[6]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

dataset = pd.read_csv("dataset.csv")
x, y = (dataset["Year"].values, dataset["Value"].values)
plt.plot(x, y, 'ro')
plt.ylabel('GDP')
plt.xlabel('Year')
```

[6]:
```
Text(0.5, 0, 'Year')
```



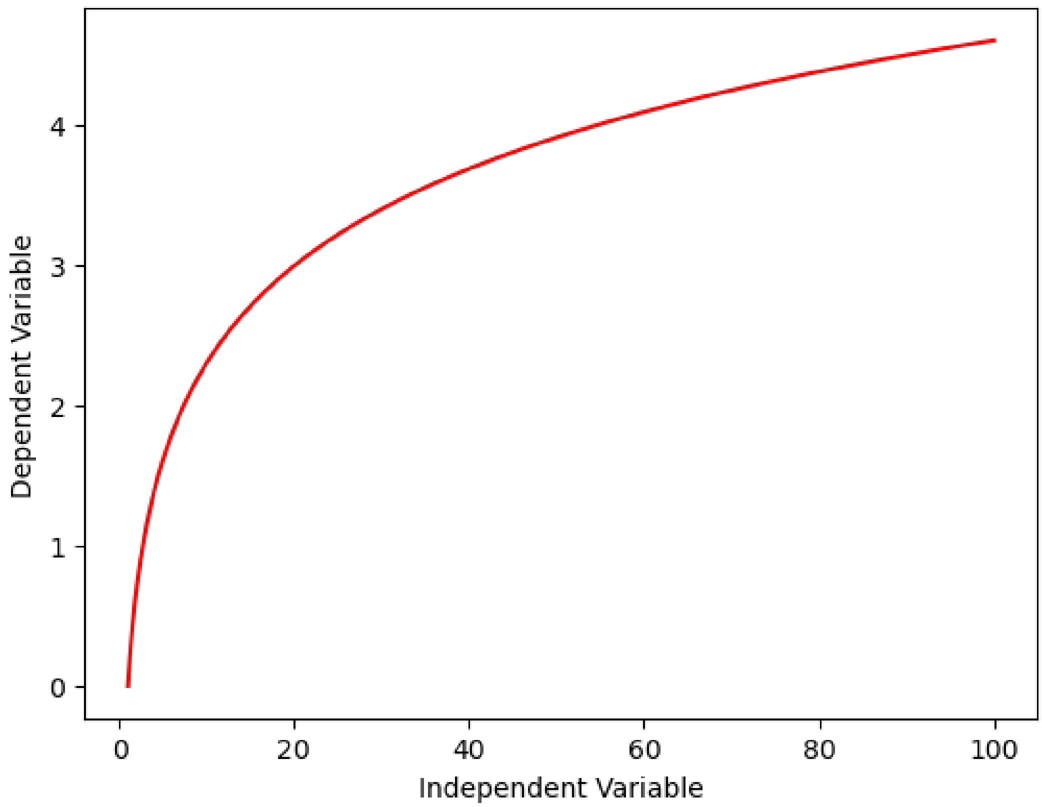
Non-linear functions can be logarithms, exponentials, ... etc

1- Logarithms

$$y = log(x)$$

[16]:
```
x = np.arange(1, 100, 0.01)
y = np.log(x)
plt.plot(x,y, 'r')
plt.ylabel('Dependent Variable')
plt.xlabel('Independent Variable')
```

[16]: Text(0.5, 0, 'Independent Variable')

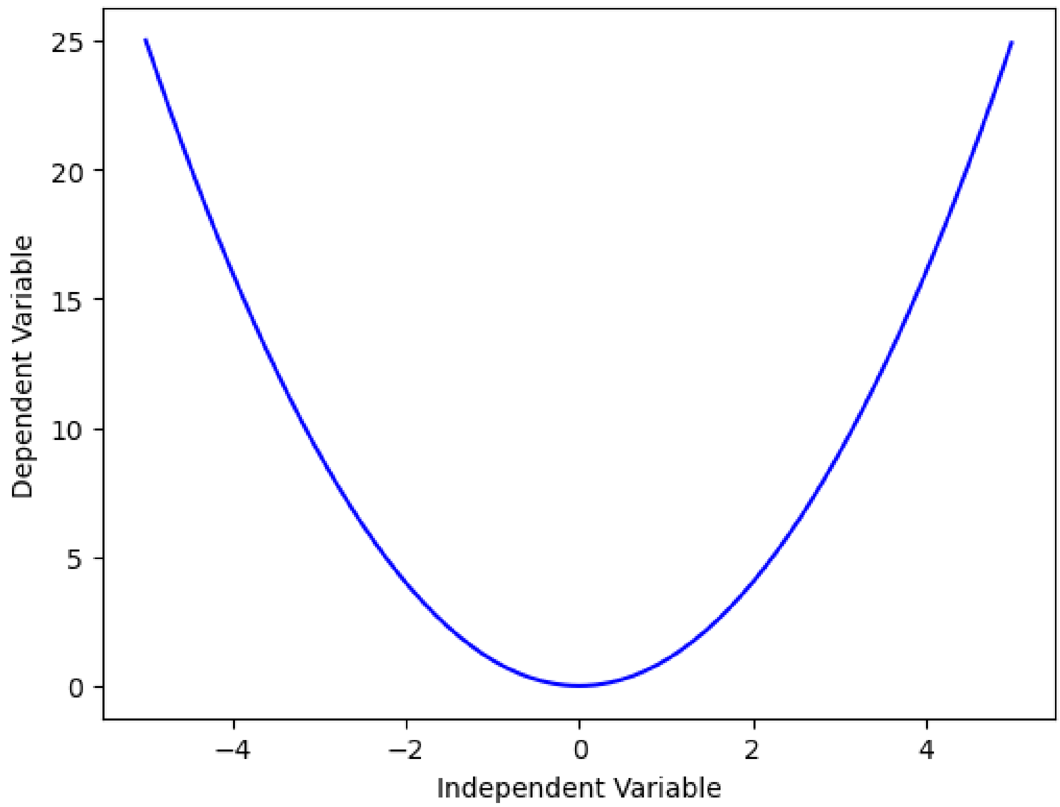


2- Quadratic

$$y = x^2$$

[27]:
```
x = np.arange(-5, 5, 0.01)
y = x**2

