

Machine Learning crash course

(Part-2)

Ahmed Hammad

*Introduction to machine learning,
linear and non-linear regression models*

Introduction to ML

Artificial intelligence

A program that can sense, act and adopt with the user

Machine learning

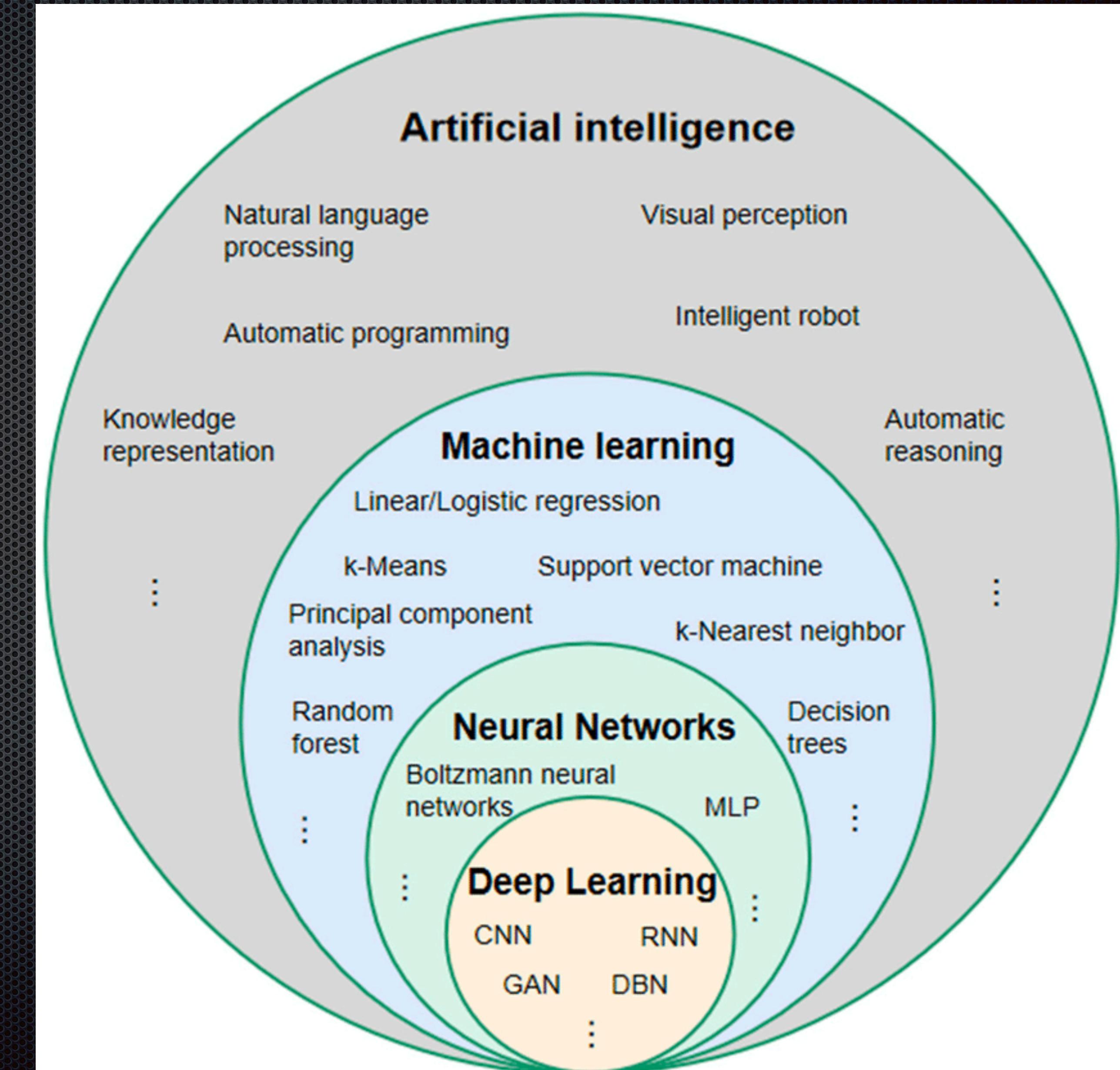
Algorithms whose performance improves as they are exposed to more data over time

Deep learning

A subset of machine learning algorithms in which the algorithms learns deeply hidden features into the data

Taken from

https://www.researchgate.net/figure/Relationship-between-artificial-intelligence-machine-learning-neural-network-and-deep_fig3_354124420



What is machine learning ?

Just remind you with ChatGPT answer

A Hi GPT

 Hello again! How can I assist you today?

A What is machine learning algorithm in one sentence?

 A machine learning algorithm is a set of mathematical instructions that enables a computer to learn patterns from data and make predictions or take actions based on those patterns.

Introduction to ML

Machine Learning Algorithms consist of two main parts: Training and Test

Just like a baby in kindergarten

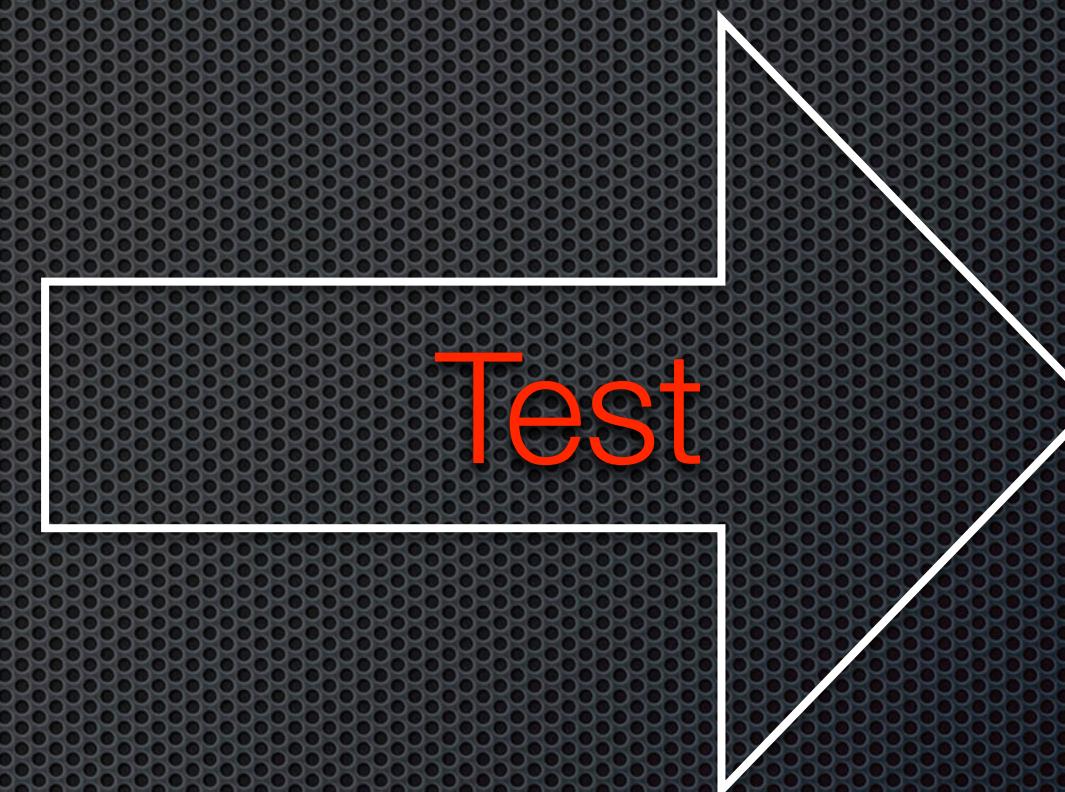
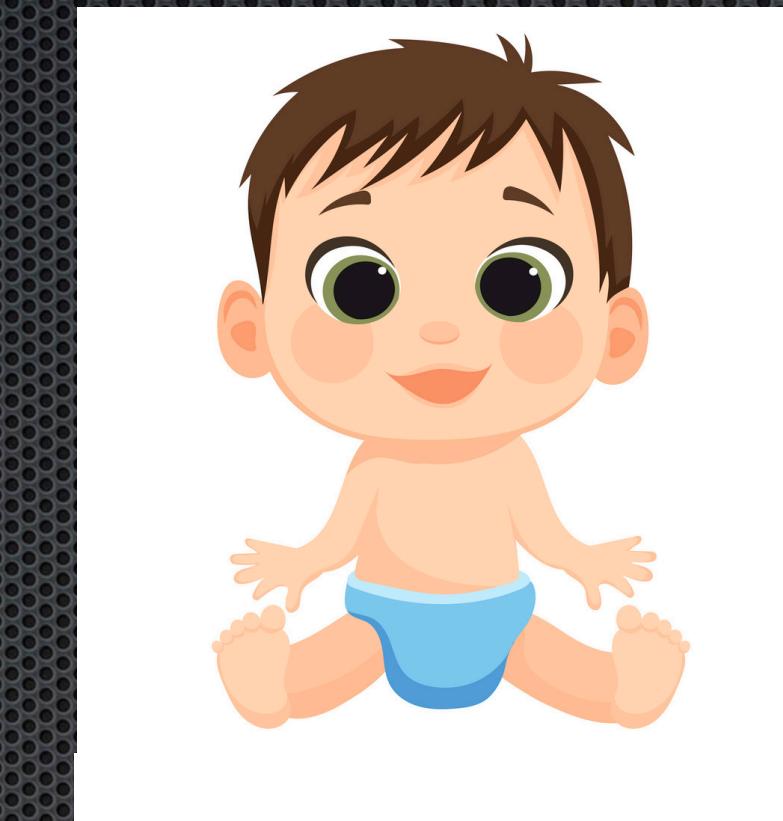
$$1+1=2$$

$$1+2=3$$

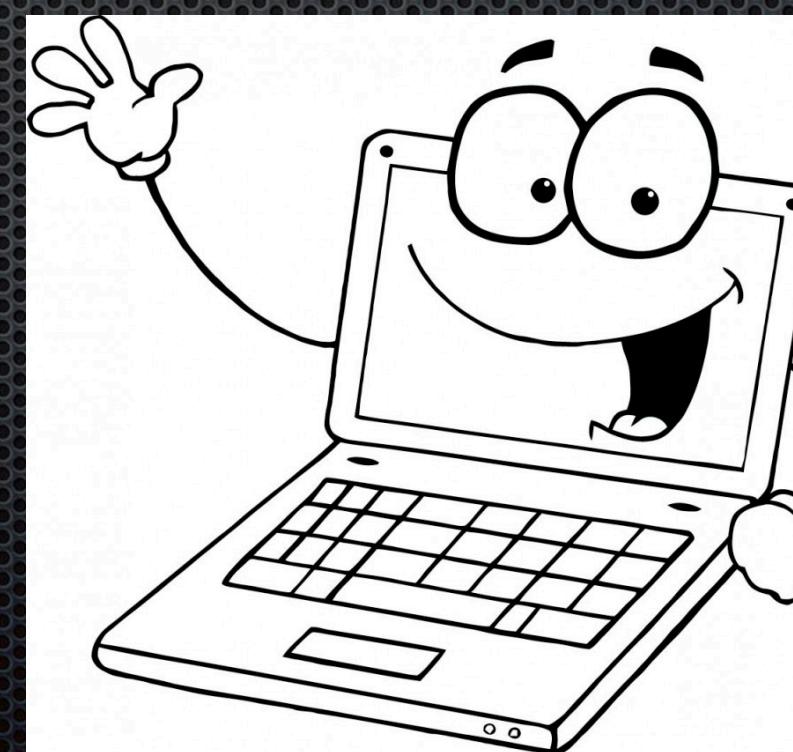
.

.

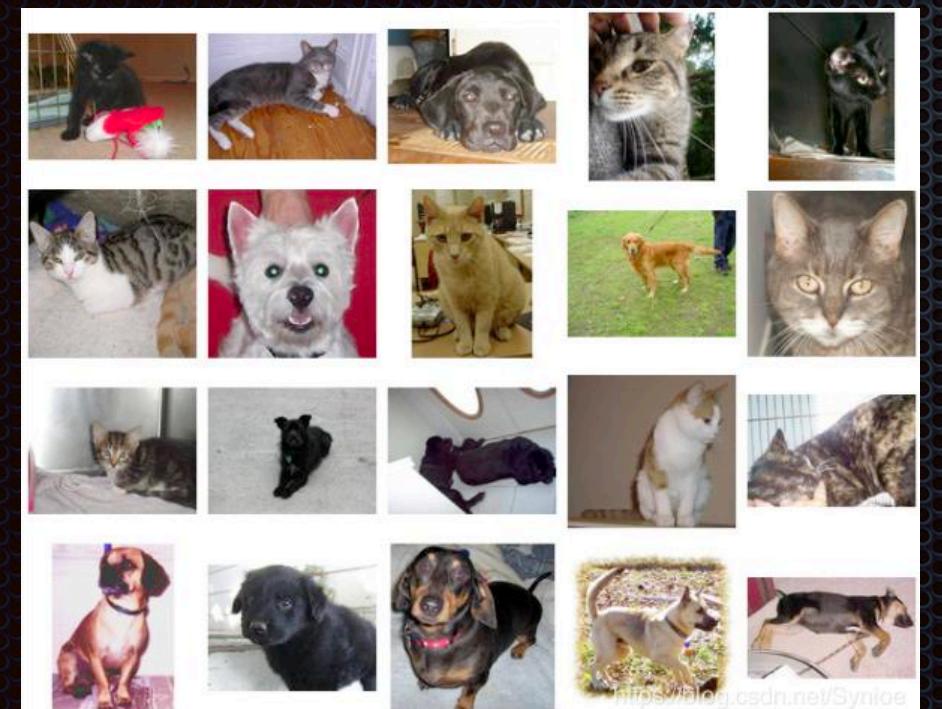
$$1+9=10$$

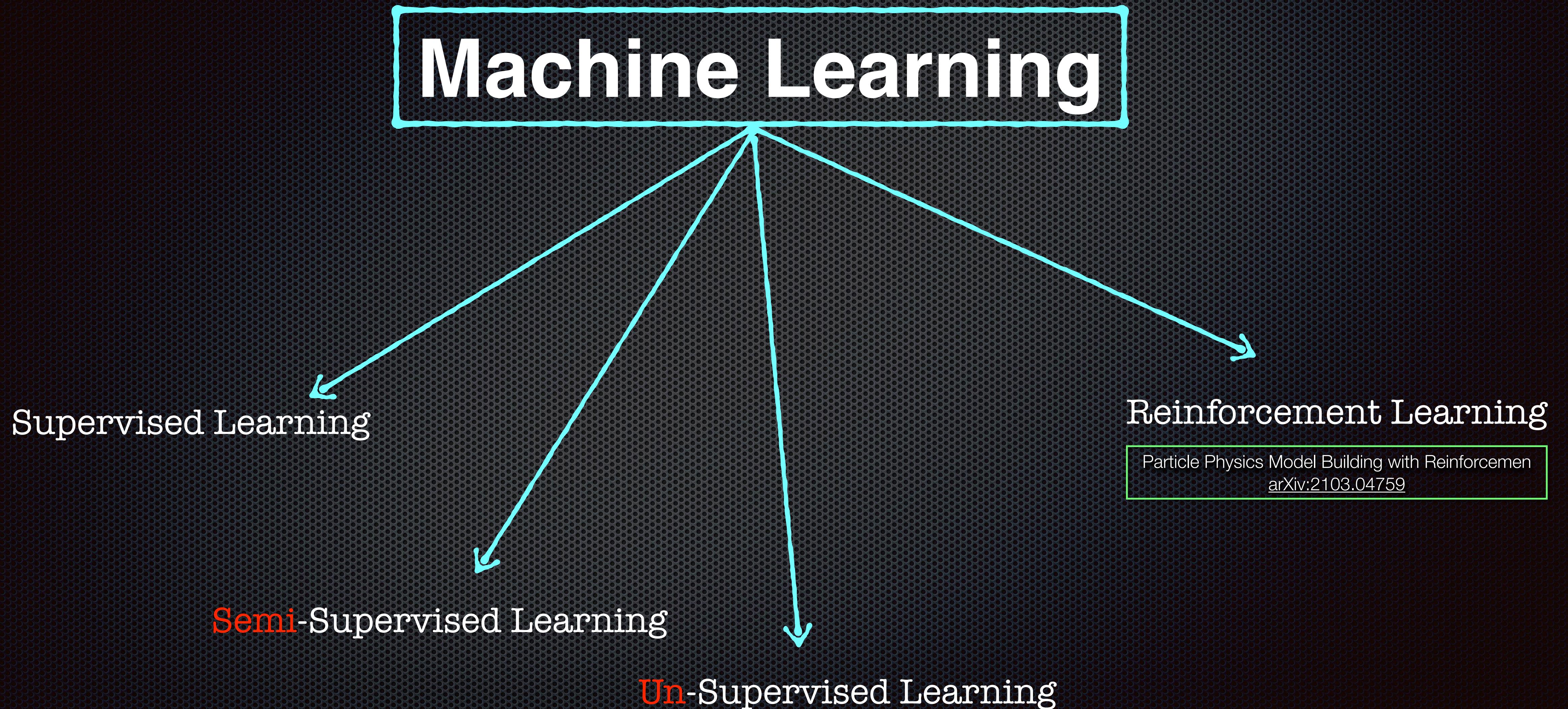


$$2+5=?$$



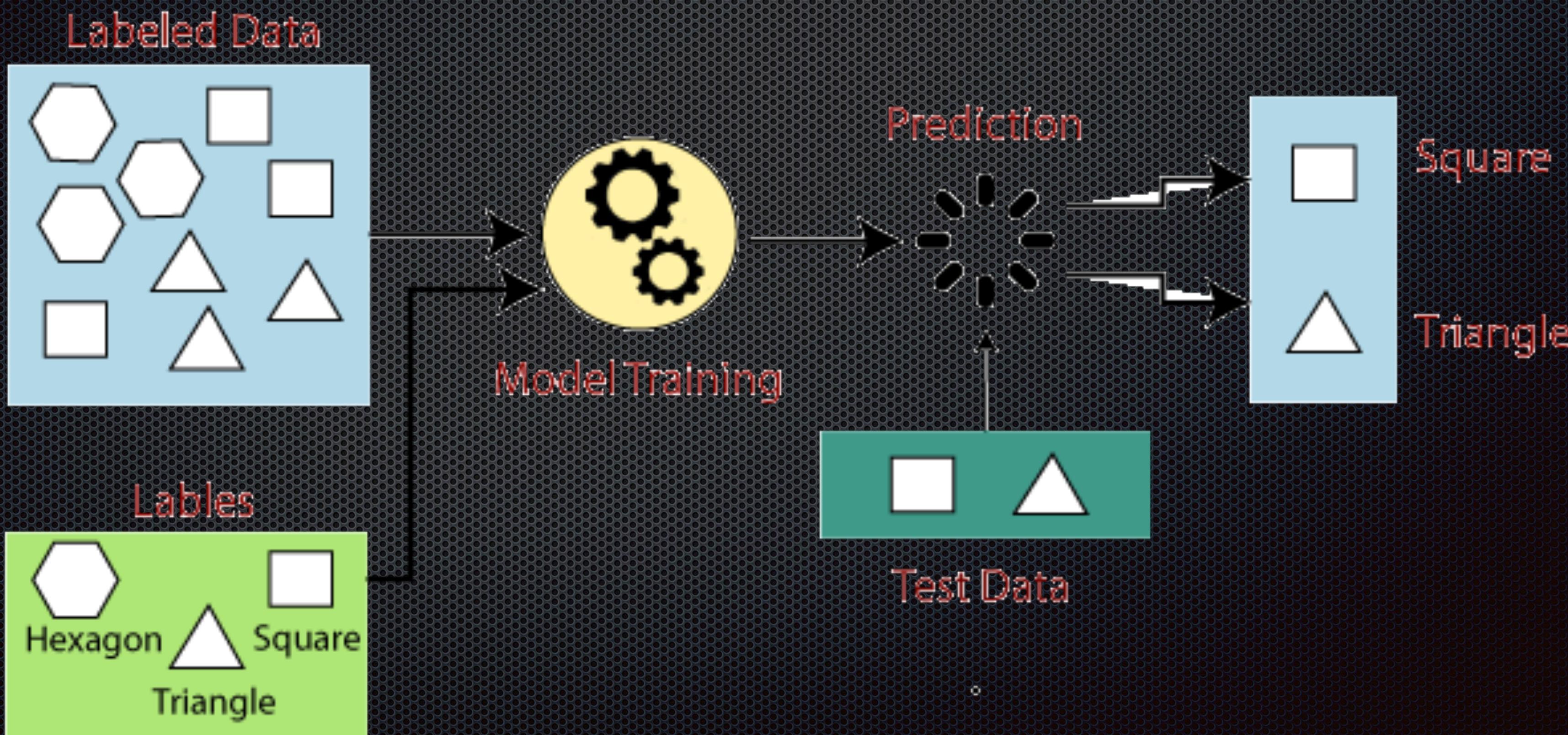
?





Supervised Learning

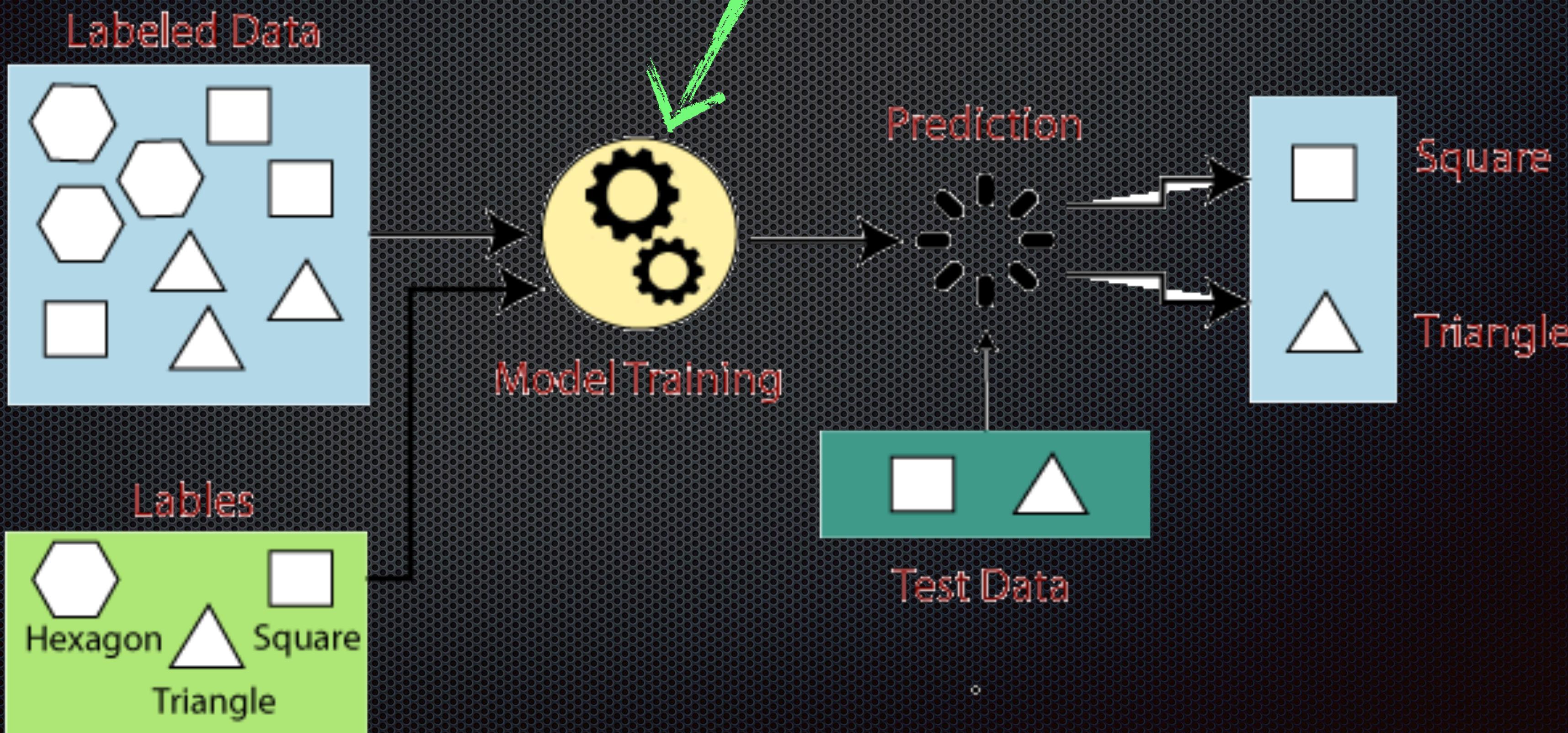
Modeling the relationship between measured features of data and some label associated with the data; once this model is determined, it can be used to apply labels to new, unknown data.



