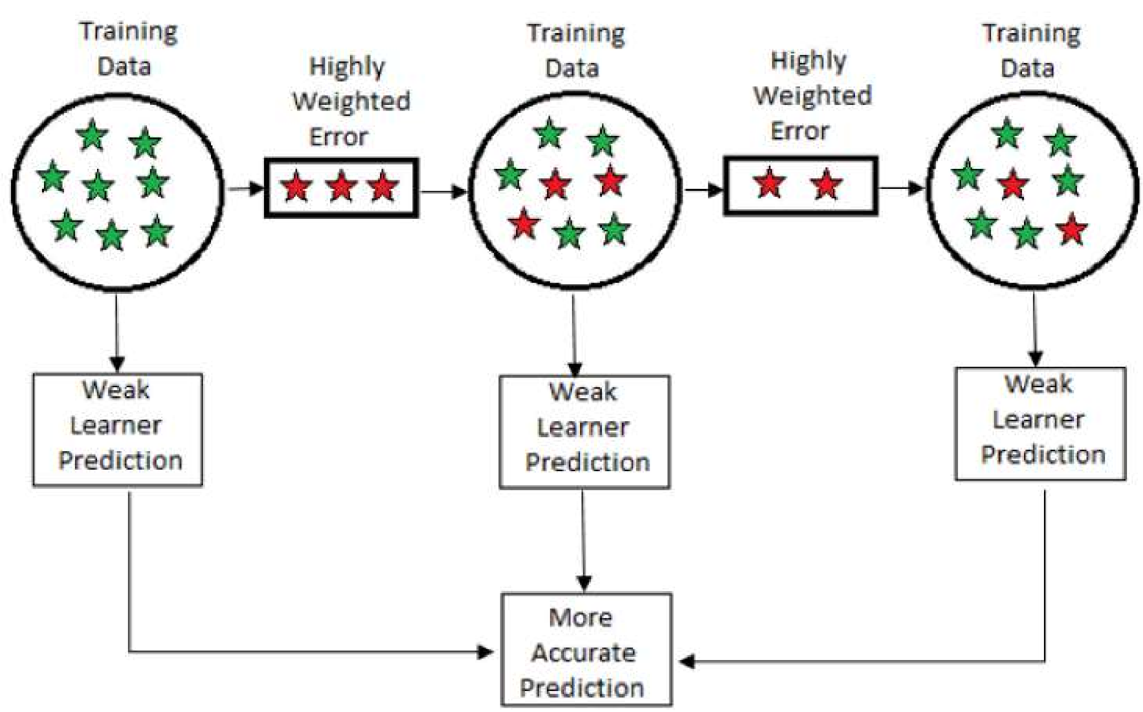
Gradient Boosting

- Is a popular machine learning algorithm that works by combining multiple weak learners, typically decision trees, to create a strong predictive model. It builds the model in a stage-wise fashion, where each new model corrects the errors made by the previous ones.
- Is effective because it learns from its mistakes iteratively, gradually improving the model's predictive performance. It's widely used in various machine learning tasks, including classification and regression, and is known for its robustness and ability to handle complex datasets. However, it may require careful tuning of hyperparameters and can be computationally expensive.

In [17]:
```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
img = mpimg.imread('image.png')
plt.figure(figsize=(10, 10))  # Adjust the width and height as needed
plt.imshow(img)
plt.axis('off')  # Turn off axis numbers and ticks
plt.show()
```



✨ Import Libraries

In [15]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeRegressor
```

```python
from sklearn.ensemble import GradientBoostingRegressor
import os
os.system("cls")
```

Out[15]: 0

✨ Implementation of Gradient Boosting From Skratch

In [2]:
```python
class Gradient_Boosting_Regressor :
    def __init__(self , num_of_models = 100, learning_rate = 0.1 ,max_depth = 2 ):
        self.num_of_models = num_of_models
        self.learning_rate = learning_rate      # fixeed for all models
        self.models = []     # list contsins the models we used
        self.max_depth = max_depth
        self.y = None
    def fit (self , X , y):
        self.y = y
        initial_predetion = np.mean(y)      # mean for y
        y_hat = np.ones_like (y) * initial_predetion   # mean as vector for all data p

        for _ in range (self.num_of_models):
            error = y - y_hat
            model = DecisionTreeRegressor(max_depth=self.max_depth)
            model.fit(X,error)
            predicted_error = model.predict(X)                 # predict error
            y_hat+= self.learning_rate*predicted_error         # y hat (we want to pre

            self.models.append(model)