plt.plot(x, y, 'b')
plt.ylabel('Dependent Variable')
plt.xlabel('Independent Variable')
```

[27]: `Text(0.5, 0, 'Independent Variable')`

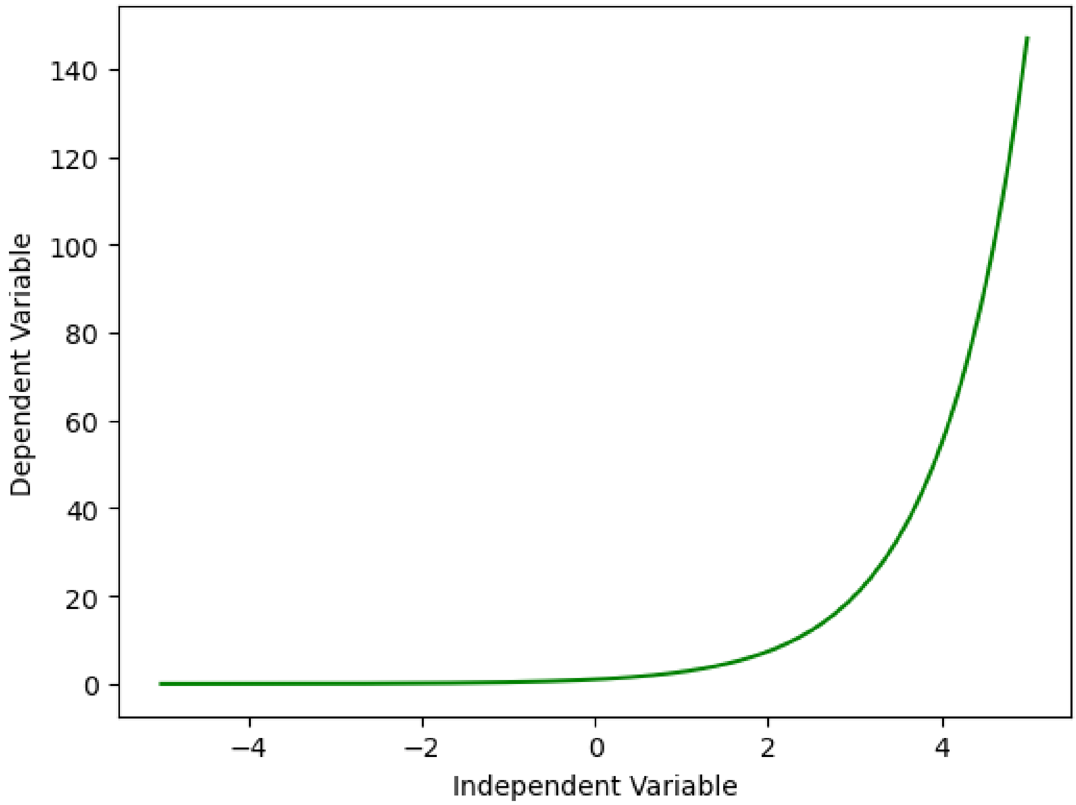


3- Exponential

$$y = e^x$$

[29]:
```
x = np.arange(-5, 5, 0.01)
y = np.exp(x)