Supervised Learning

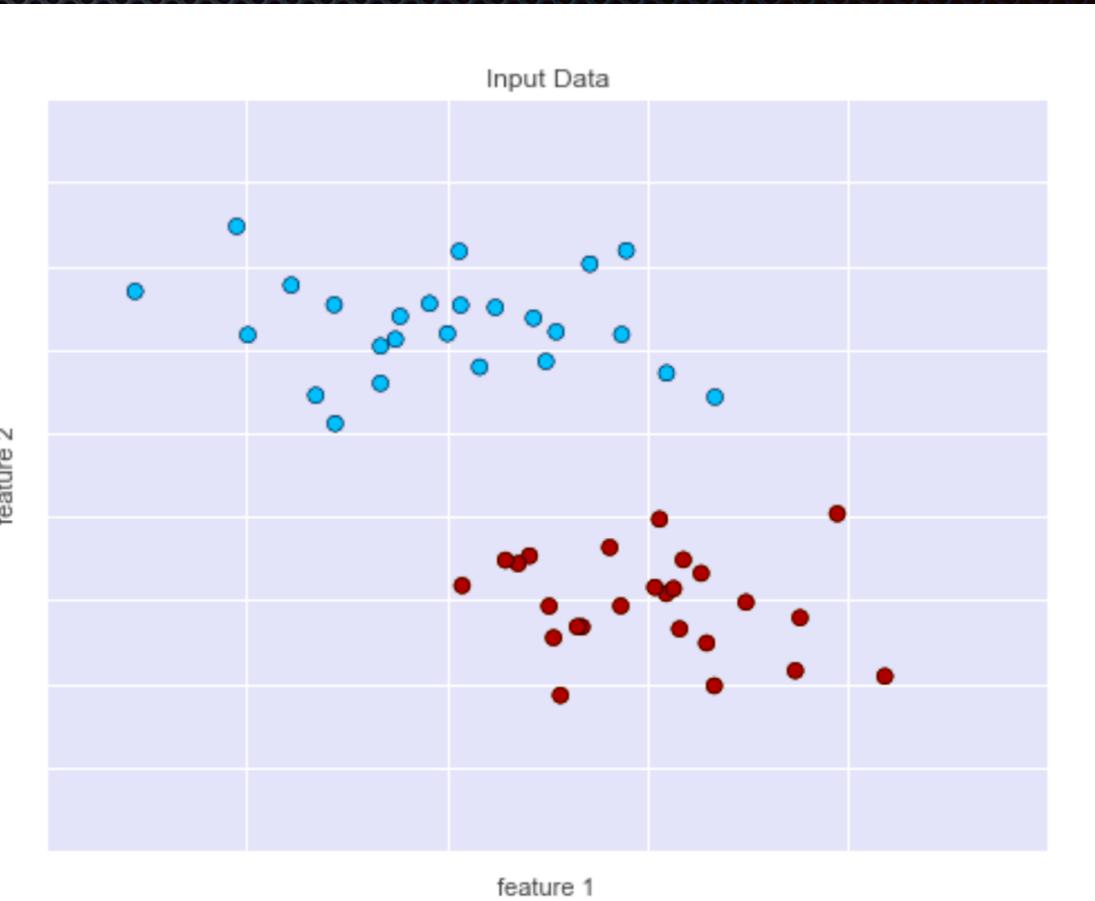
Modeling
label as

For the Supervised learning the complexity is how to train your model to find the best classifier for the given data

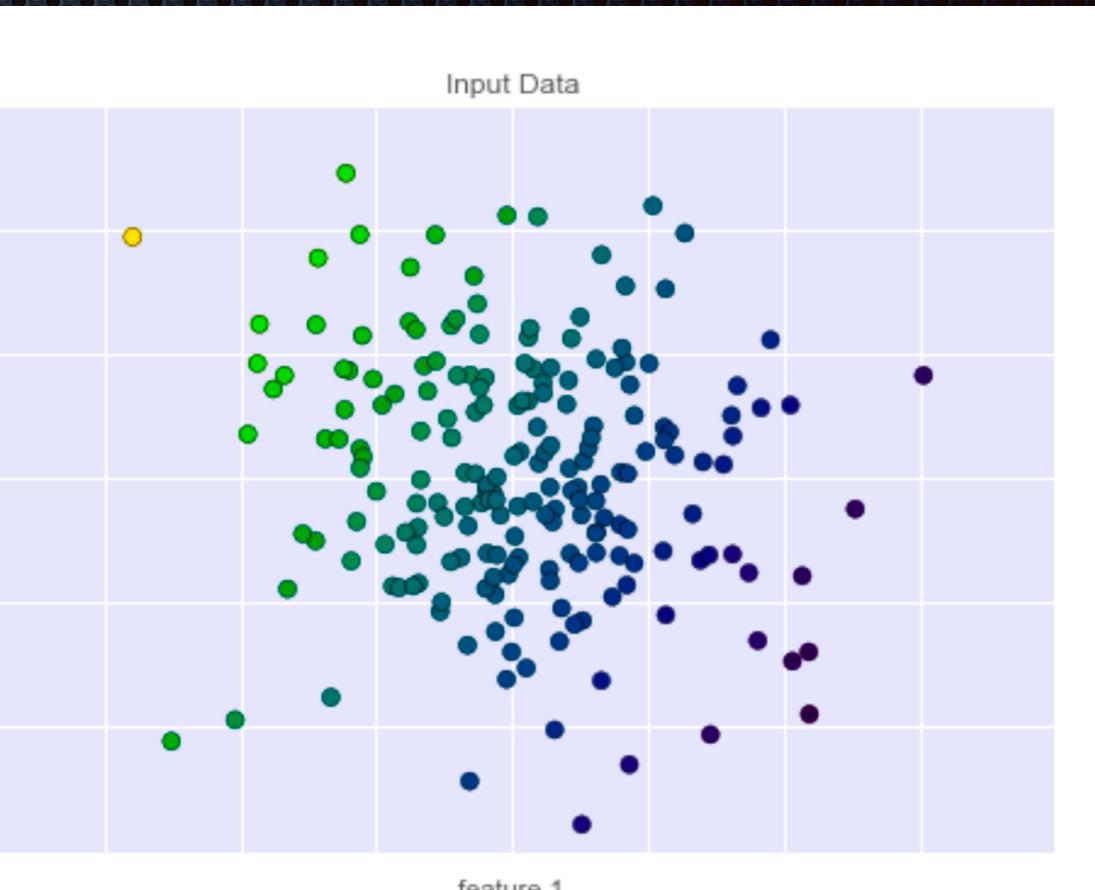


Supervised Learning

Classification : For Binary (**colored**) data set



Regression : For Continuous (**colored**) data set



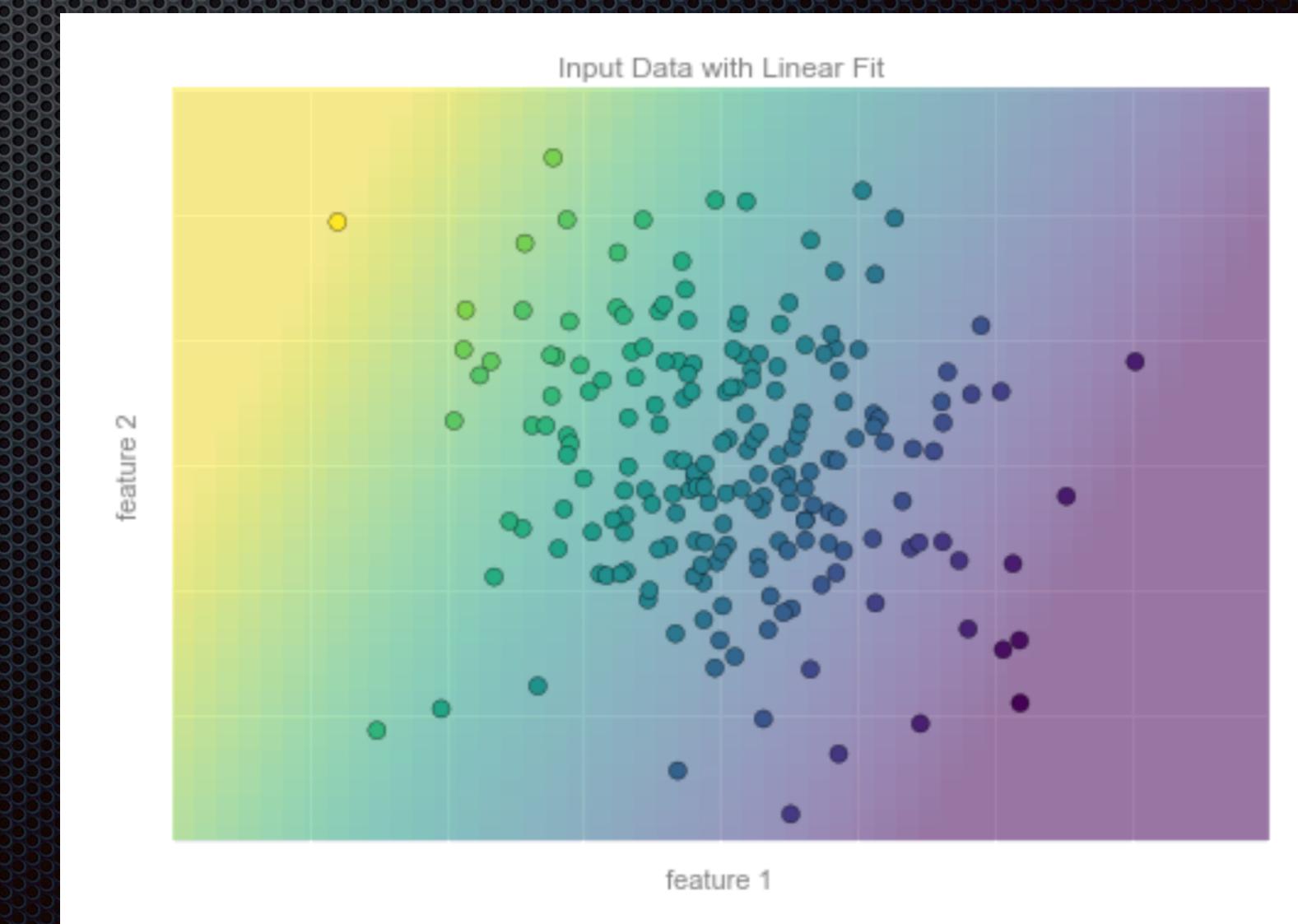
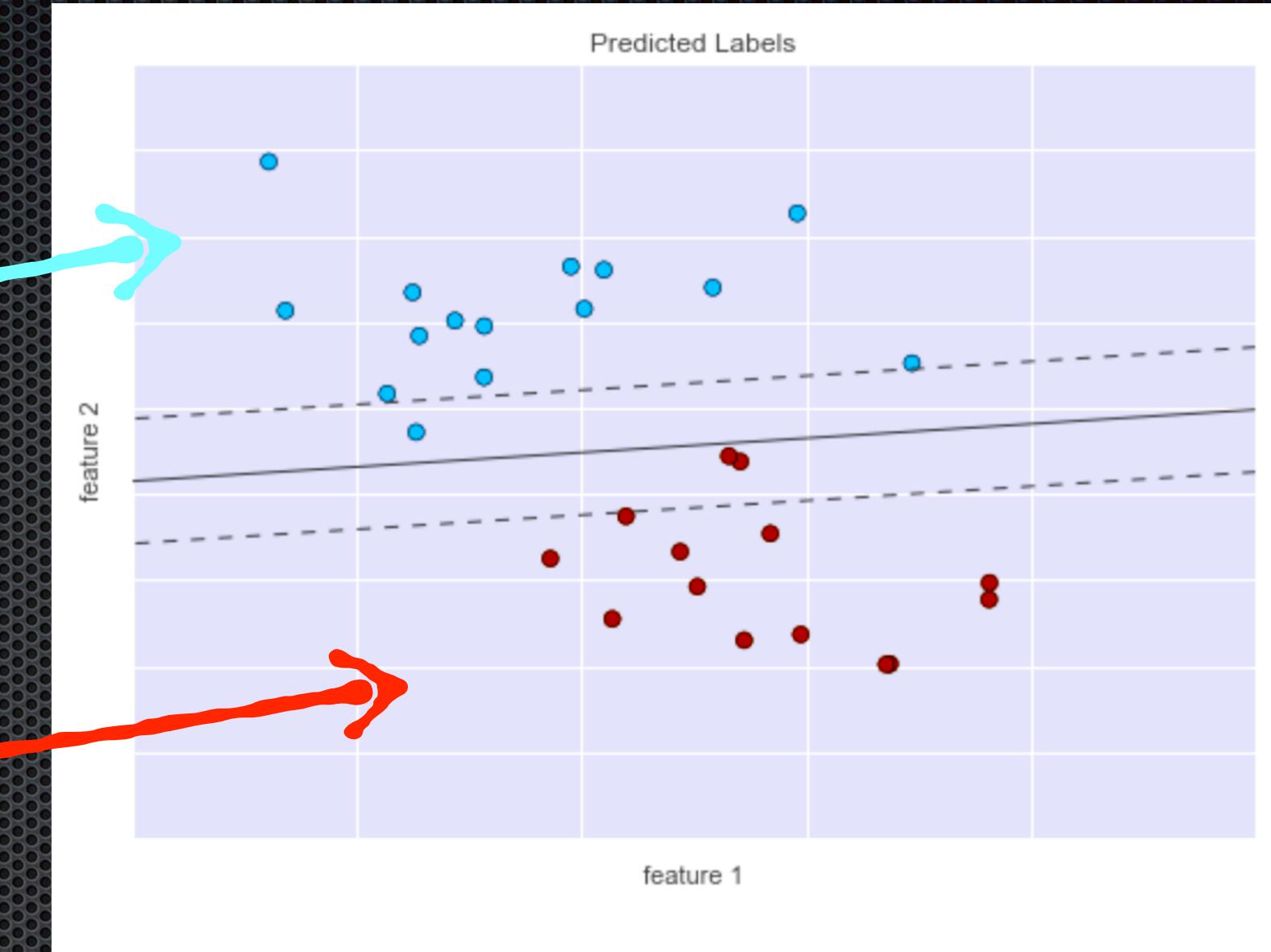
Supervised Learning

Blue points = 0

Linear classification

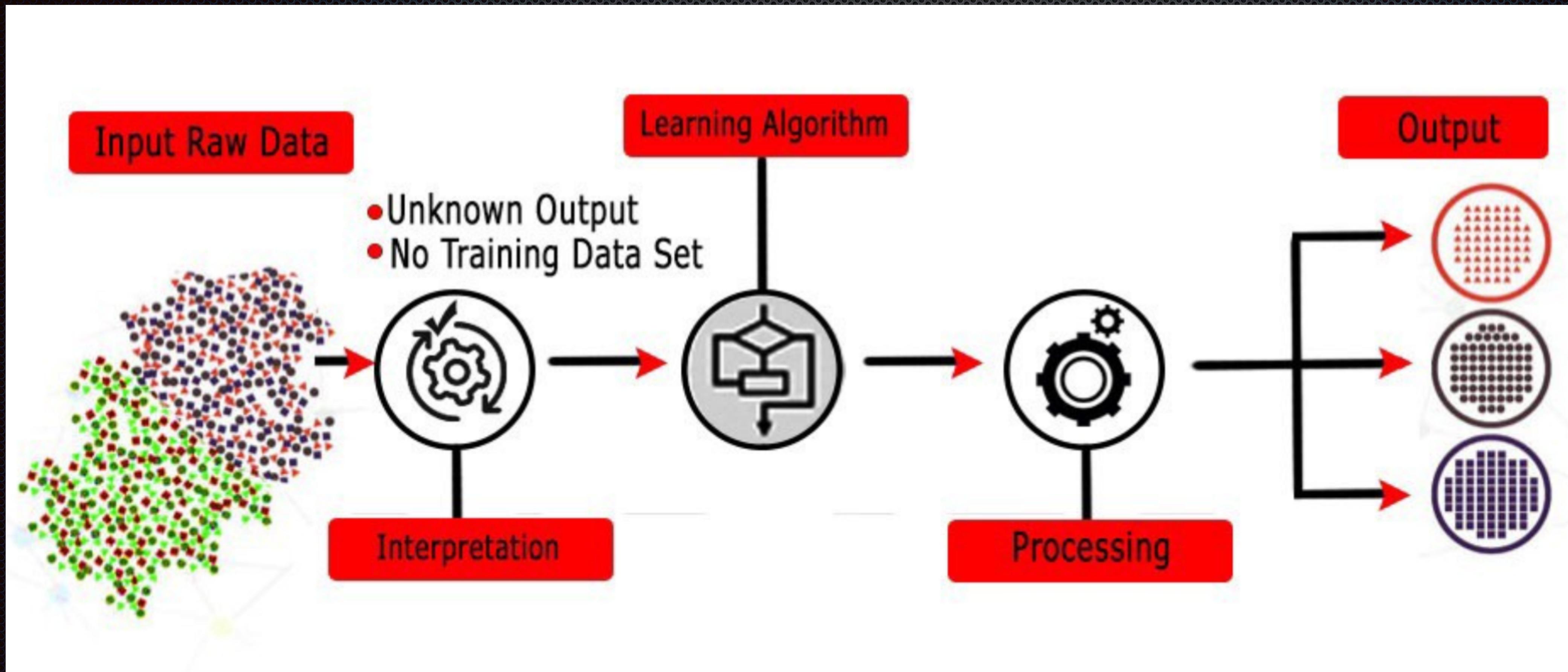
Red points = 1

Classifier: continuous color spectrum



Unsupervised Learning

Modeling the features of a dataset without reference to any label,
and is often described as “letting the dataset speaks for itself.”



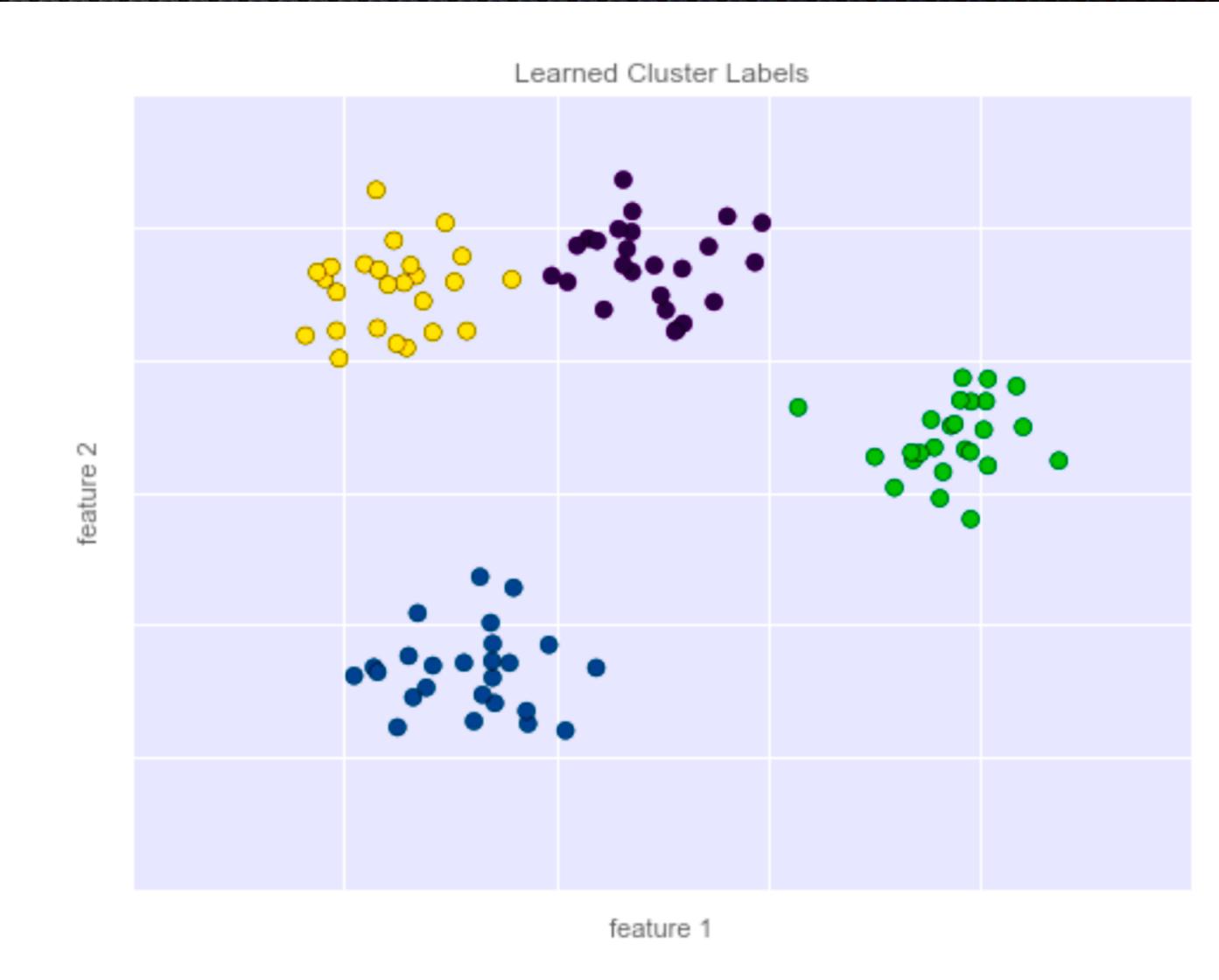
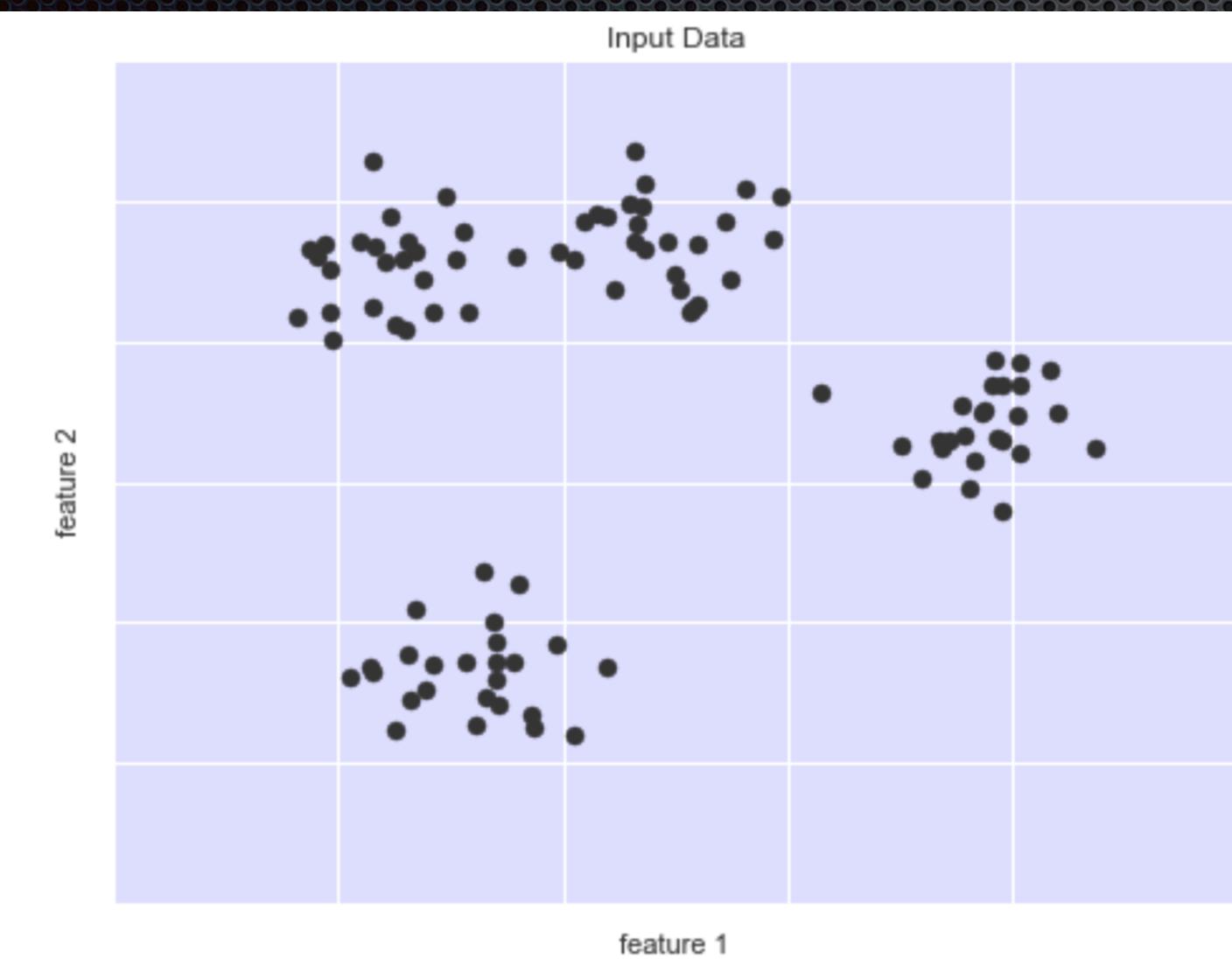
Unsupervised Learning