    def predict(self , X):    # to predict new data point
        # sum of initial prediction (mean) and error of each model multiply of learnin
        y_hat = np.mean(self.y)    # initail value
        for model in self.models:
            y_hat += self.learning_rate * model.predict(X)
        return y_hat
```

✨ Loading Data

In [3]:
```python
data = pd.read_csv("data.csv")
data
```

Out[3]:

	X	y
0	0.093949	0.639861
1	0.101092	0.100920
2	0.195939	0.194688
3	0.301127	0.296597
4	0.355180	0.347759
...	...	...
75	4.818314	-0.043969
76	4.882297	-0.985600
77	4.883805	-0.985344
78	4.893092	-0.983718
79	4.941869	-0.973785

80 rows × 2 columns

✨ Split Data (X , y)

In [4]:
```
X = data.drop("y", axis = 1).values
y = data["y"].values
```

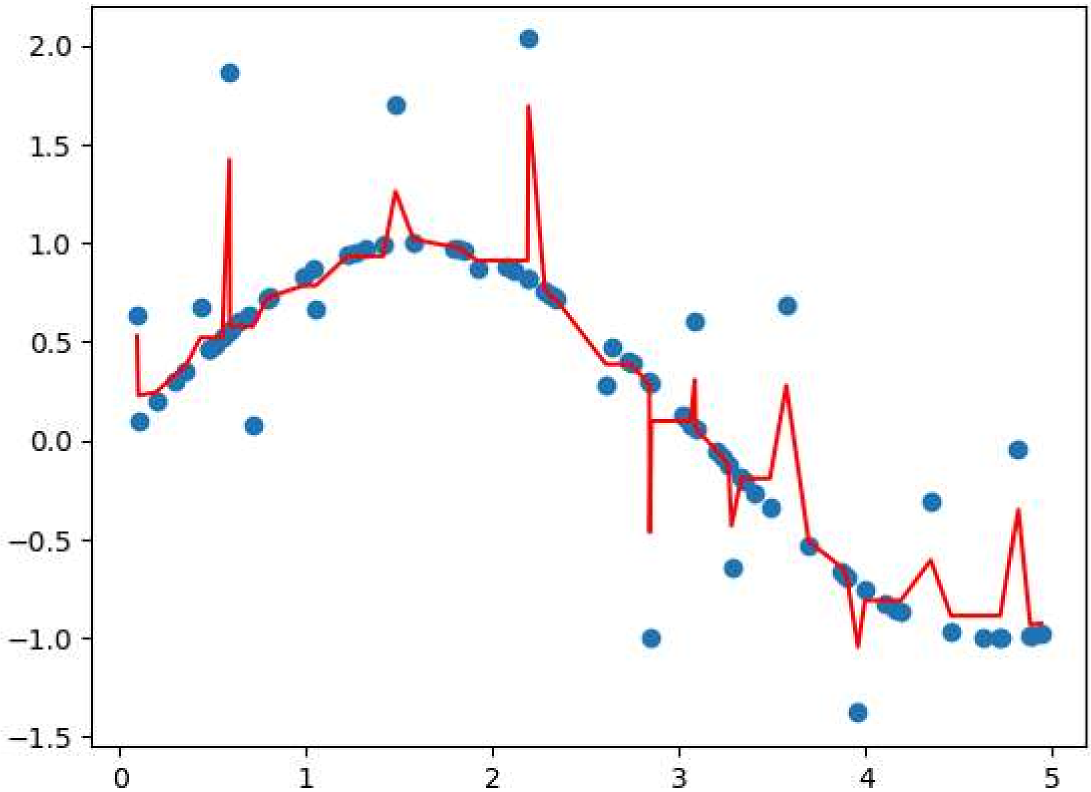
✨ Use Model Which we built from Sktarch

In [5]:
```