plt.plot(x, y, 'g')
plt.ylabel('Dependent Variable')
plt.xlabel('Independent Variable')
```

[29]:
```
Text(0.5, 0, 'Independent Variable')
```



4- Sigmoidal/Logistic

$$\frac{1}{1+e^{\beta_1(x-\beta_2)}}$$

$$\beta_1 Controlsthecurve'ssteepnes$$

$$\beta_2 Slidesthecurveonthex-axis$$

Define a sigmoid function

[44]:
```
def sigmoid(x, Beta_1, Beta_2):
     y = 1 / (1 + np.exp(-Beta_1*(x-Beta_2)))
     return y
```

Normalize our data

[45]:
```
x_data, y_data = (dataset["Year"].values, dataset["Value"].values)
xdata = x_data / max(x_data)
ydata = y_data / max(y_data)
```

Split data into train/test

[64]:
```
msk = np.random.rand(len(dataset)) < 0.8
train_x = xdata[msk]
test_x = xdata[~msk]
train_y = ydata[msk]
test_y = ydata[~msk]
```

find best betas accouring to the train_x and train_y (x,y) using curve_fit function

[59]:
```
from scipy.optimize import curve_fit
betas, pcov = curve_fit(sigmoid, train_x, train_y)
betas
```

[59]:
```
array([686.71406377,   0.99728684])
```

Compute the Predicted y base on the proposed function

[66]:
```
Predicted_y = sigmoid(test_x, *betas)
```

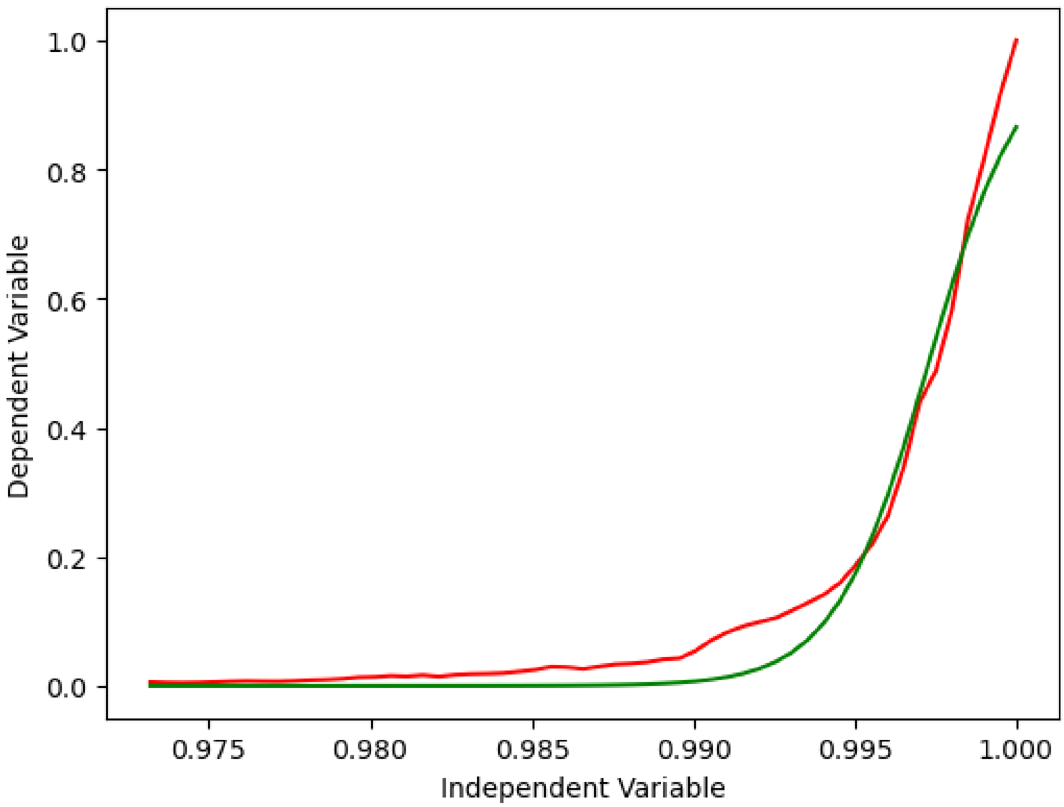
Result

[67]:
```
from sklearn.metrics import r2_score
print("R2-score: %.2f" % r2_score(Predicted_y , test_y) )
```