Unsupervised Learning

No labels

Classification problem

Clustering

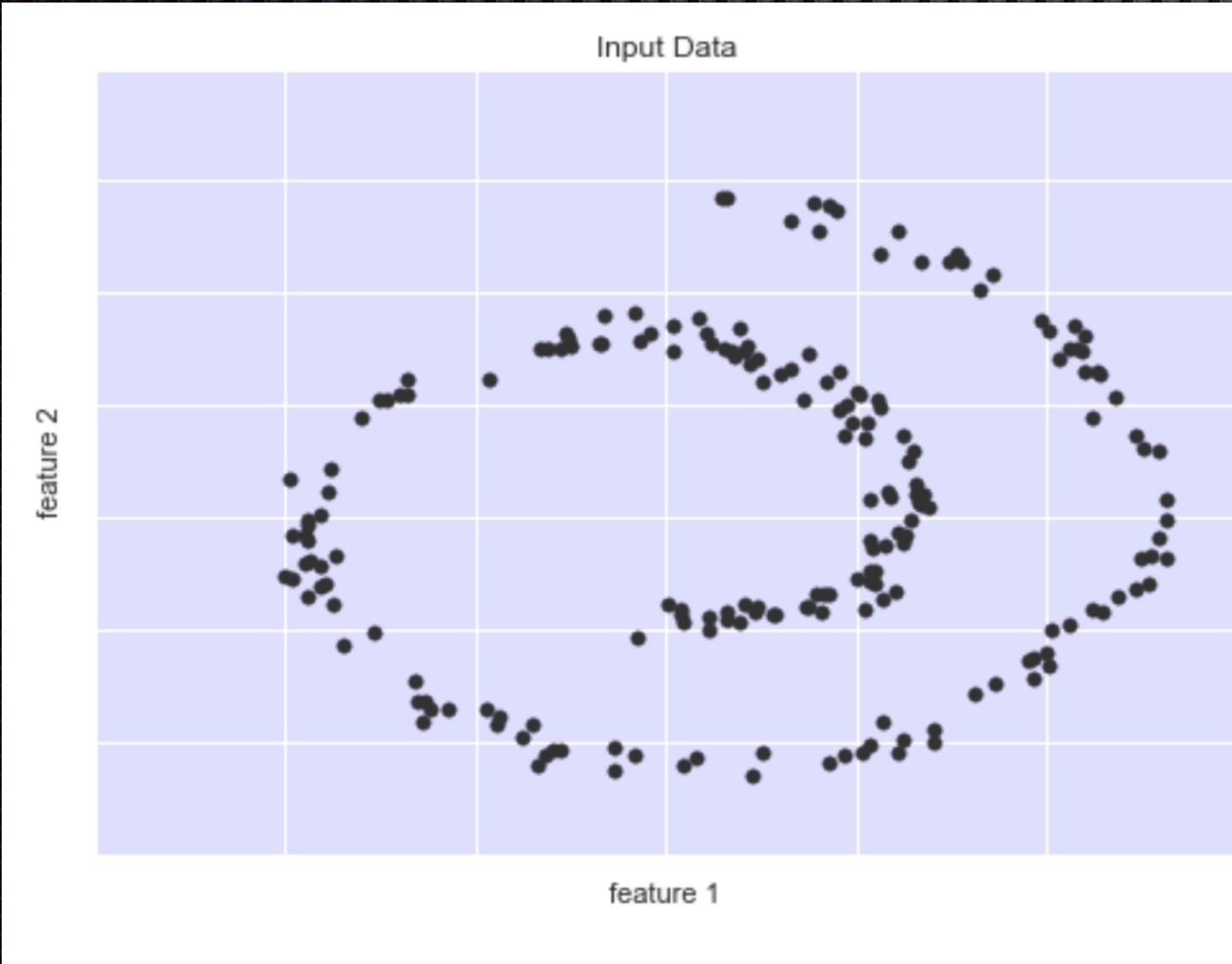


Unsupervised Learning

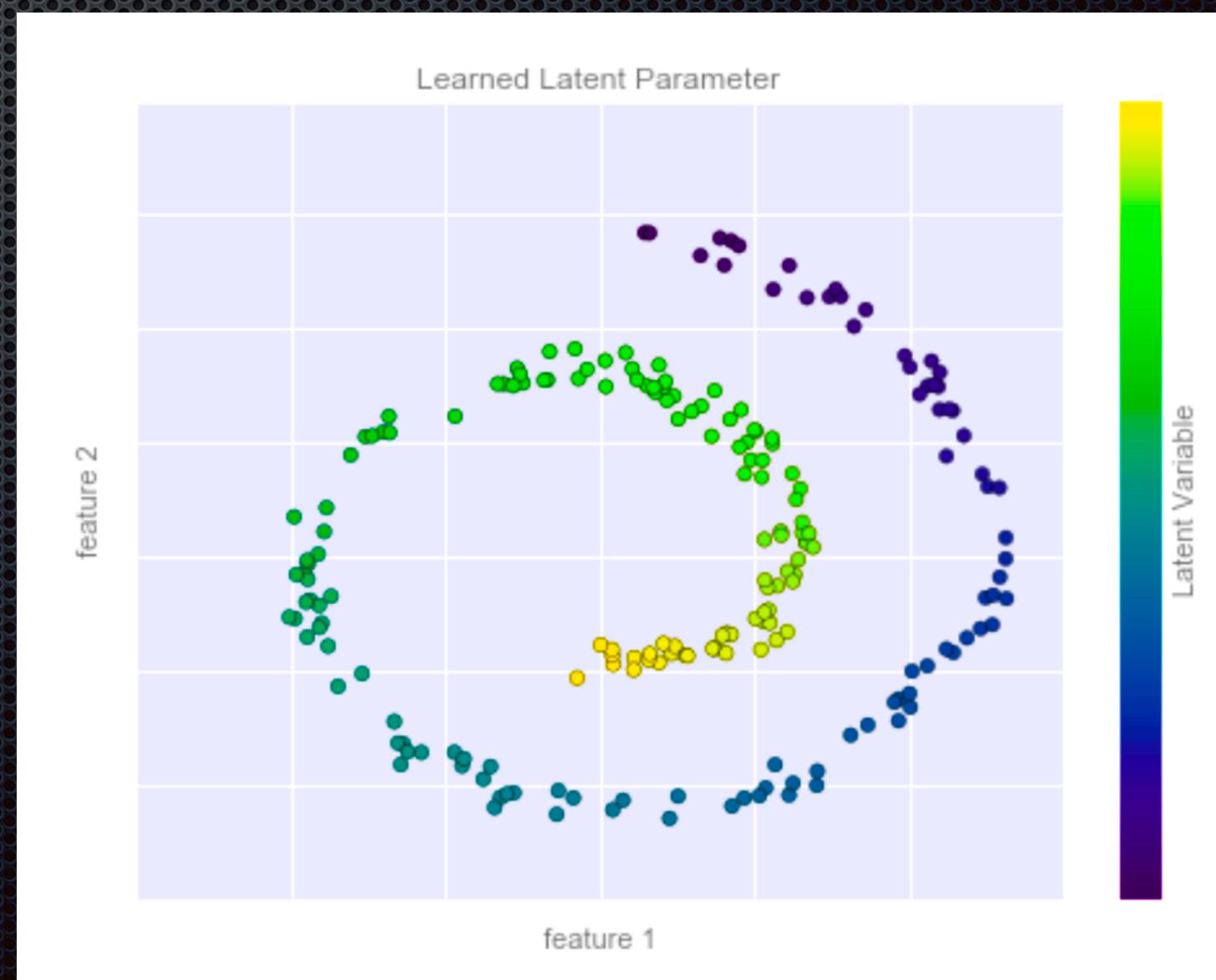
Unsupervised Learning

No labels

Regression problem

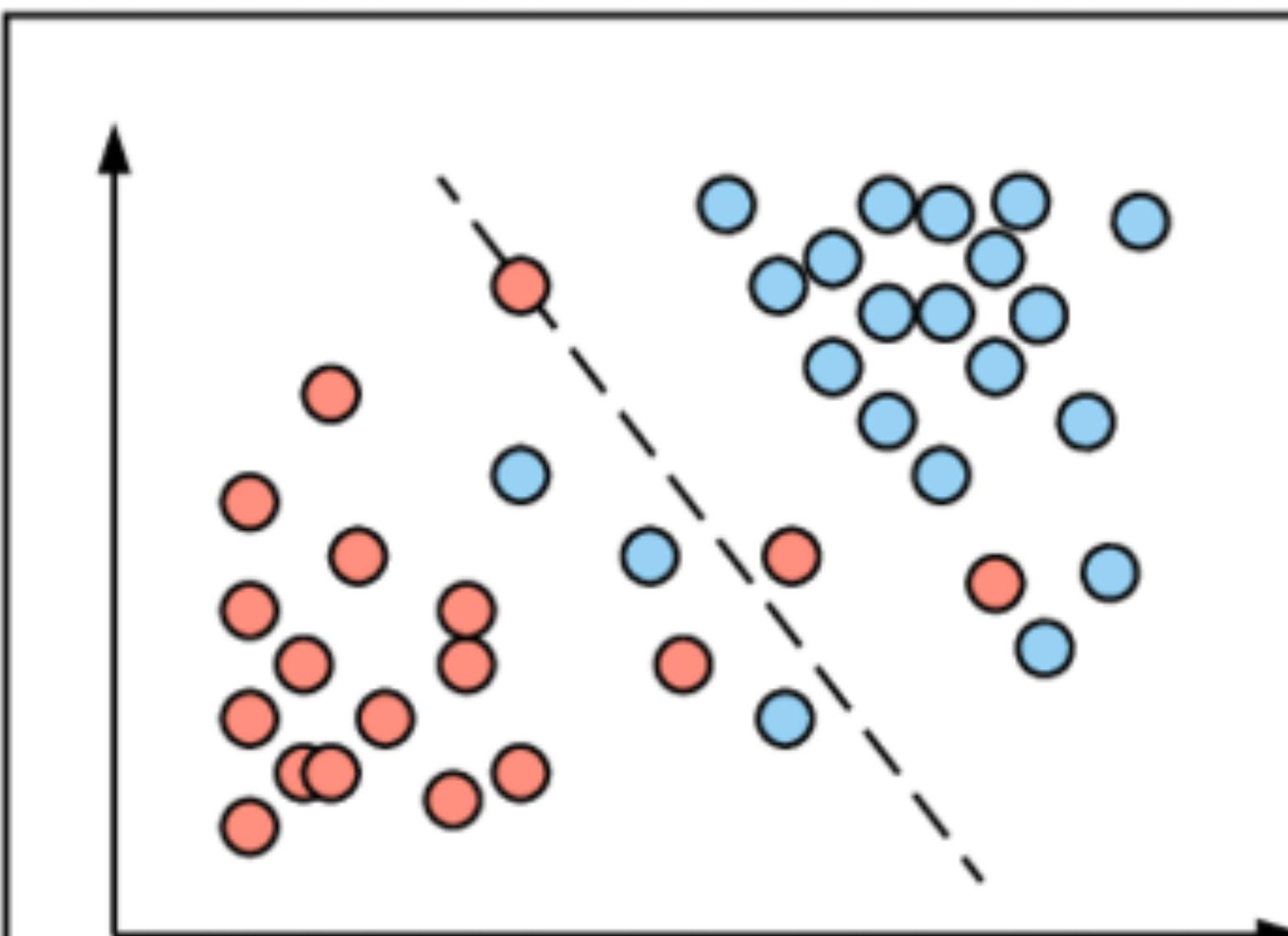


Clustering

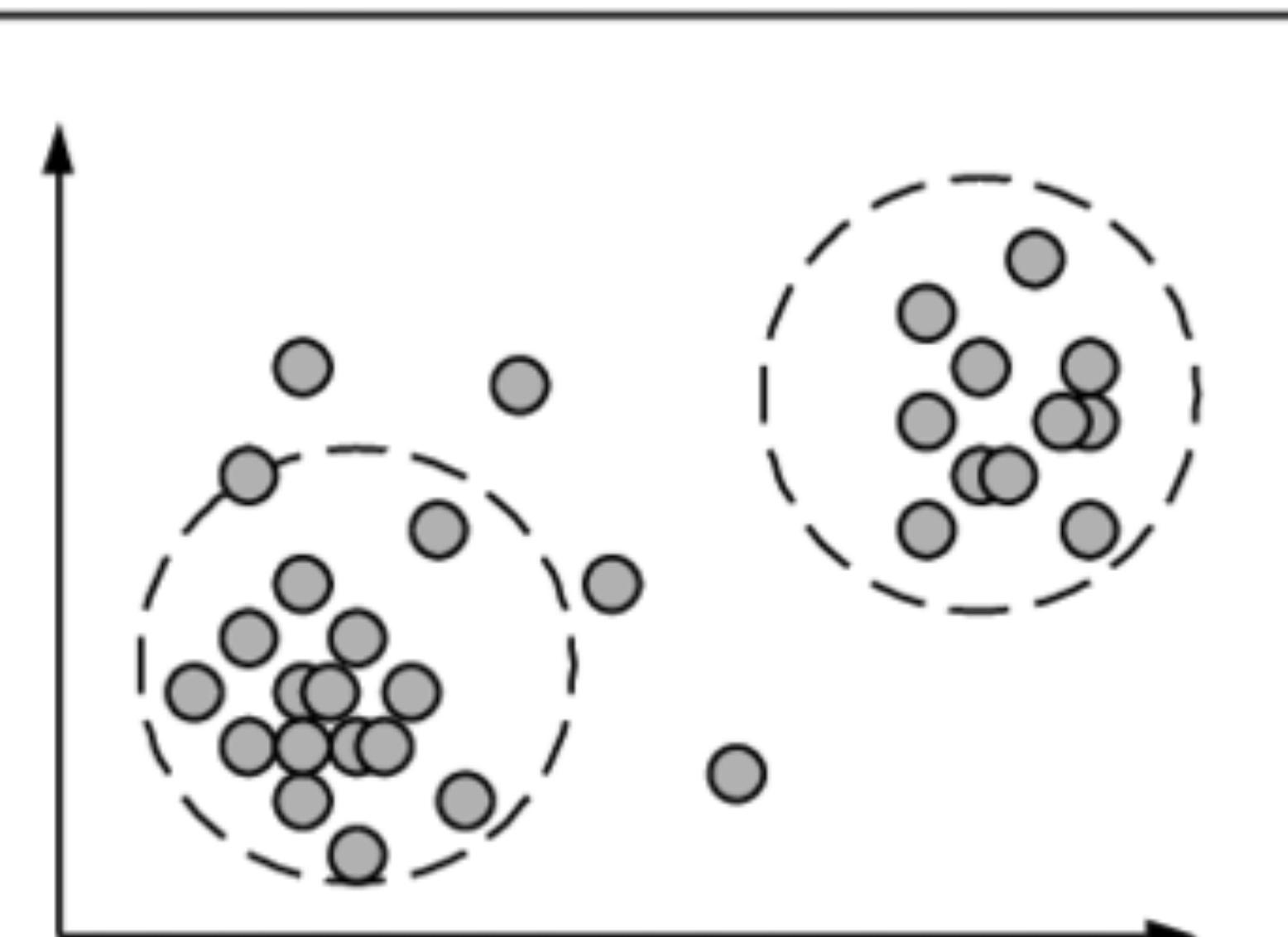


Examples

Supervised Learning vs Unsupervised Learning



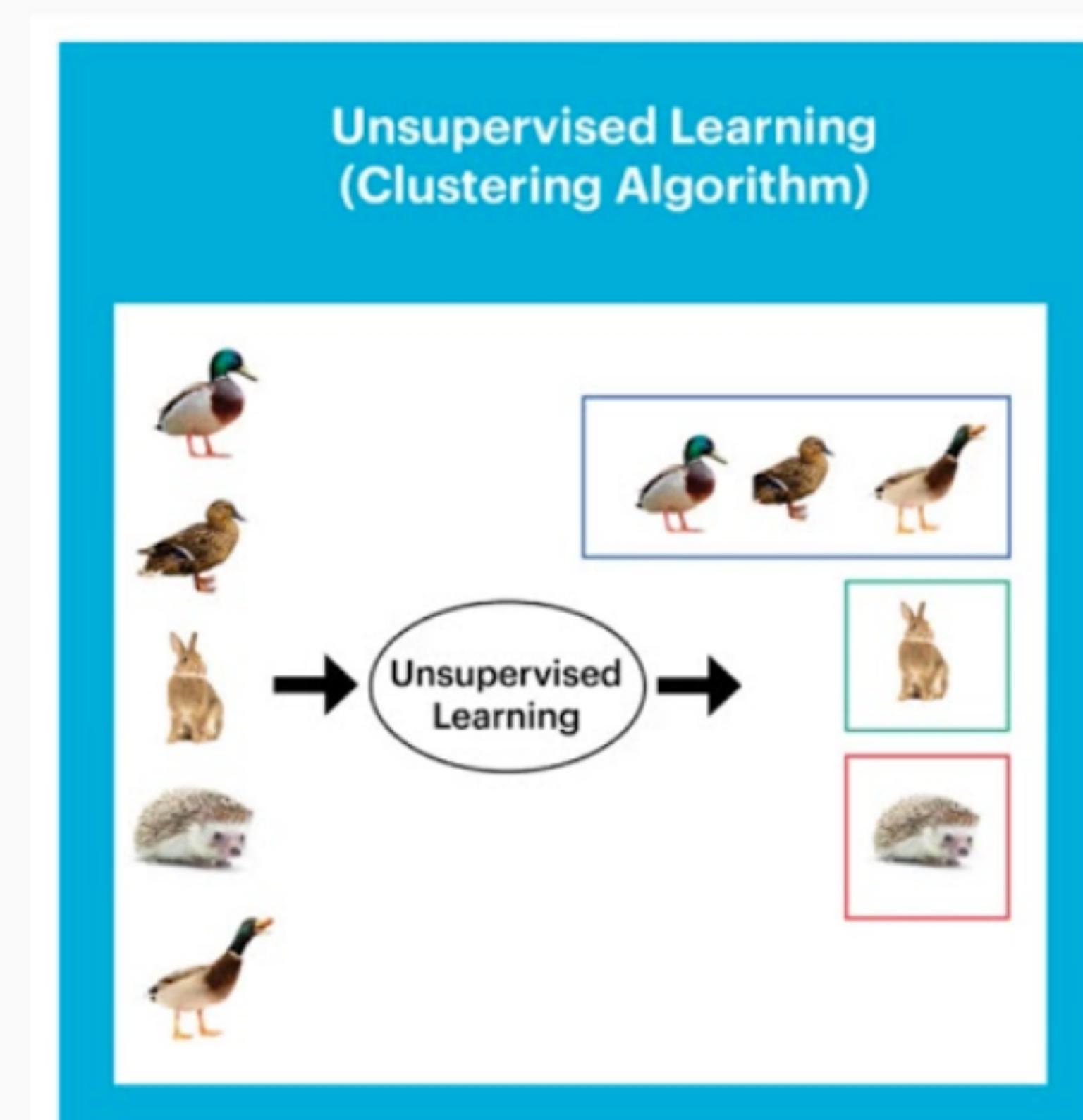
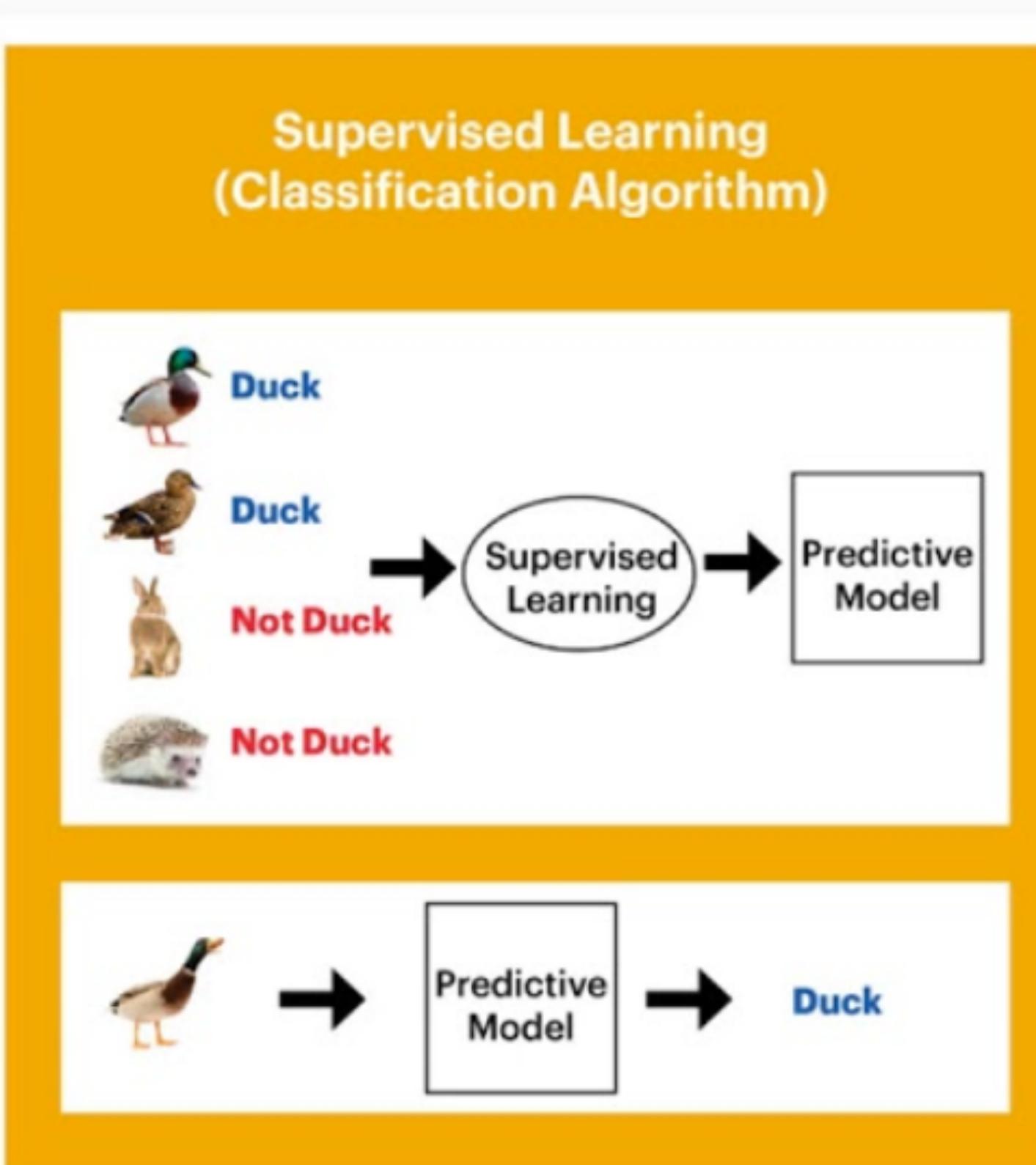
Supervised learning