model = Gradient_Boosting_Regressor(num_of_models=100)
model.fit(X,y)
```

✨ Predict and Visulaization

In [6]:
```
y_pred = model.predict(X)
plt.scatter(X,y)
plt.plot(X,y_pred,c = "r")
```

Out[6]:
```
[<matplotlib.lines.Line2D at 0x18a2854fb50>]
```



🕵️ Note :

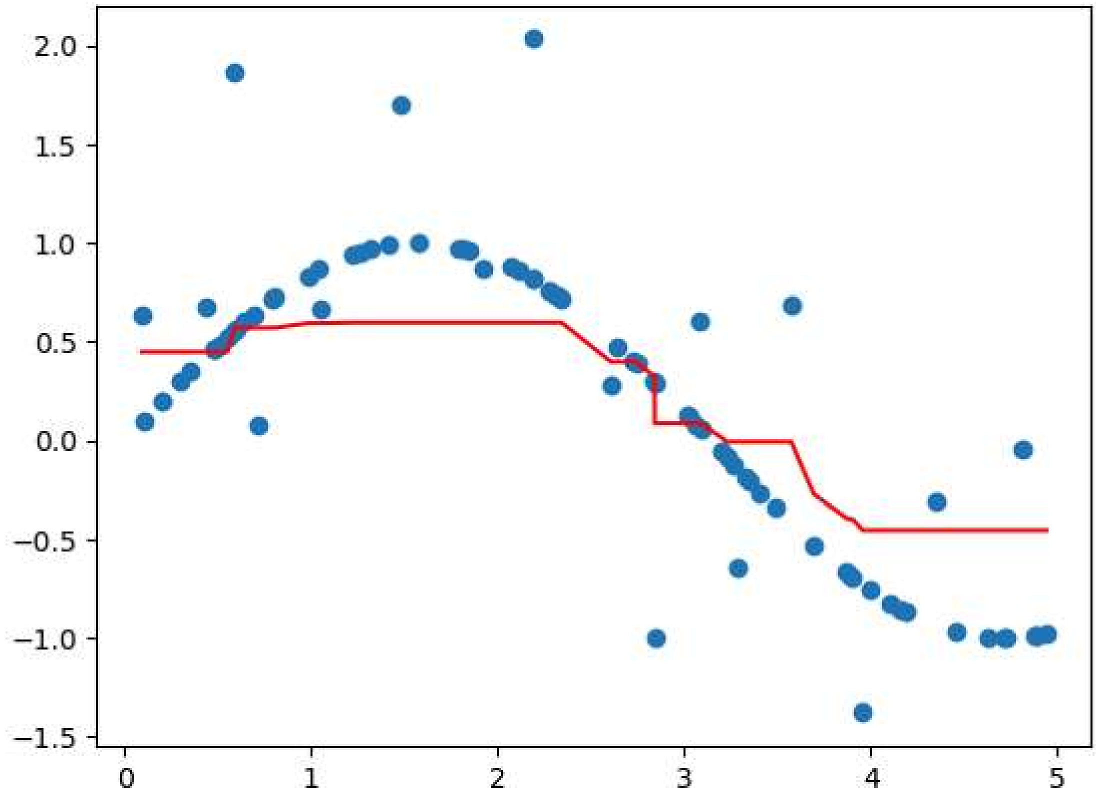
- There is overfitting we can reduce it by reducing the value of learning_rate

✨ Model after reducing learning_rate

In [7]:
```
model = Gradient_Boosting_Regressor(num_of_models=100 ,learning_rate=0.01)
model.fit(X,y)
```

In [8]:
```
y_pred = model.predict(X)
plt.scatter(X,y)
plt.plot(X,y_pred,c = "r")
```

Out[8]:
```
[<matplotlib.lines.Line2D at 0x18a28608bd0>]
```



🕵️ Note :

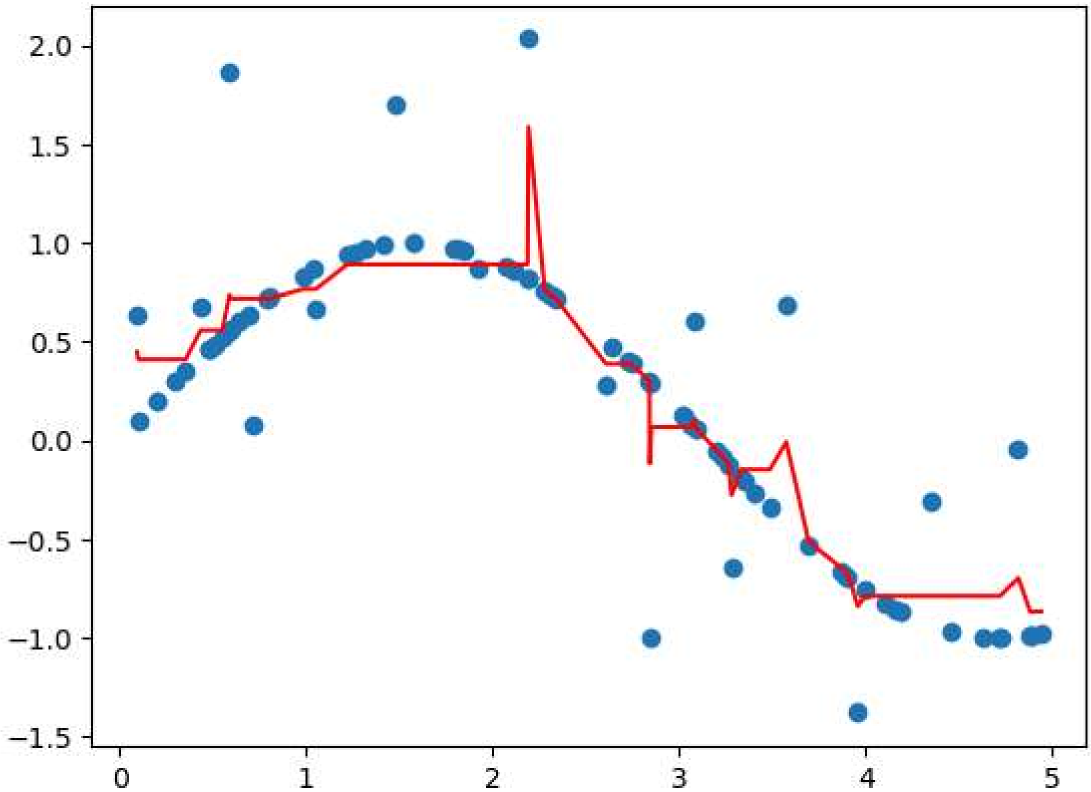
- There is underfitting we can reduce it by adding more models (weak learners)

✨ Model after Maximize the number of models

In [9]:
```