```
R2-score: 0.98
```

[69]:
```
plt.plot(xdata, ydata, 'r')
y = sigmoid(xdata, *betas)
plt.plot(xdata, y, 'g' )
plt.ylabel('Dependent Variable')
plt.xlabel('Independent Variable')
```

[69]:
```
Text(0.5, 0, 'Independent Variable')
```

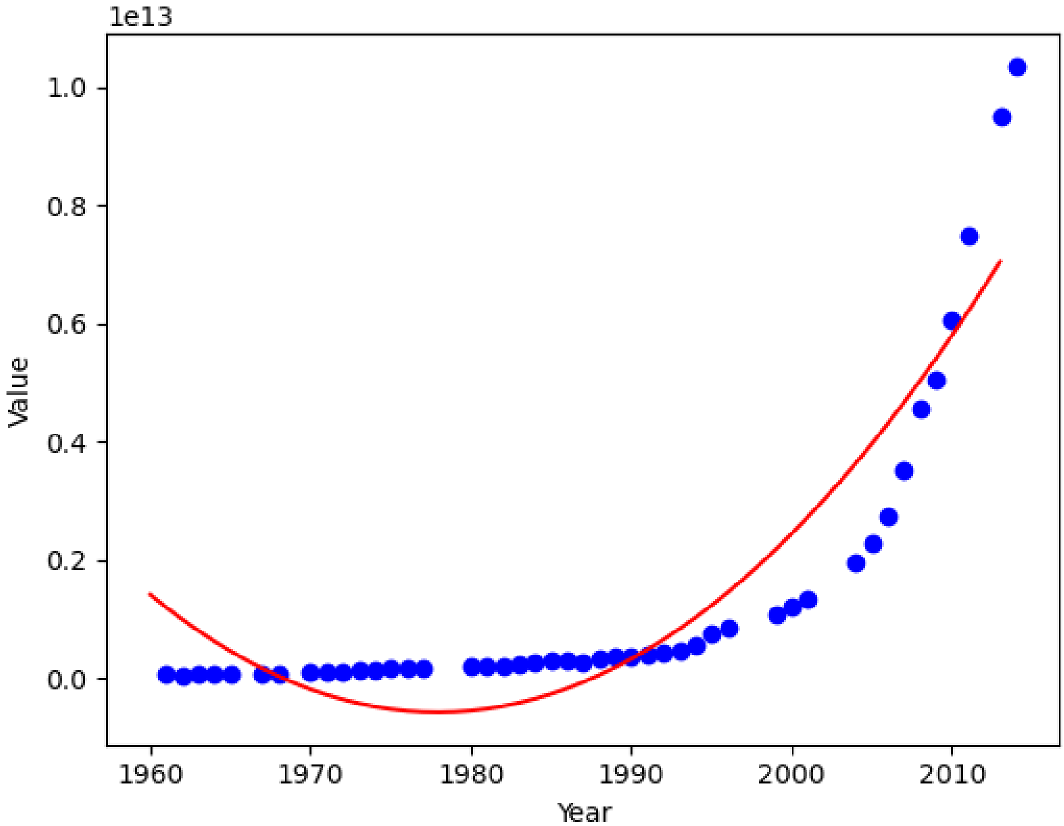


Polynomial regression

[71]:
```
dataset = pd.read_csv('dataset.csv')
msk = np.random.rand(len(dataset)) < 0.8
train = dataset[msk]
test = dataset[~msk]
from sklearn.preprocessing import PolynomialFeatures
from sklearn import linear_model
train_x = np.asanyarray(train[['Year']])
train_y = np.asanyarray(train[['Value']])