Unsupervised learning

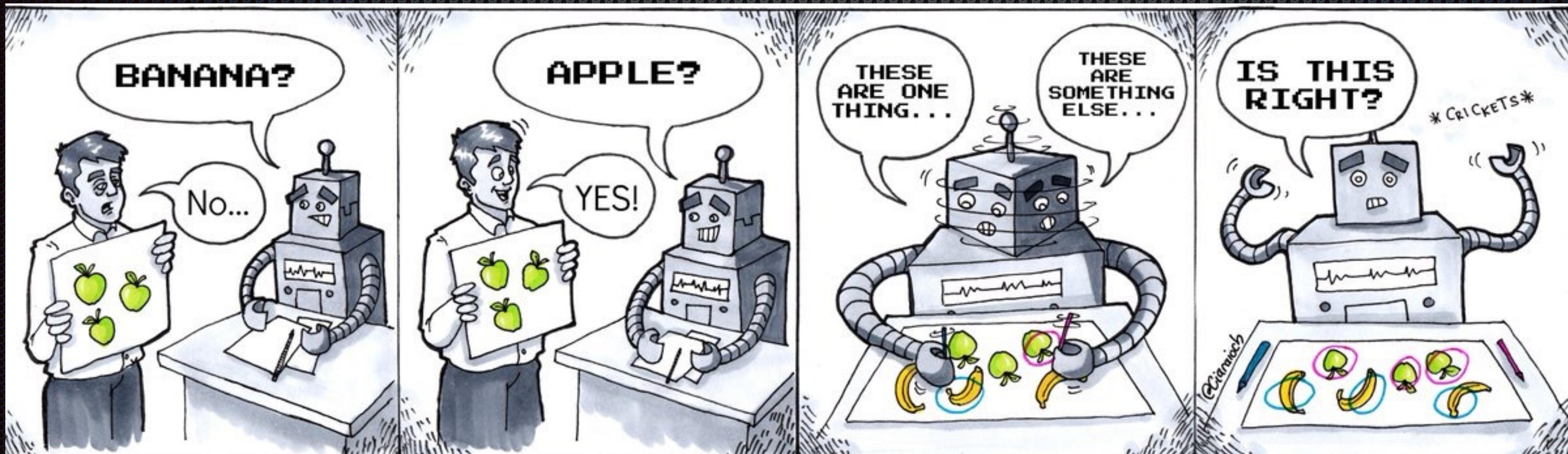
Examples

Supervised Learning vs Unsupervised Learning



Examples

Supervised Learning vs Unsupervised Learning



Supervised Learning

Unsupervised Learning

Supervised learning training

Features (X)

X_1
 X_2
:
 X_n

Labels (Y)

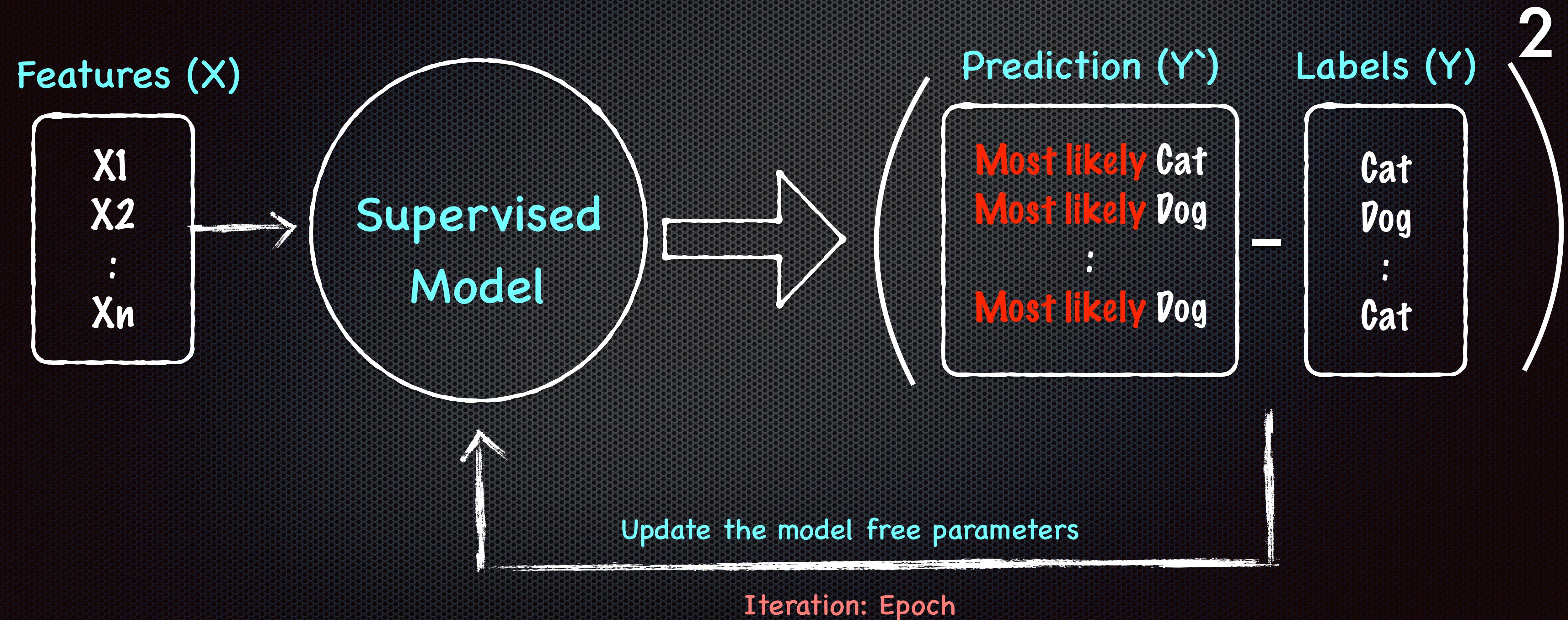
Cat
Dog
:
Cat

Supervised Model

Prediction (Y')

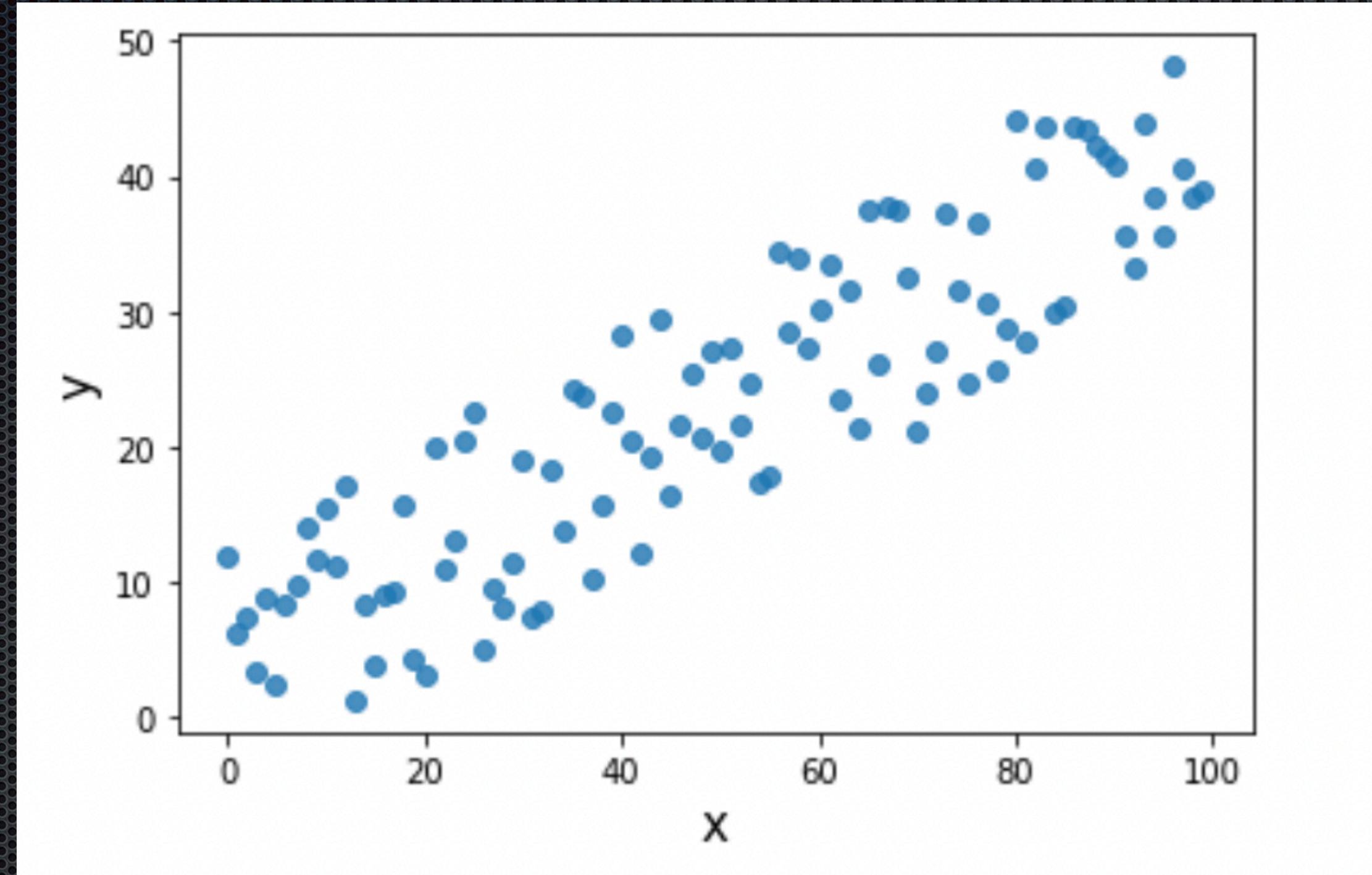
Most likely Cat
Most likely Dog
:
Most likely Dog

Supervised learning training



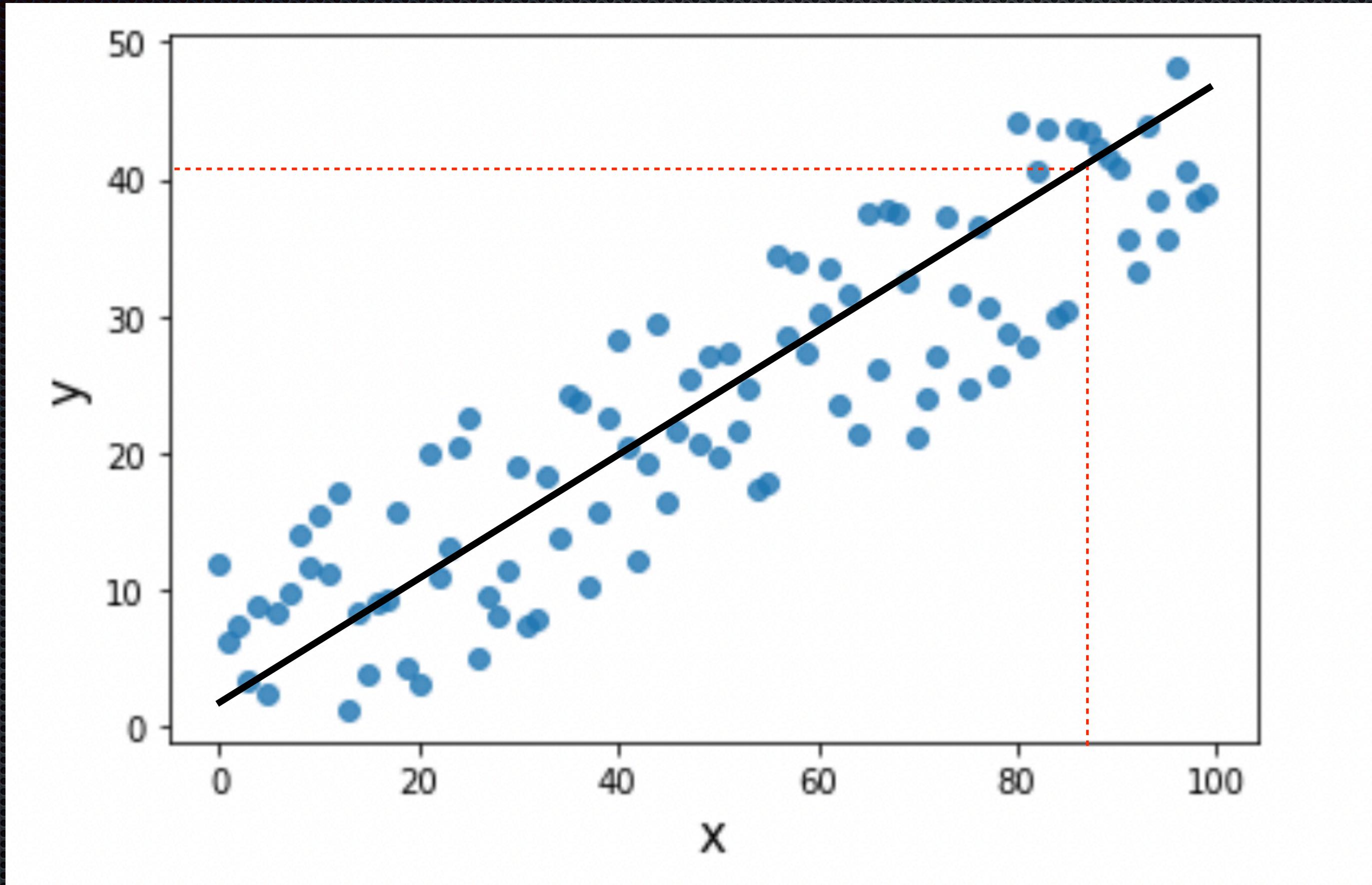
Linear regression

For a continuous data set X



Given new (unseen) x point, can you predict the corresponding Y ?

Linear regression

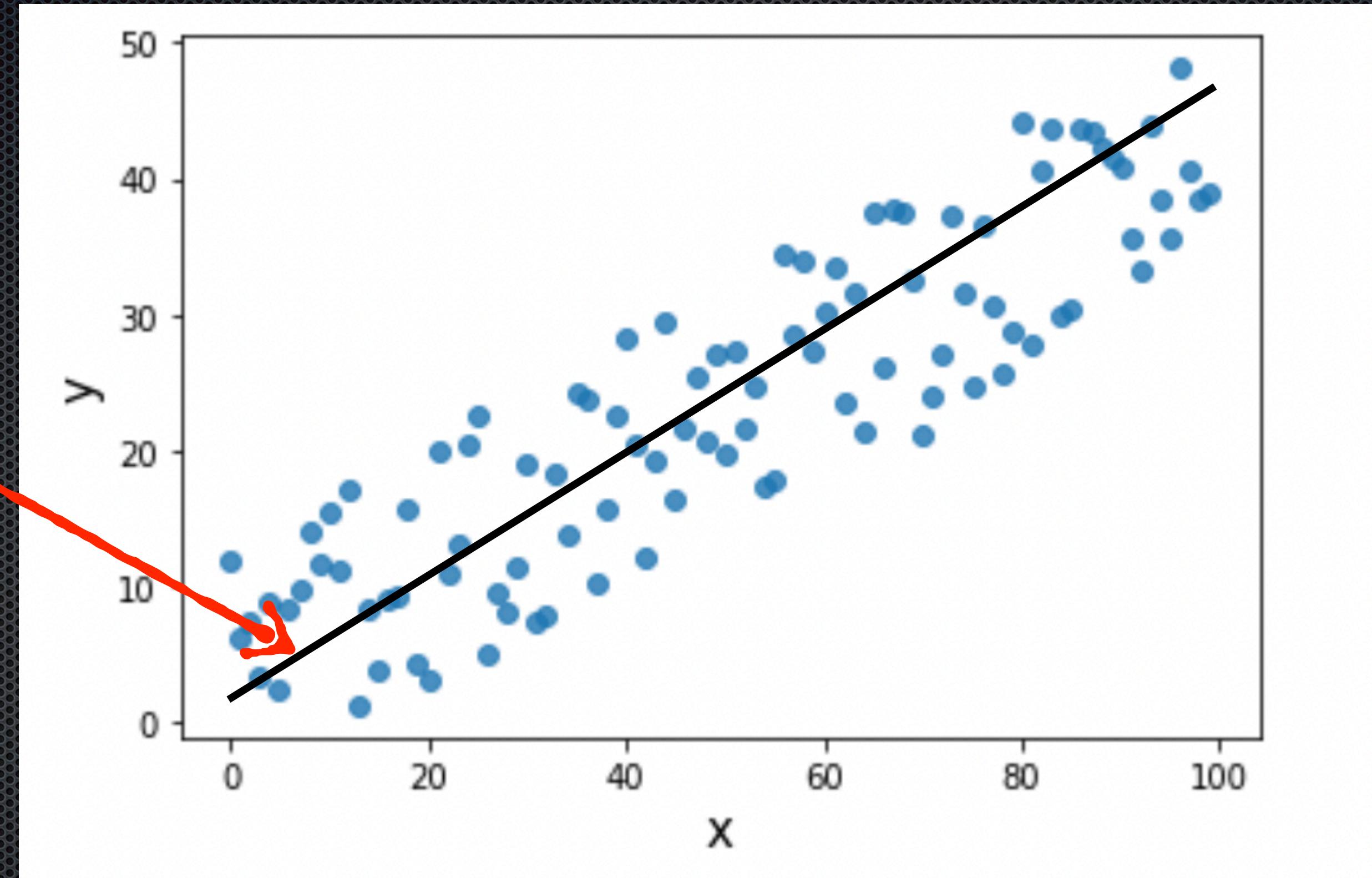


Once we found the line that best fit the data we can interpret the **Y** for new **x** points

Linear regression

How to find the line that fit the given data ?

$$\hat{Y} = B_0 + B_1 x$$



With given \mathbf{Y} and \mathbf{x} we try to find B_0 and B_1 that fit the line to the data

Linear regression

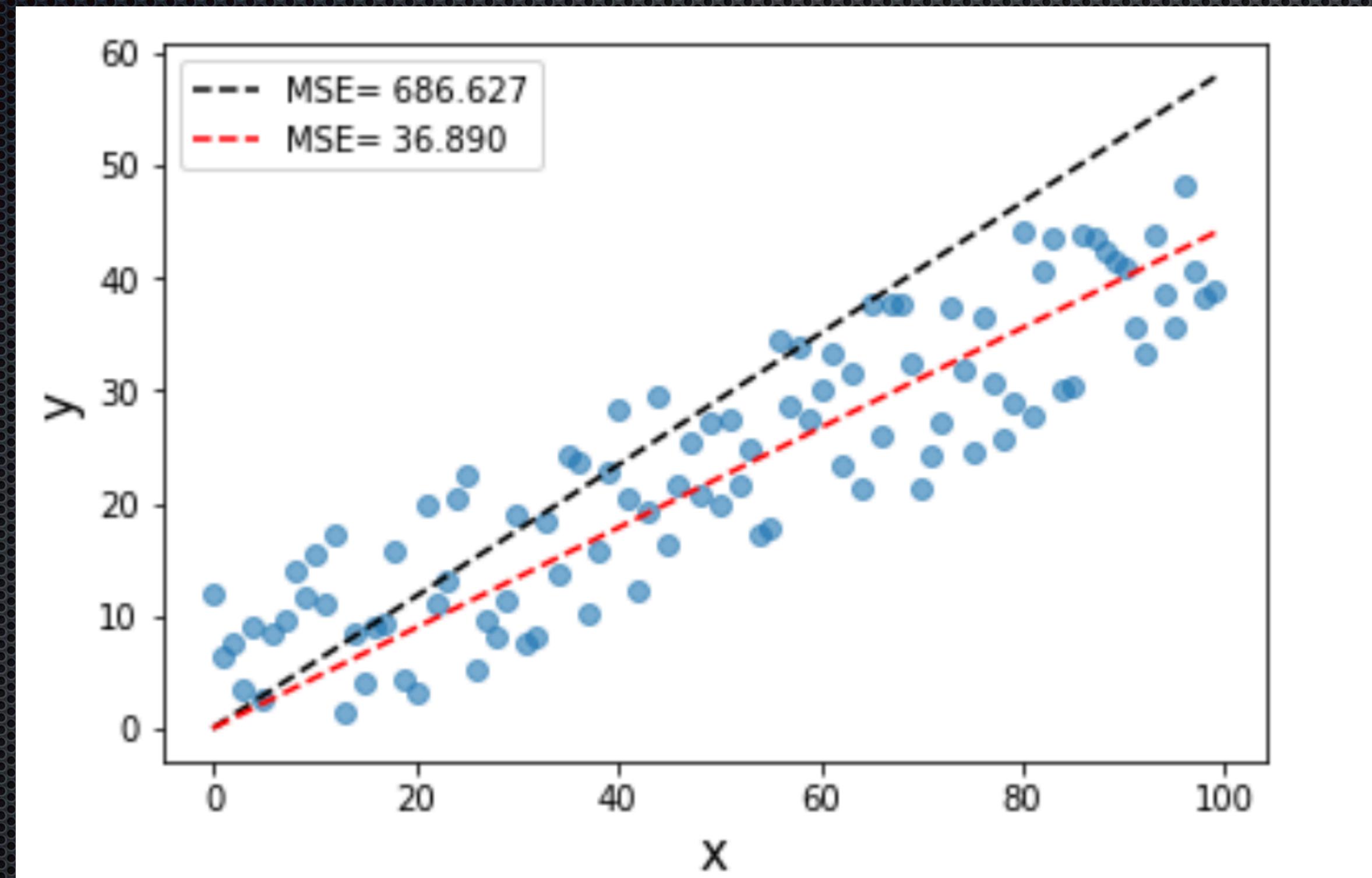
Question:

We can draw infinite number of lines that can fit the data!!
Which line shall we consider ?