model = Gradient_Boosting_Regressor(num_of_models=400 ,learning_rate=0.01)
model.fit(X,y)
```

In [10]:
```
y_pred = model.predict(X)
plt.scatter(X,y)
plt.plot(X,y_pred,c = "r")
```

Out[10]:
```
[<matplotlib.lines.Line2D at 0x18a286a8550>]
```



🕵 Note :

- The model become able to generalize better
  - we can use best value for num_of_models and learning_rate using (parameter tuning)

✨ Use built in algorithm from sikit learn

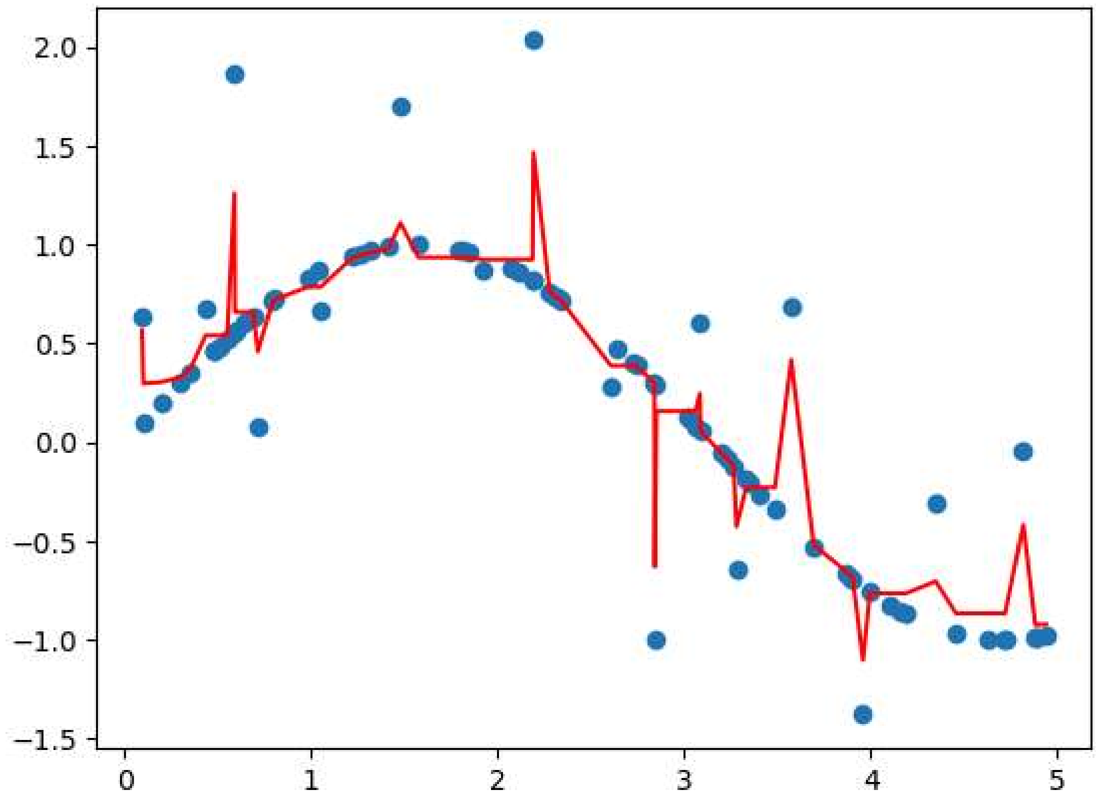
In [11]:
```
model = GradientBoostingRegressor(n_estimators= 400 , learning_rate= 0.01 )
model.fit(X,y)
```

Out[11]:
```
GradientBoostingRegressor
GradientBoostingRegressor(learning_rate=0.01, n_estimators=400)
```

✨ Predict and visualization

In [12]:
```
y_pred = model.predict(X)
plt.scatter(X,y)
plt.plot(X,y_pred,c = "r")
```

Out[12]:
```
[<matplotlib.lines.Line2D at 0x18a283f3090>]
```



- Thanks 💝