test_x = np.asanyarray(test[['Year']])
test_y = np.asanyarray(test[['Value']])
poly = PolynomialFeatures(degree=2)

# make the scalling and fed them to poly system
train_x_poly = poly.fit_transform(train_x)

# after convert them linearn using linear to predict
clf = linear_model.LinearRegression()
predict_y_ = clf.fit(train_x_poly, train_y)
```

```
# The coefficients
print ('Coefficients: ', clf.coef_)
print ('Intercept: ',clf.intercept_)
plt.scatter(train.Year, train.Value,  color='blue')
XX = np.arange(1960, 2014, 1)
yy = clf.intercept_[0]+ clf.coef_[0][1]*XX+ clf.coef_[0][2]*np.power(XX, 2)
plt.plot(XX, yy, '-r' )
plt.xlabel("Year")
plt.ylabel("Value")

from sklearn.metrics import r2_score

test_x_poly = poly.transform(test_x)

predict_y_ = clf.predict(test_x_poly)

print("Mean absolute error: %.2f" % np.mean(np.absolute(predict_y_ - test_y)))
print("Residual sum of squares (MSE): %.2f" % np.mean((predict_y_ - test_y) **␣
 ↪2))
print("R2-score: %.2f" % r2_score(test_y,predict_y_ ) )
```

```
Coefficients:  [[ 0.00000000e+00 -2.45363725e+13  6.20256769e+09]]
Intercept:  [2.42649132e+16]
Mean absolute error: 989078789402.62
Residual sum of squares (MSE): 1288032271814066496864256.00
R2-score: 0.78
```



Conclusion The main objective of this experiment is to develop a model based on the sigmoid function. The obtained result is compared with polynomial regression, and the results show that using a sigmoid is more promising than a polynomial. We achieved 98% accuracy using the sigmoid function and 78% accuracy using Pynomail.