Linear regression

Question:

We can draw infinite number of lines that can fit the data!!
Which line shall we consider ?

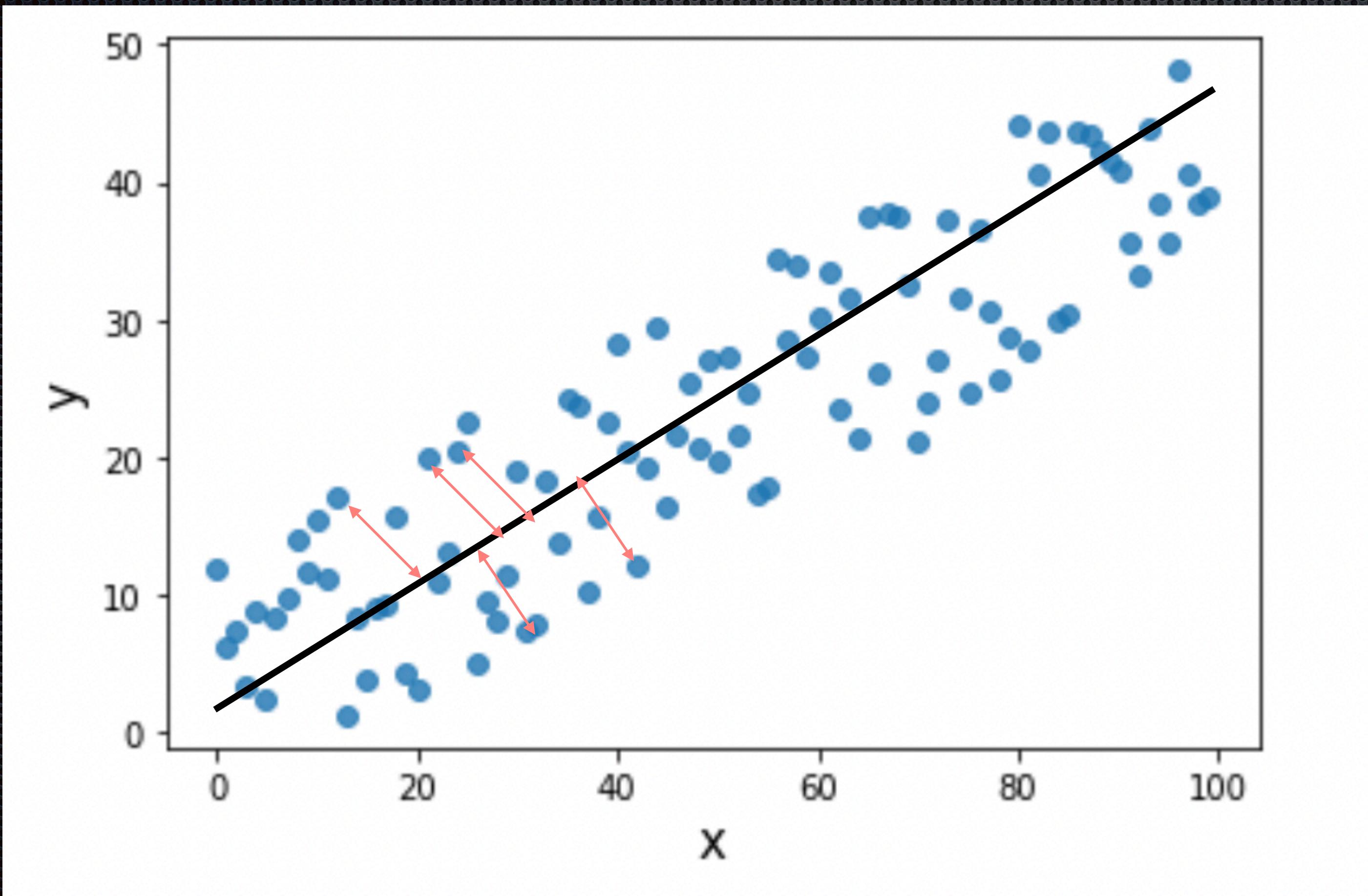


We have to consider the line that minimizes the **error function**

Linear regression-loss function

Loss function:

It mostly quantifies the difference between the model predictions and the true values



Linear regression-loss function

Types of linear regression loss functions

Absolute mean error:

$$\text{AME} = \frac{1}{m} \sum_{i=1}^m |Y_i - \hat{Y}_i| = \frac{1}{m} \sum_{i=1}^m |Y_i - (B_0 + B_1 x_i)|$$

Mean square error:

$$\text{MSE} = \frac{1}{m} \sum_{i=1}^m |Y_i - \hat{Y}_i|^2 = \frac{1}{m} \sum_{i=1}^m |Y_i - (B_0 + B_1 x_i)|^2$$

Root mean square error:

$$\text{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^m |Y_i - \hat{Y}_i|^2} = \sqrt{\frac{1}{m} \sum_{i=1}^m |Y_i - (B_0 + B_1 x_i)|^2}$$

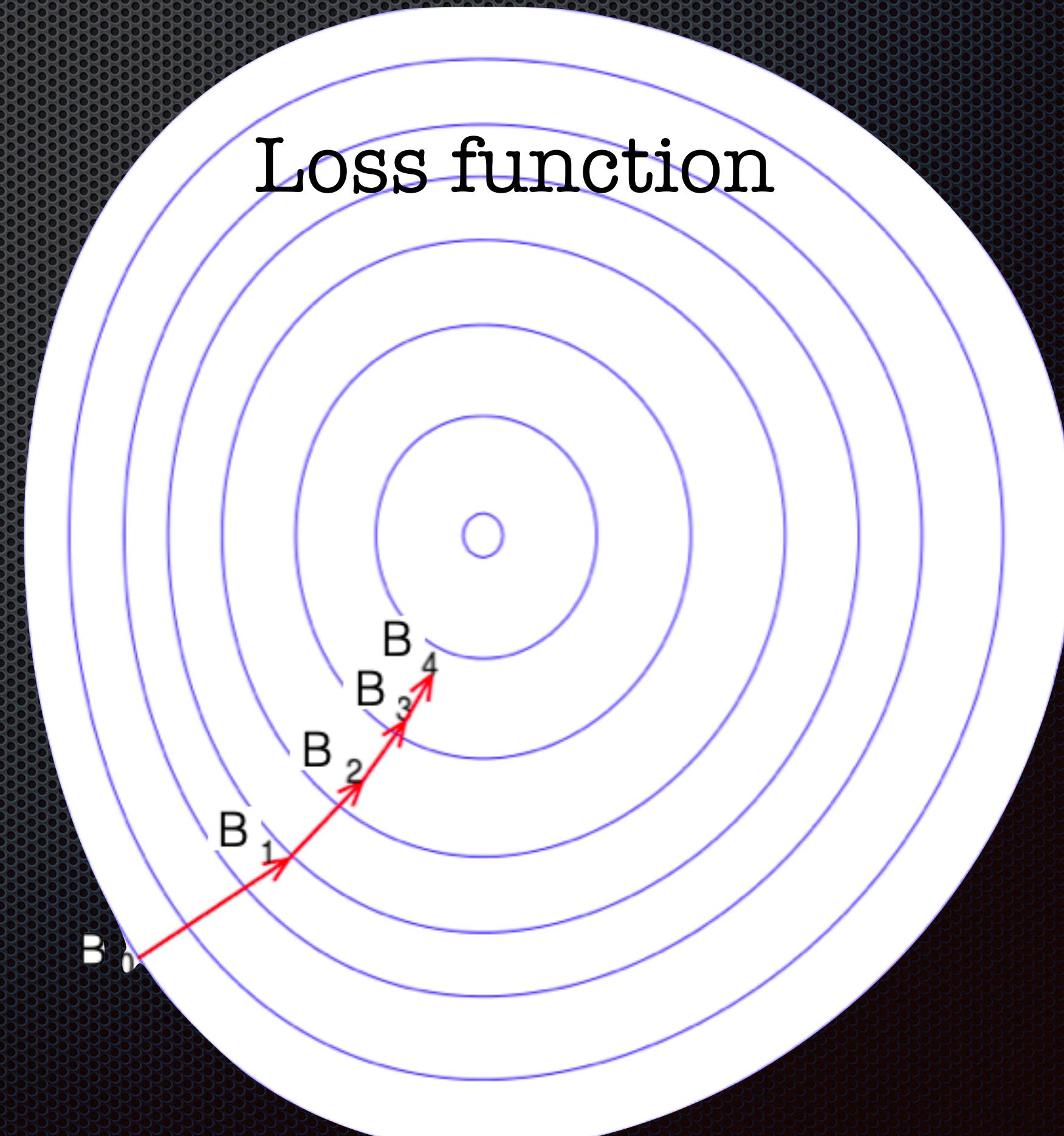
Gradient Descent method

Question:

Well, now we know that to find the best fit line we need to minimize the loss function, but how ??

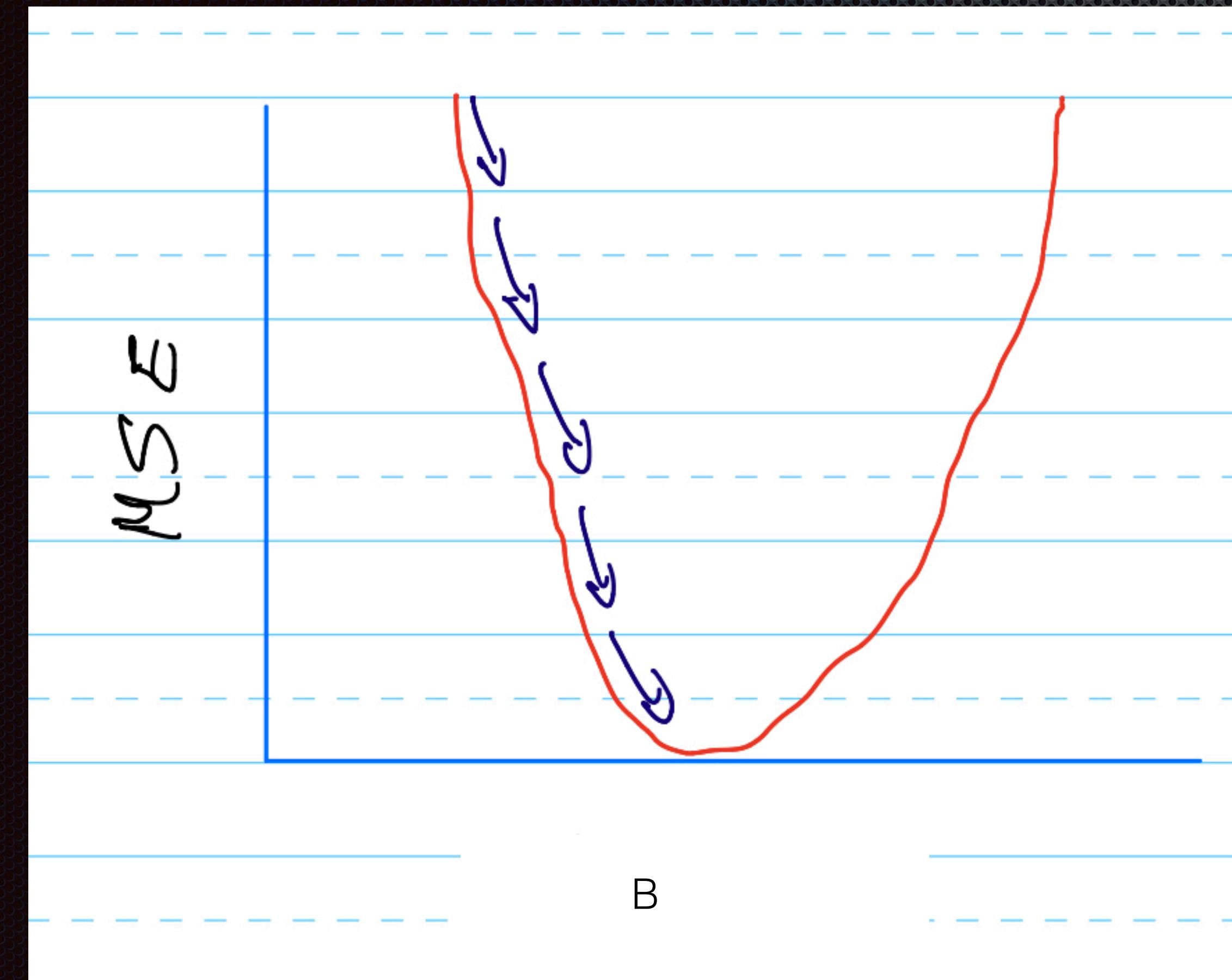
Find the best fit parameters using the gradient descent method

$$B_{\text{new}}^i = B_{\text{old}}^i - \eta \nabla \text{Loss}(B_{\text{old}}^i)$$



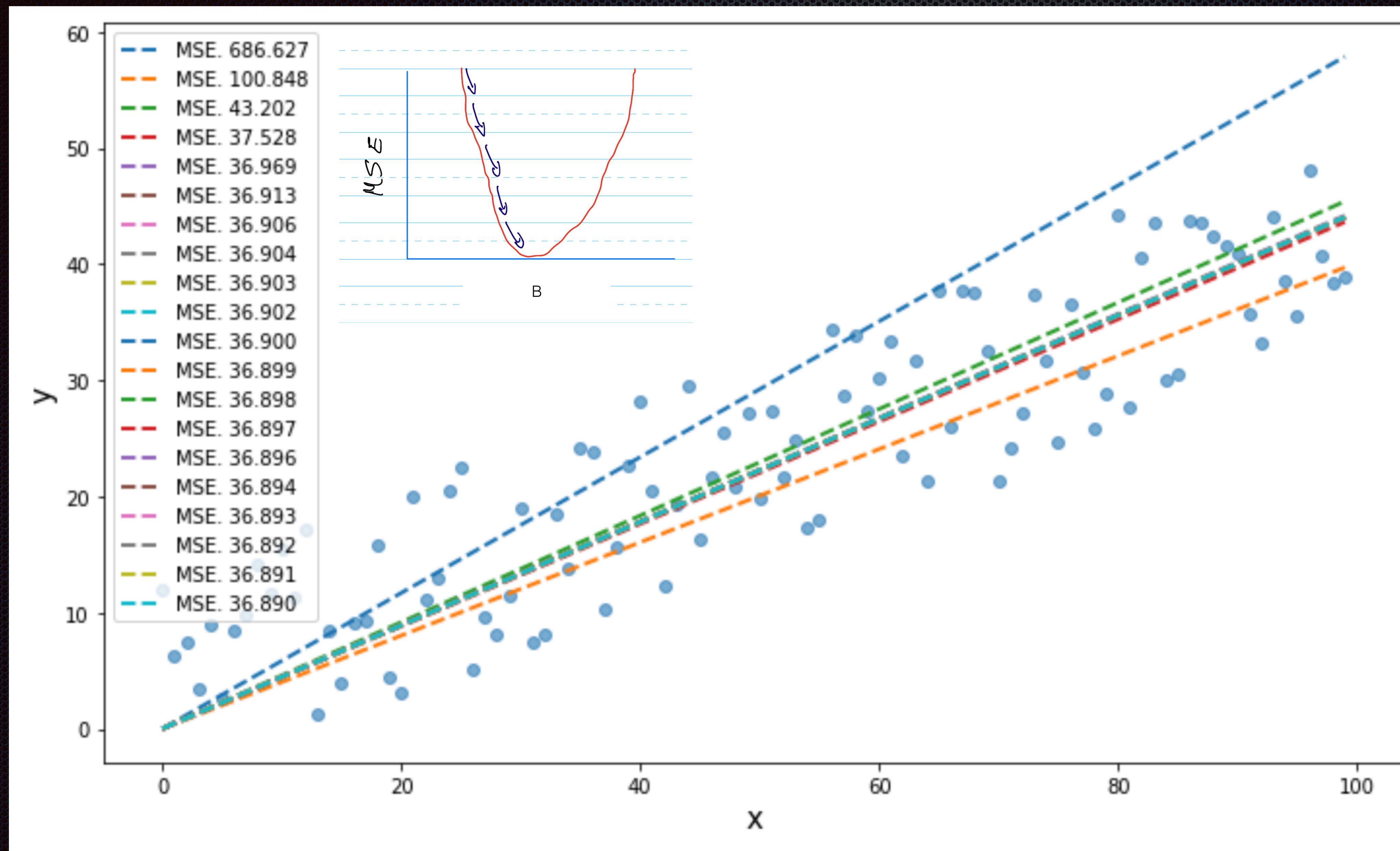
Gradient Descent method

Given a number of iteration, every iteration we update the parameters and calculate the error function until we hit the global minimum



$$B_{\text{new}}^i = B_{\text{old}}^i - \eta \nabla \text{MSE}(B_{\text{old}}^i)$$

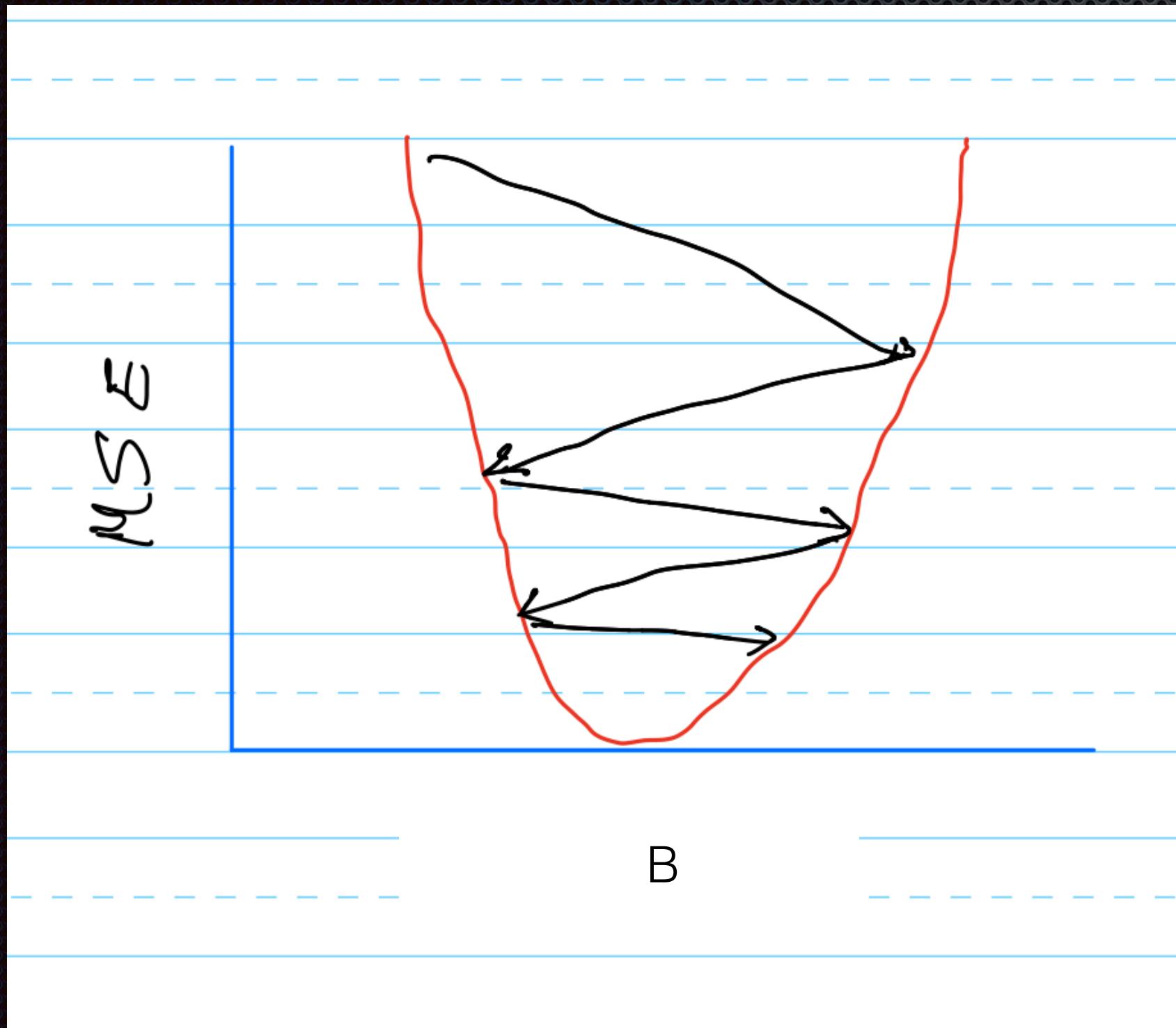
Gradient Descent method



Learning rate

$$B_{\text{new}}^i = B_{\text{old}}^i - \eta \nabla \text{Loss}(B_{\text{old}}^i)$$

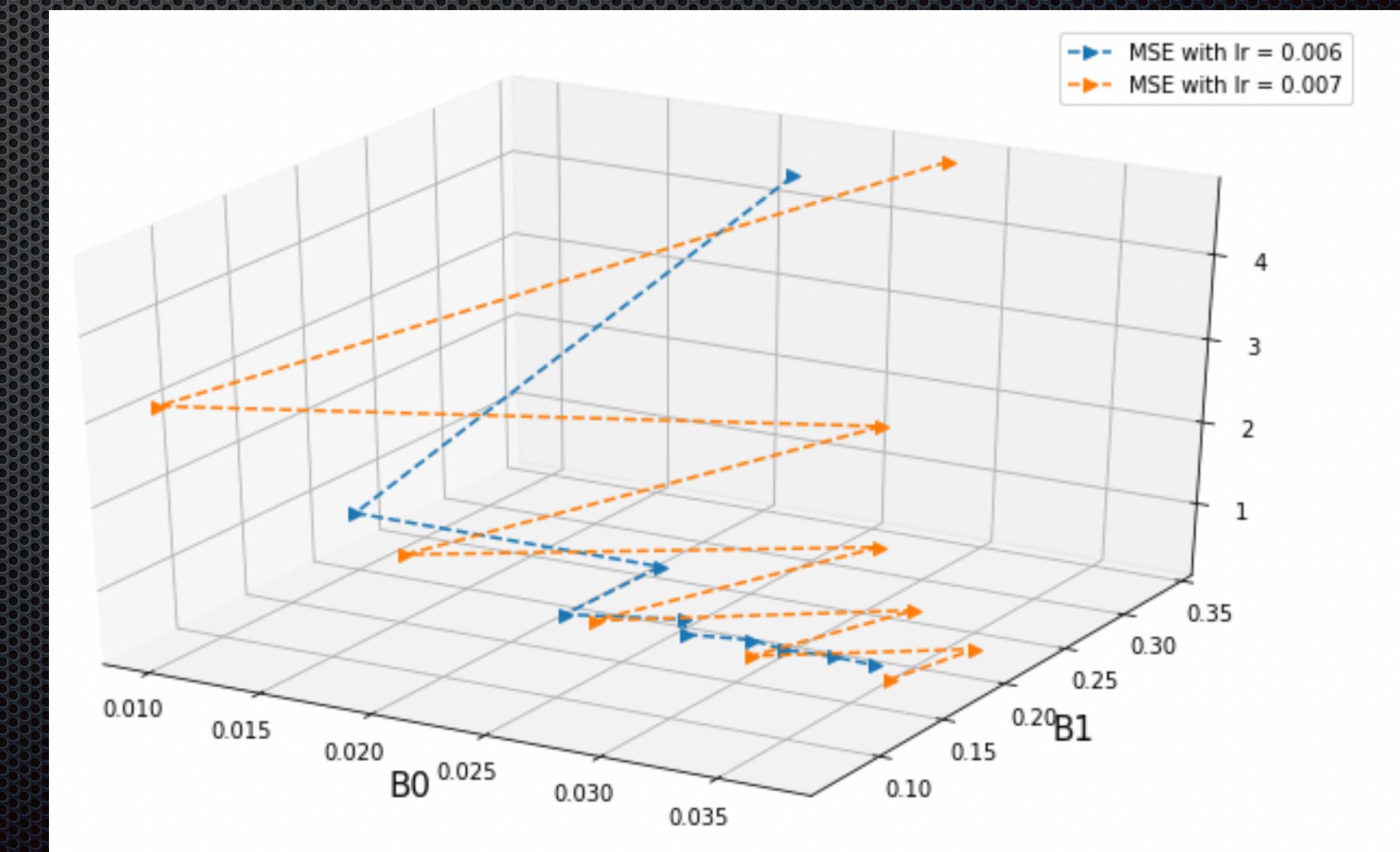
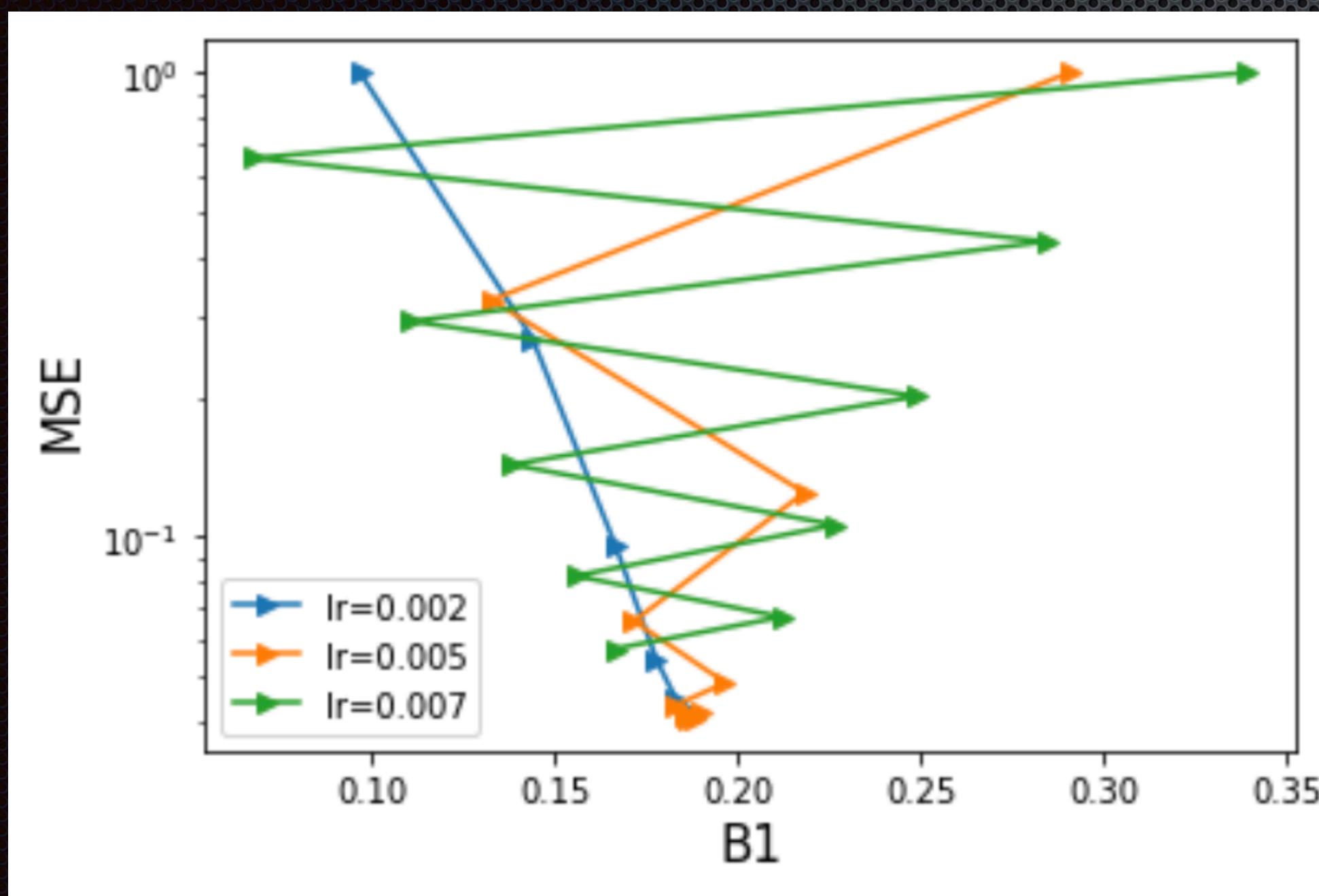
η Is called the learning rate which controls the descent rate of the loss function



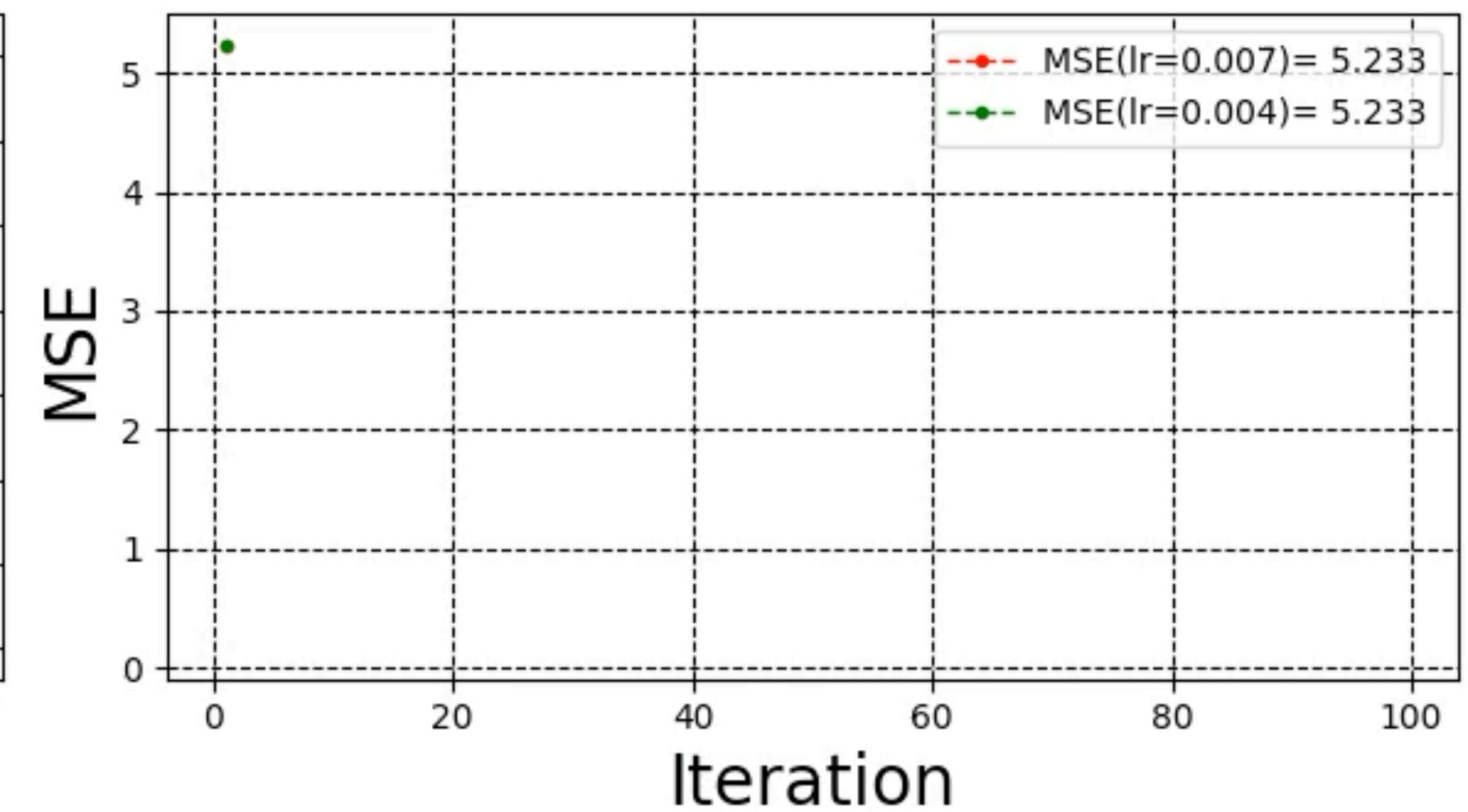
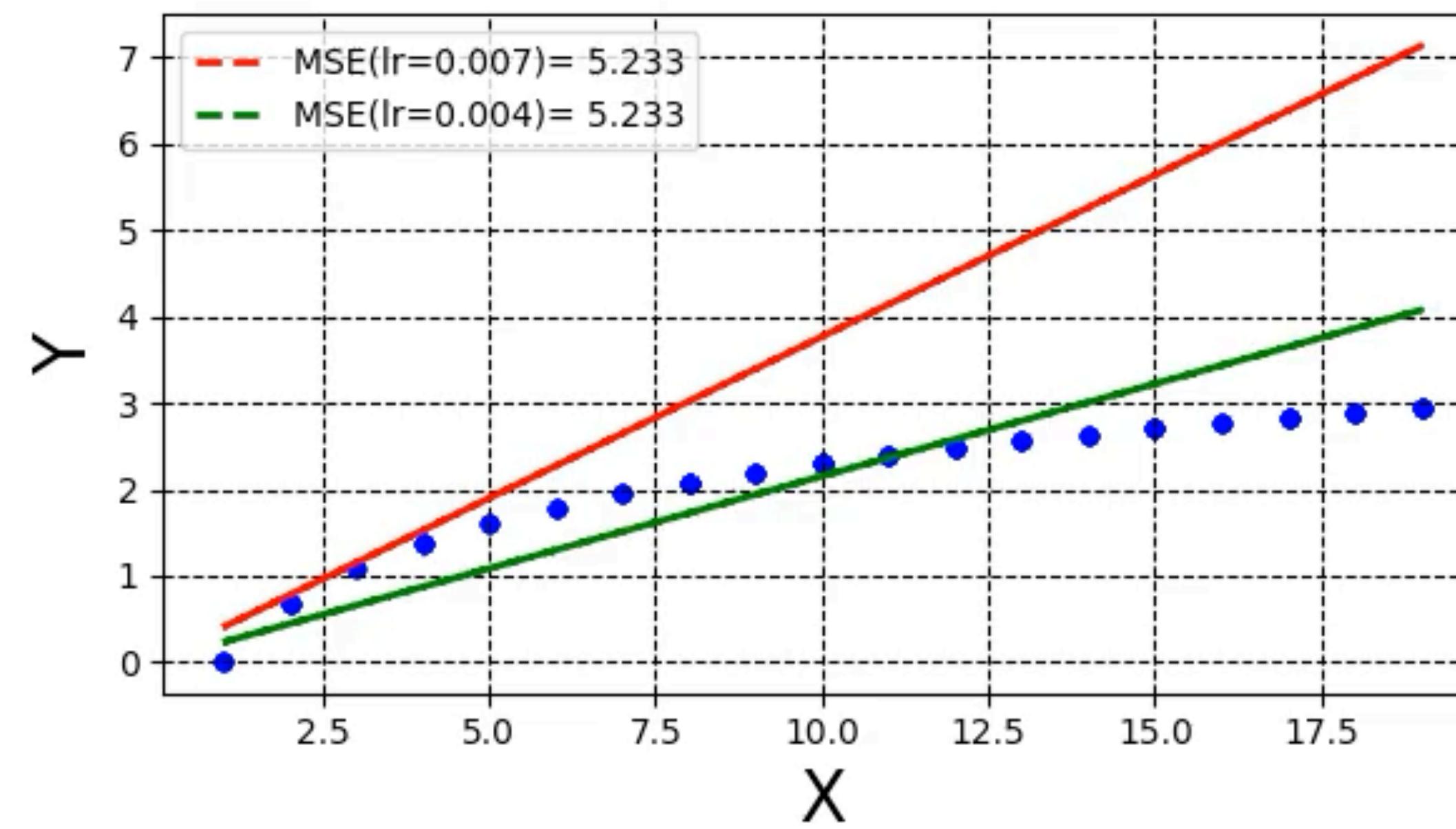
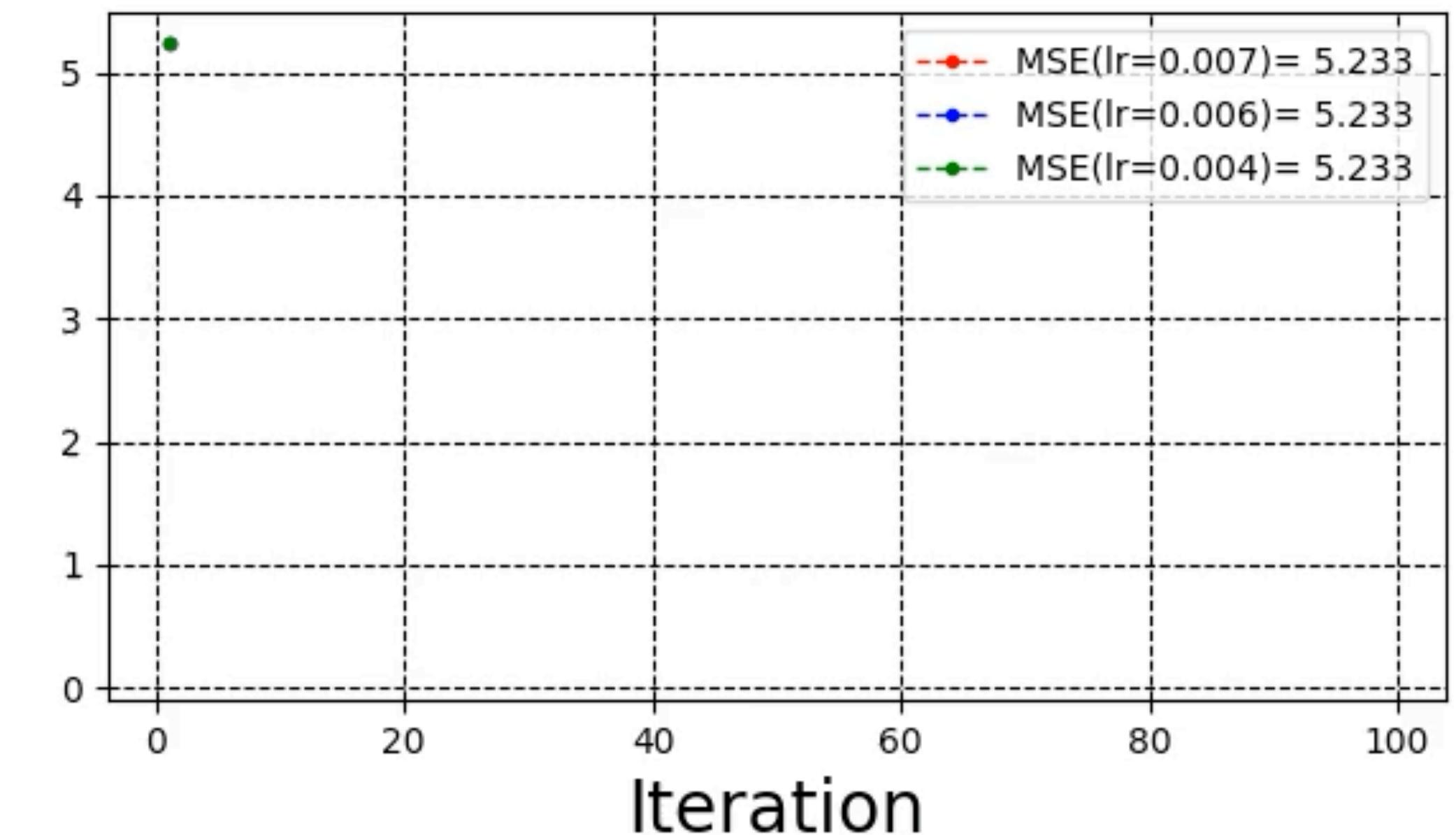
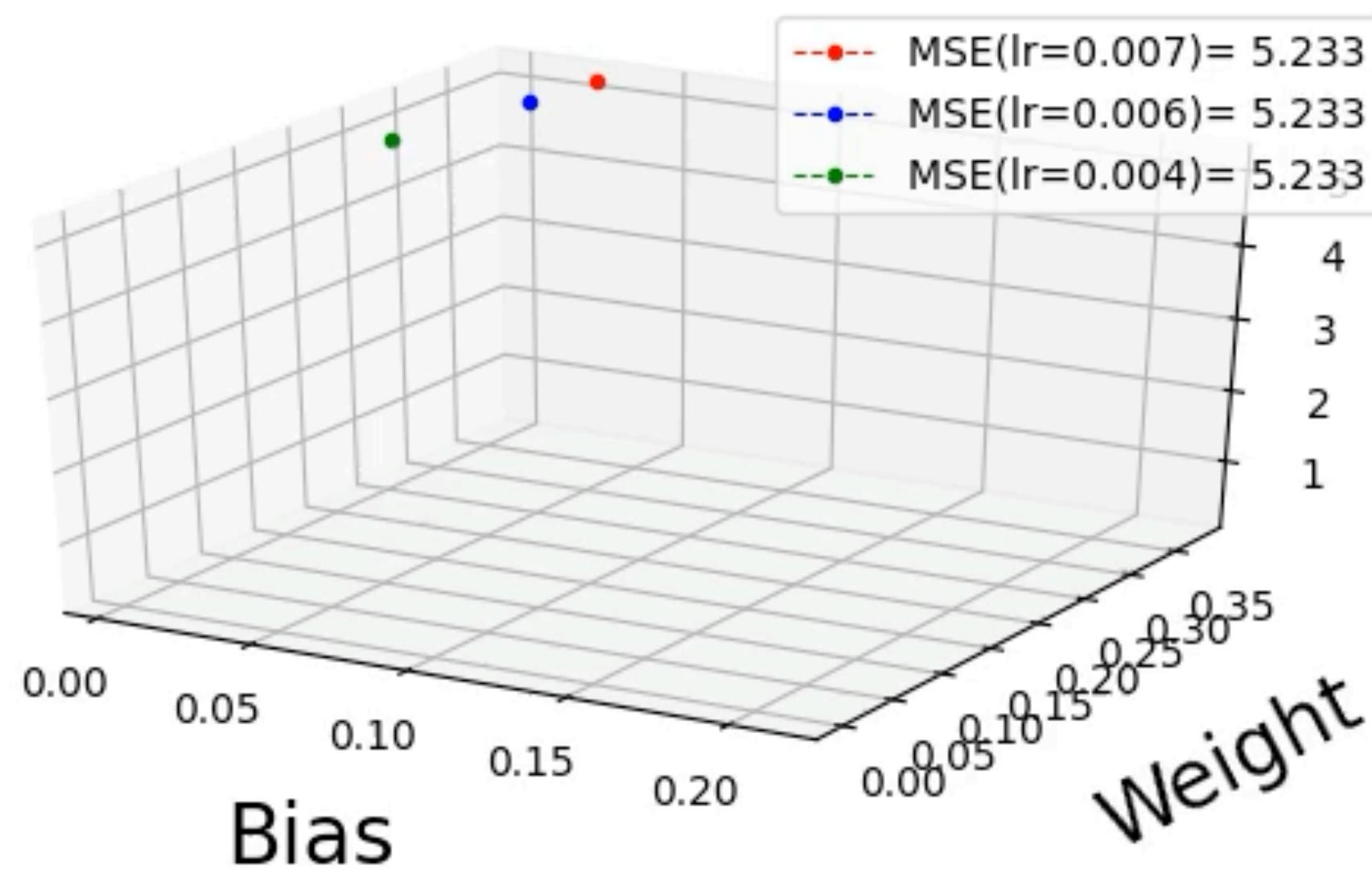
For large learning rate the function oscillates and we will not able to reach the minimum

Learning rate

Effect of different learning rates



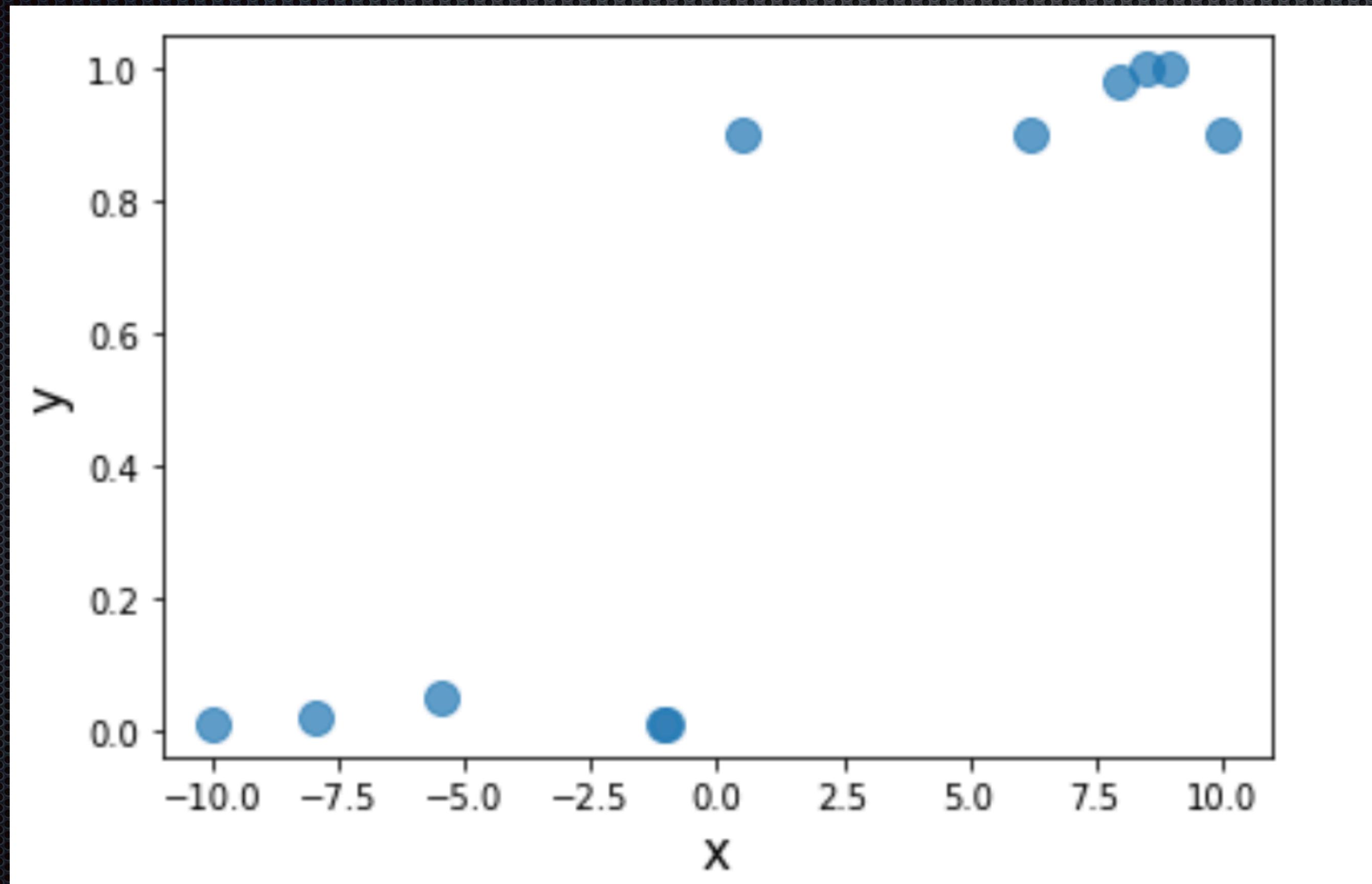
Learning rate



Categorical data

Question:

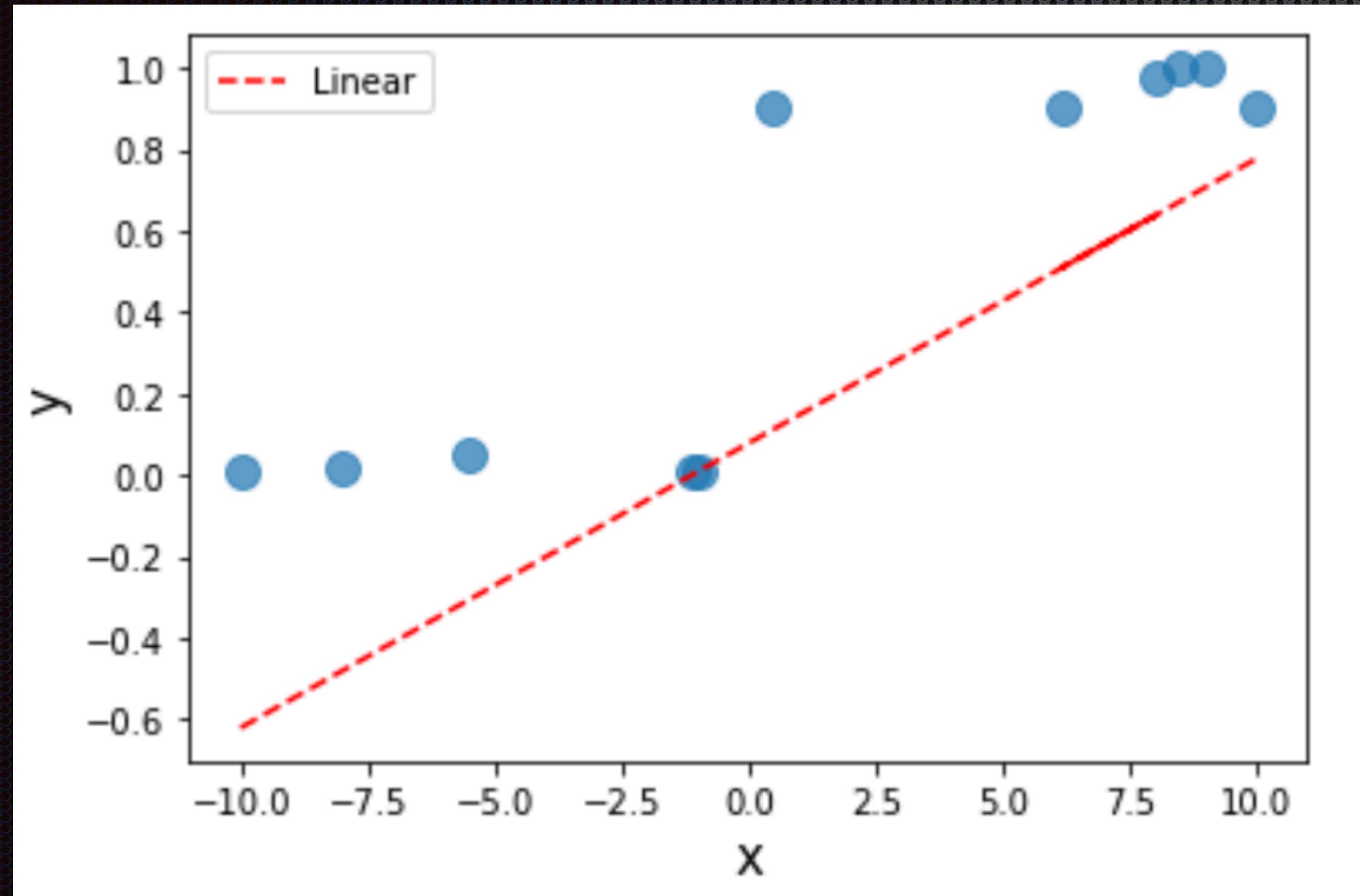
Can we repeat the previous steps for categorical data ?



Categorical data

Question:

Can we repeat the previous steps for categorical data ?

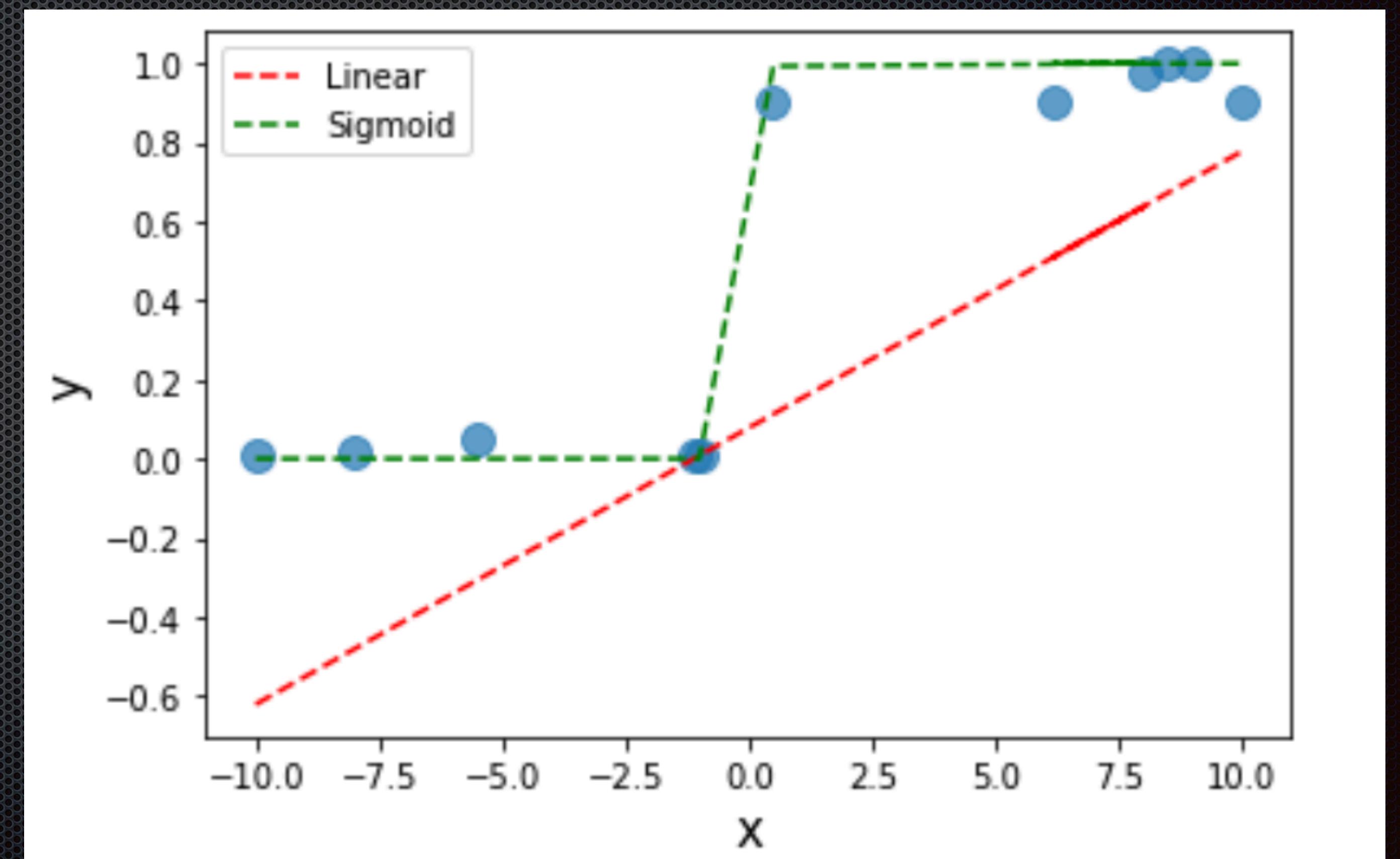


It seems not!! But why ?

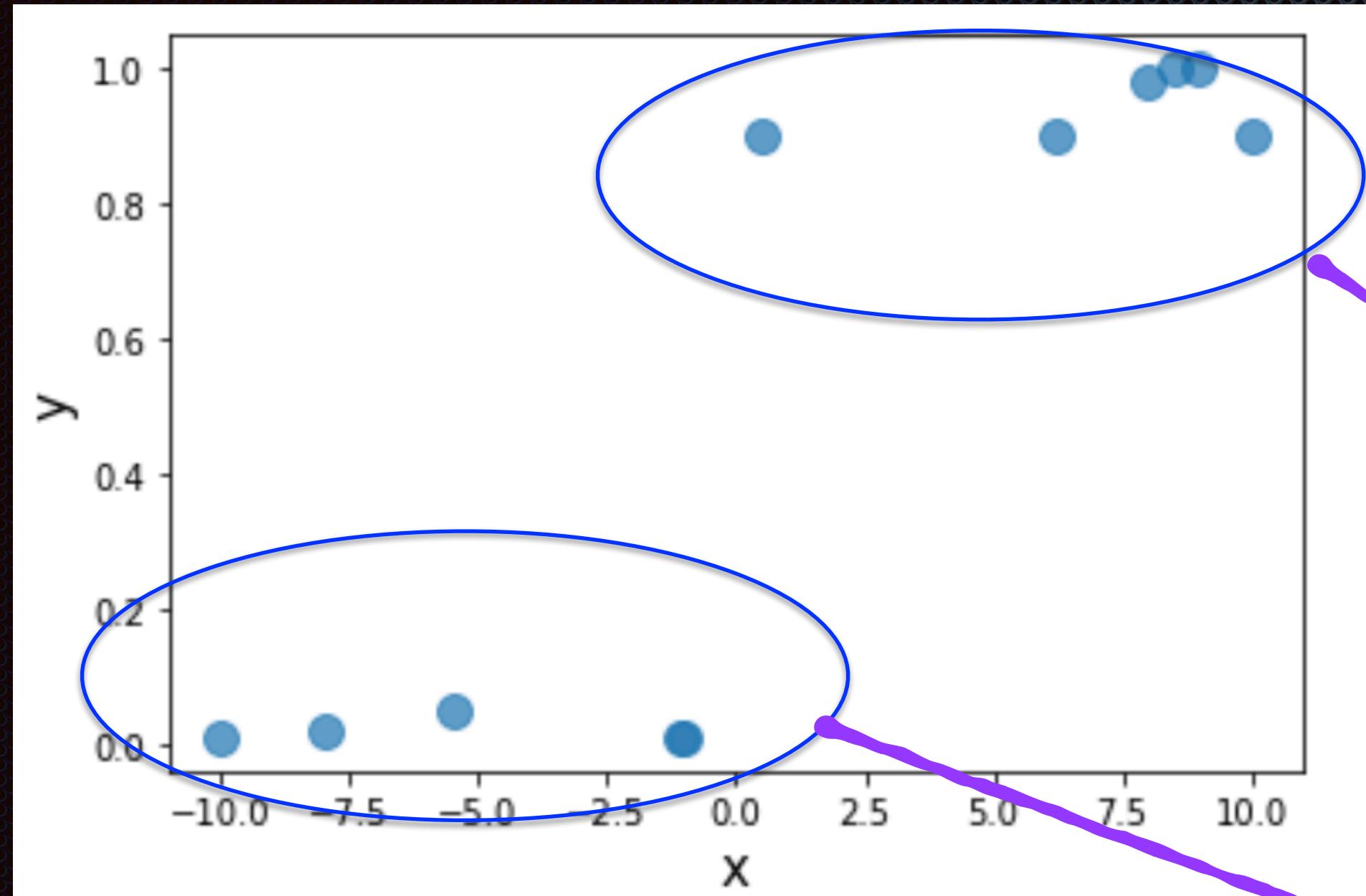
Categorical data

To fit categorical data we need a non linear fitting function

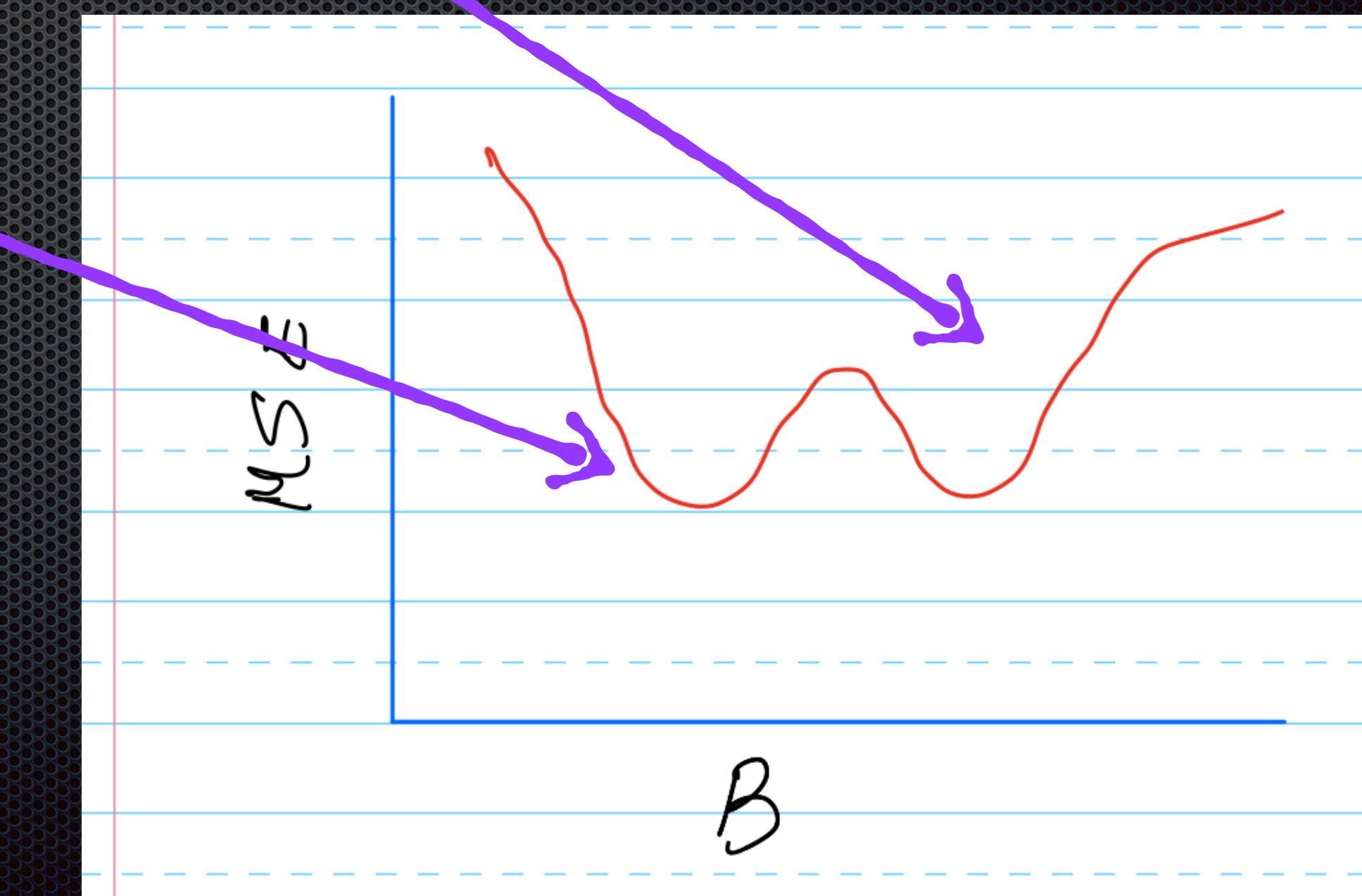
$$\text{Sigmoid} = \frac{1}{1 + e^{-\hat{y}}} = \frac{1}{1 + e^{-(B_0 + B_1 x)}}$$



Categorical data



In the case of categorical data the MSE will develop many local minima and will be hard to converge



Categorical data-Loss function

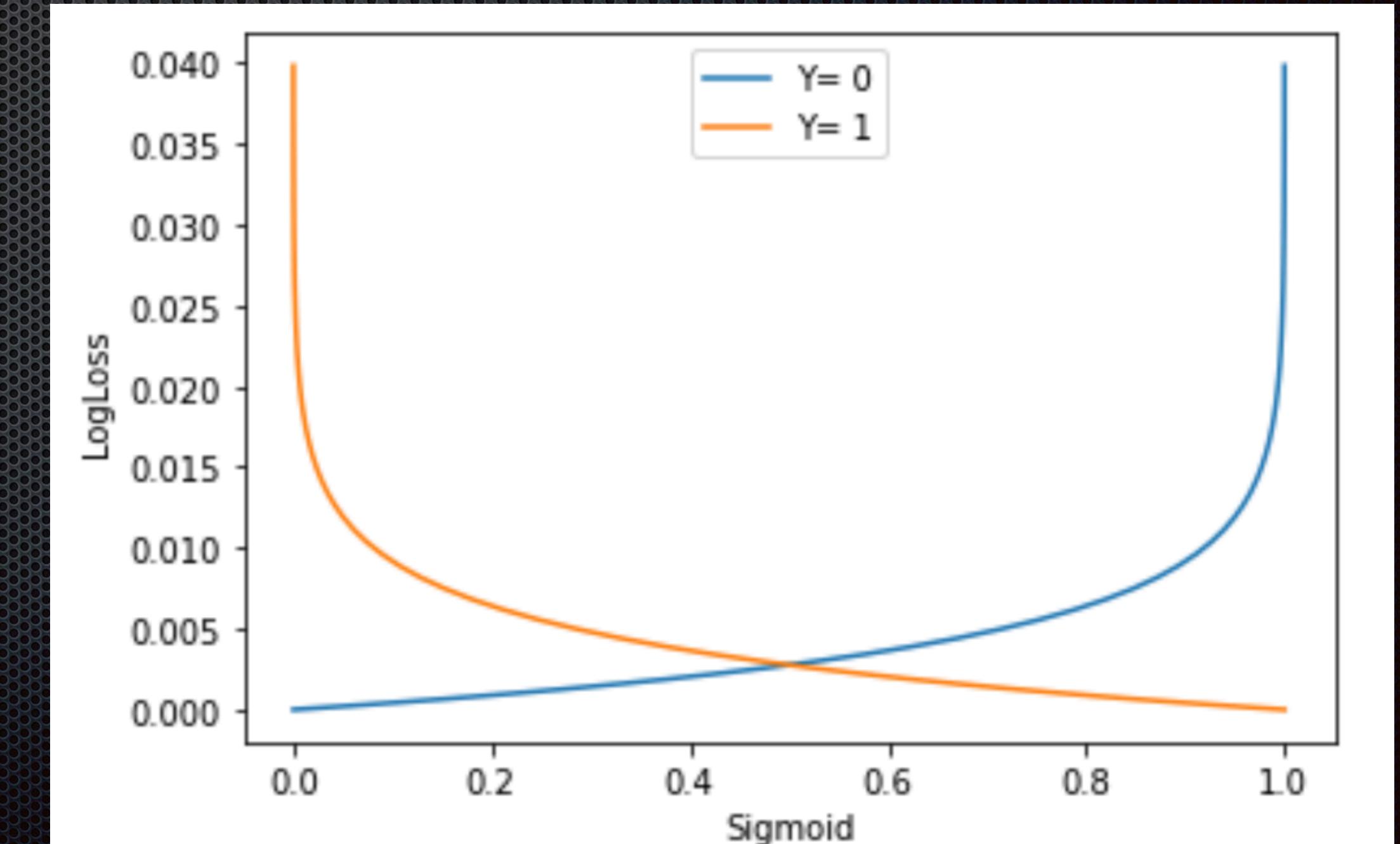
Entropy Loss for Categorical data

$$\text{Entropy Loss} = -\frac{1}{m} \sum_{i=1}^m \left[Y_i \log(\hat{Y}_i) + (1 - Y_i) \log(1 - \hat{Y}_i) \right]$$

The model can converge to a global minimum

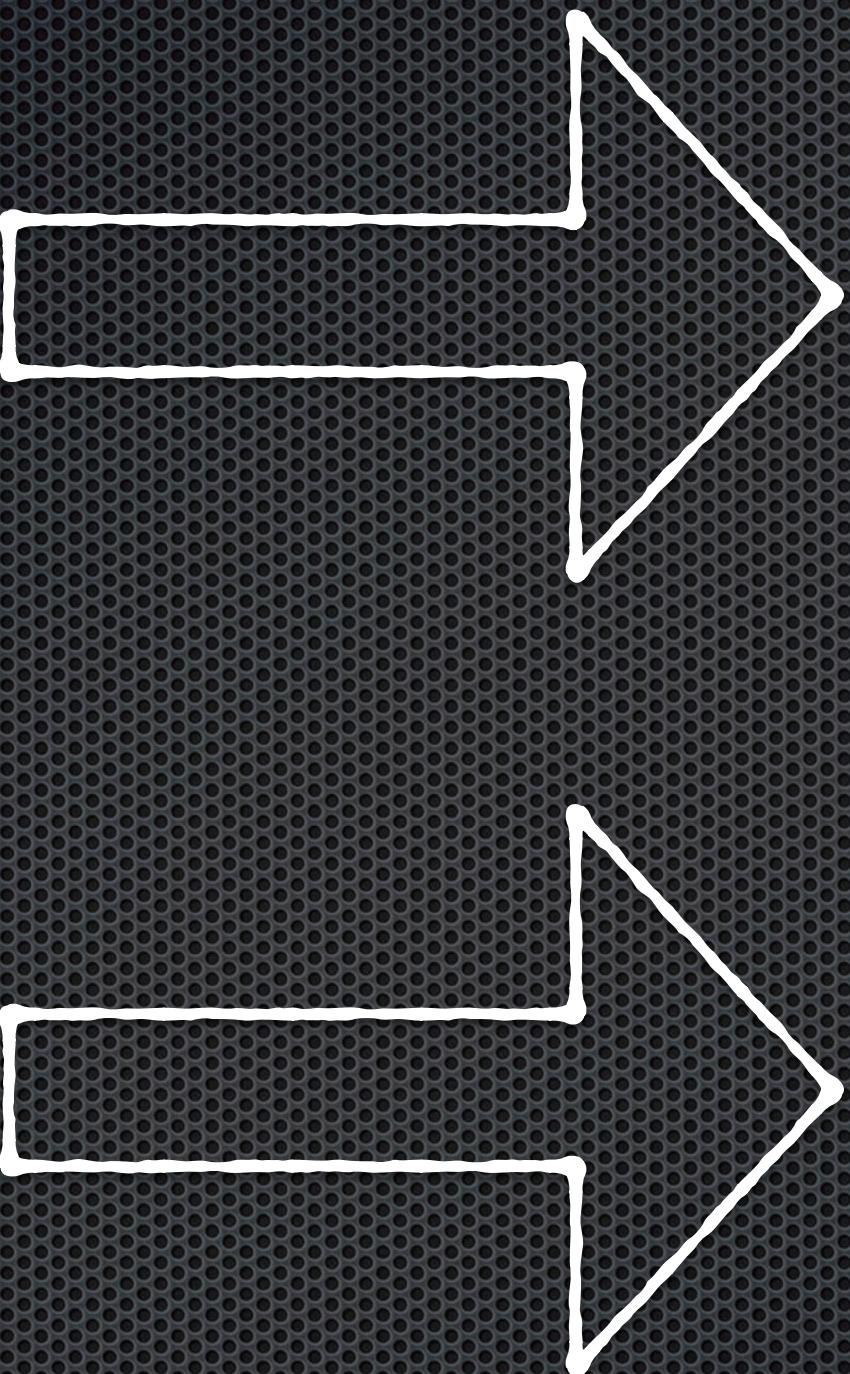
From Information theory

$$\text{Entropy} = \log\left(\frac{1}{P}\right)$$



Loss functions

Continuous data



Categorical data

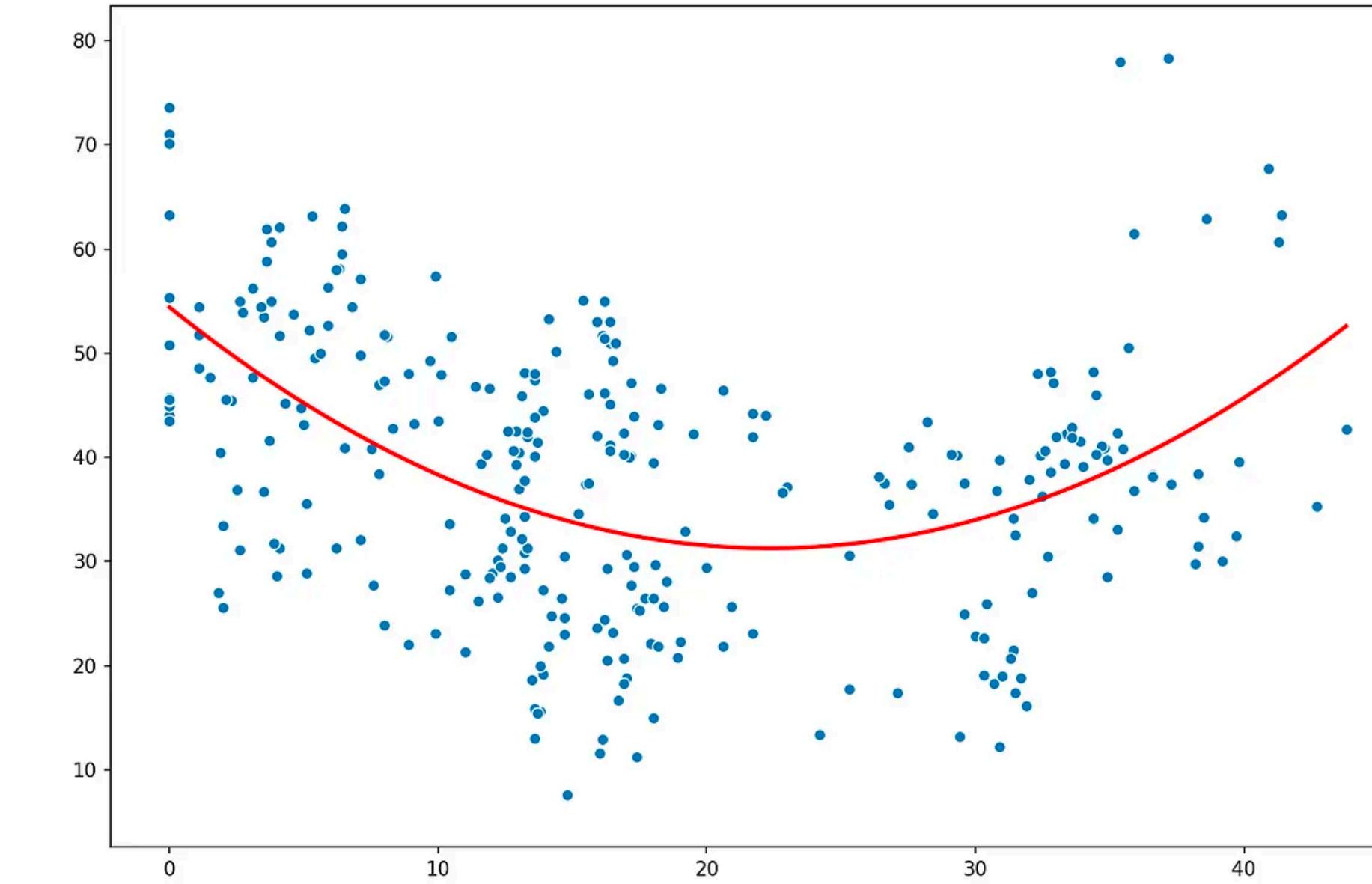
Mean error functions

Entropy loss functions

Polynomial regression model

We can fit the continuous data with polynomial model of power 2

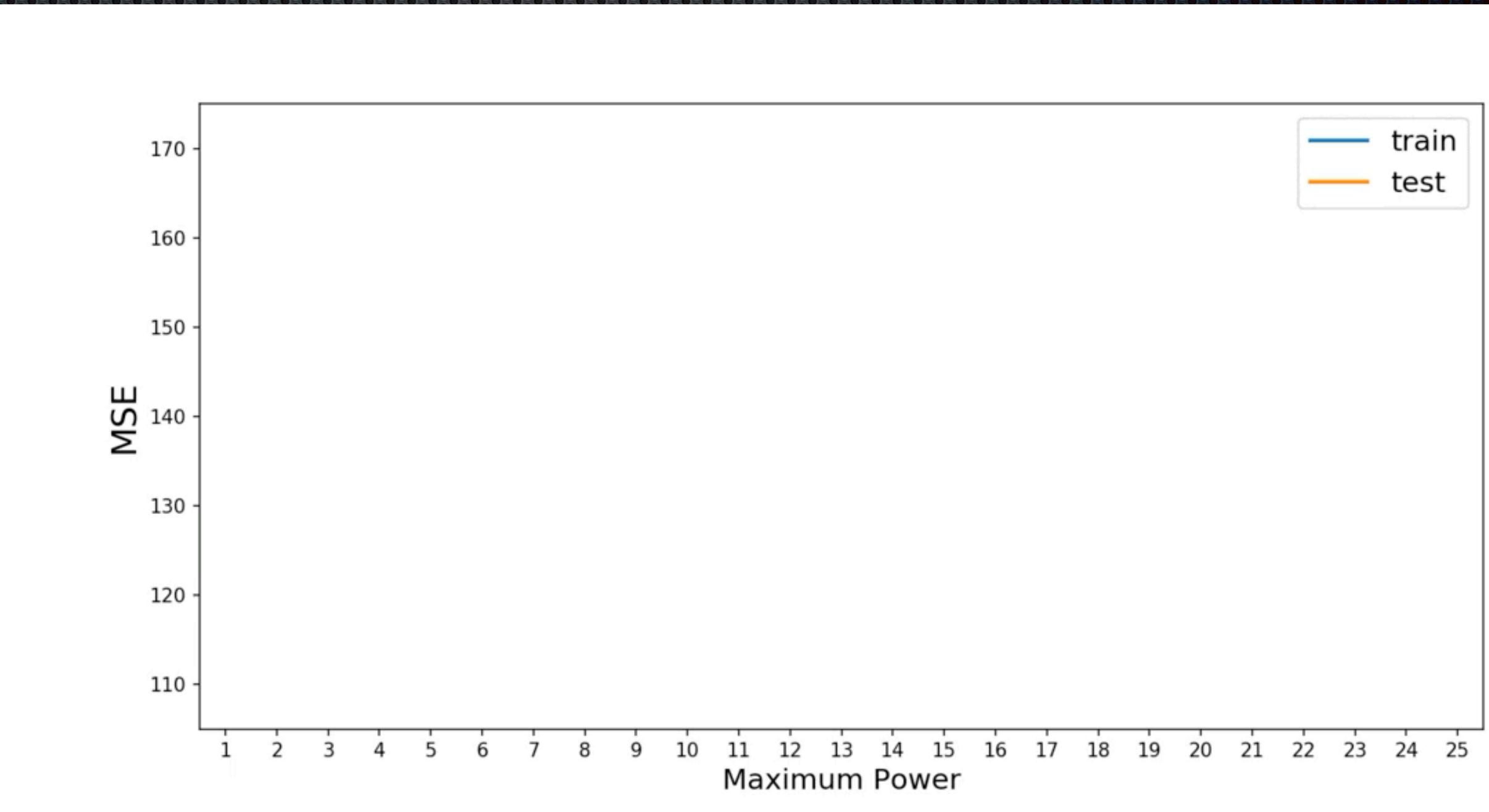
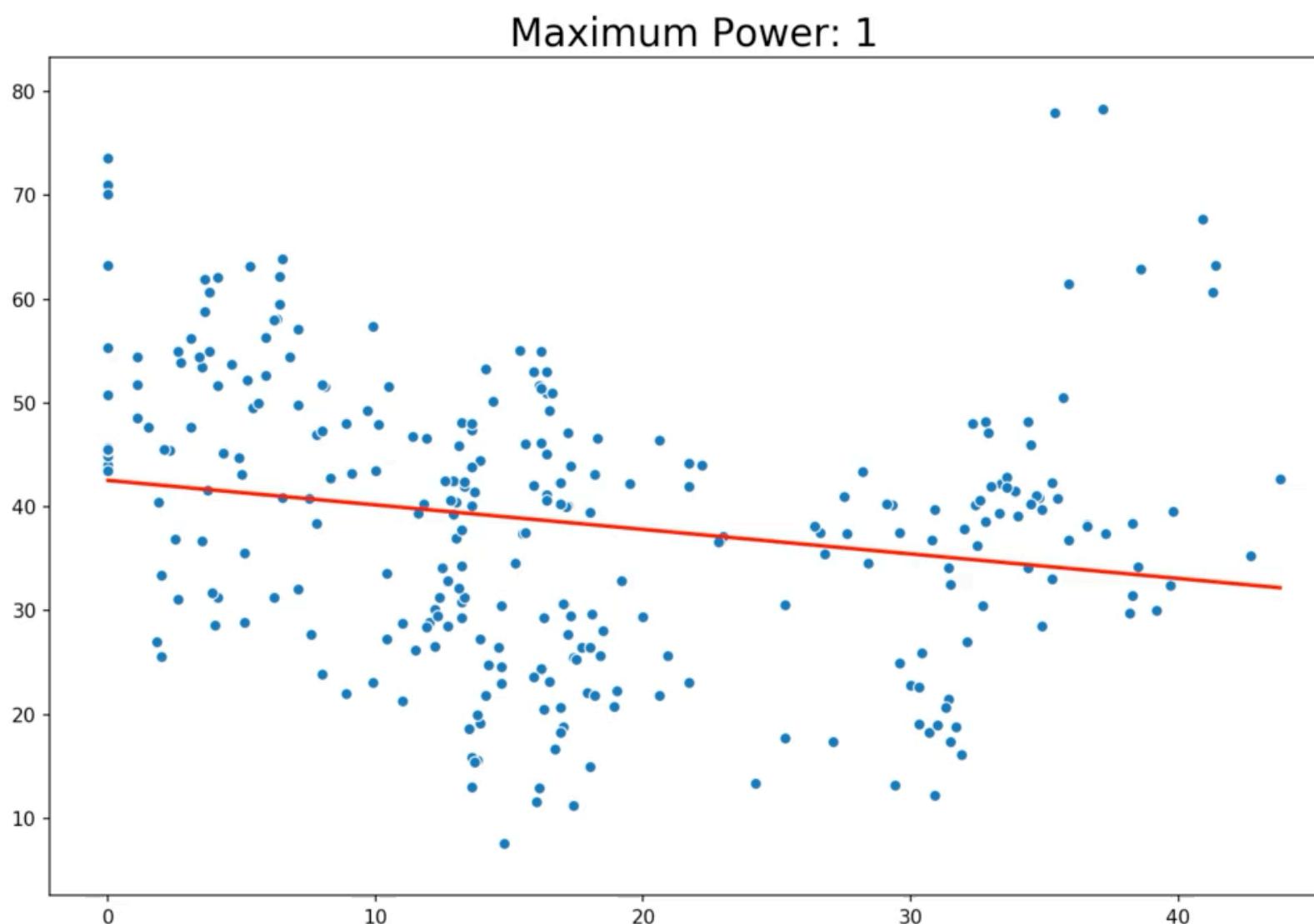
$$\hat{Y} = \omega_1 x + \omega_2 x^2 + B_0$$



Adding more powers to the polynomial model adds more non-linearity to the fitted function. How many powers fit the data best?

Polynomial regression model

$$\hat{Y} = \omega_1 x + \omega_2 x^2 + \dots + \omega_{25} x^{25} + B_0$$

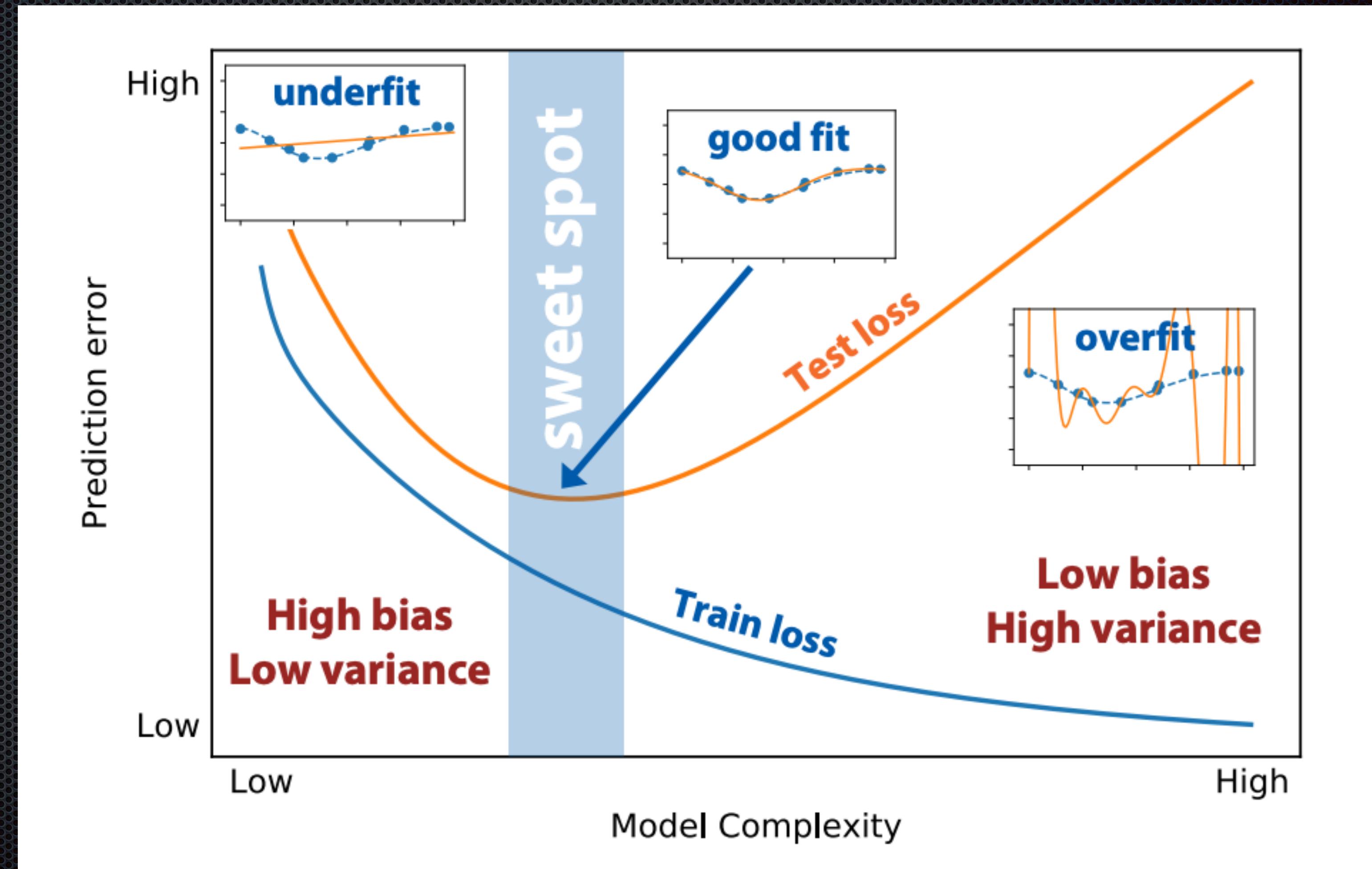


Why the training loss is much better than the test loss function ??

Underfitting & Overfitting

Adding more powers the model has the freedom to learn not only the pattern into the data but it learns the noise in the data as well.

To avoid the overfitting problem we need to regularize the increasing number of powers



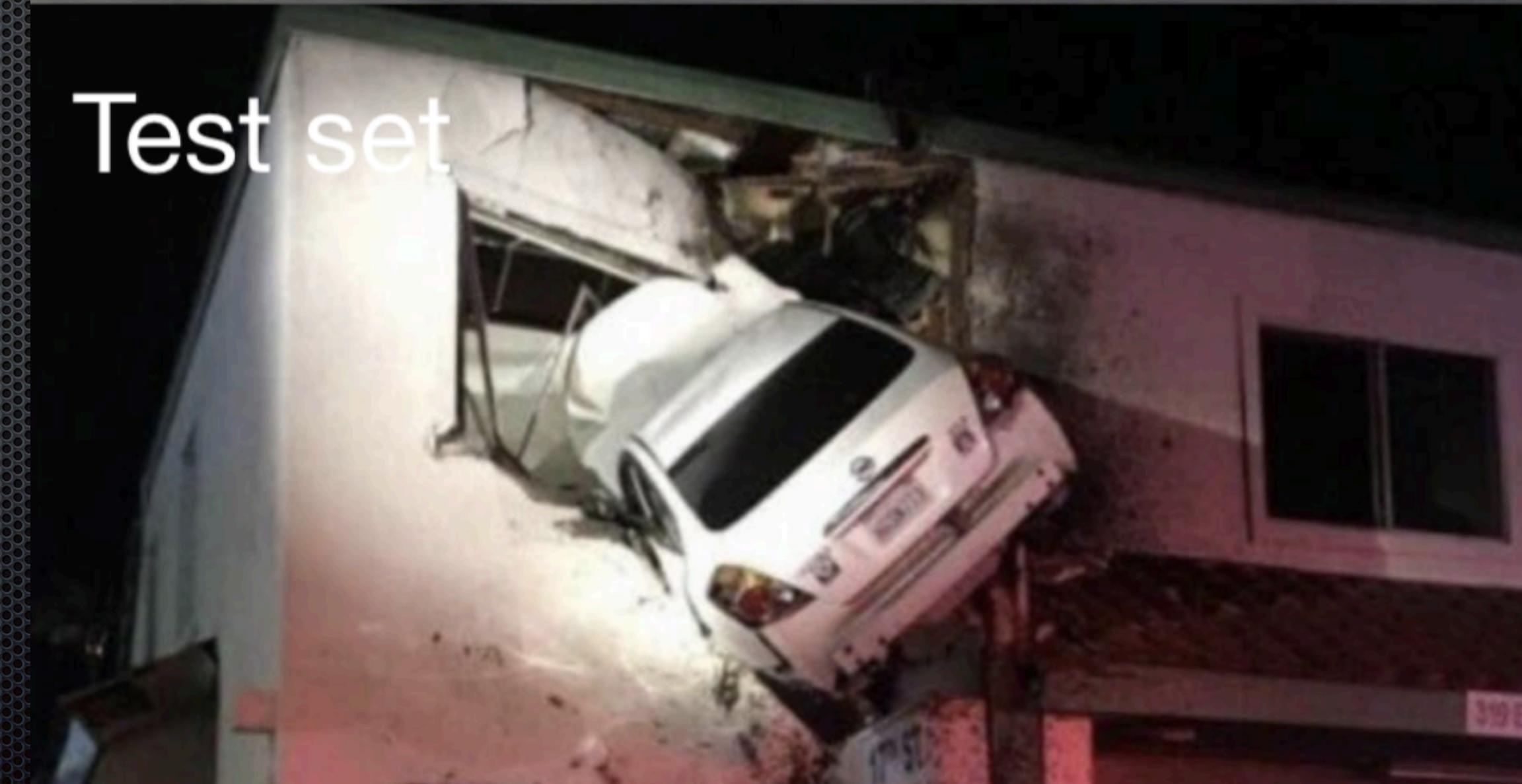
Overfitting danger

OVERFITTING

Training set

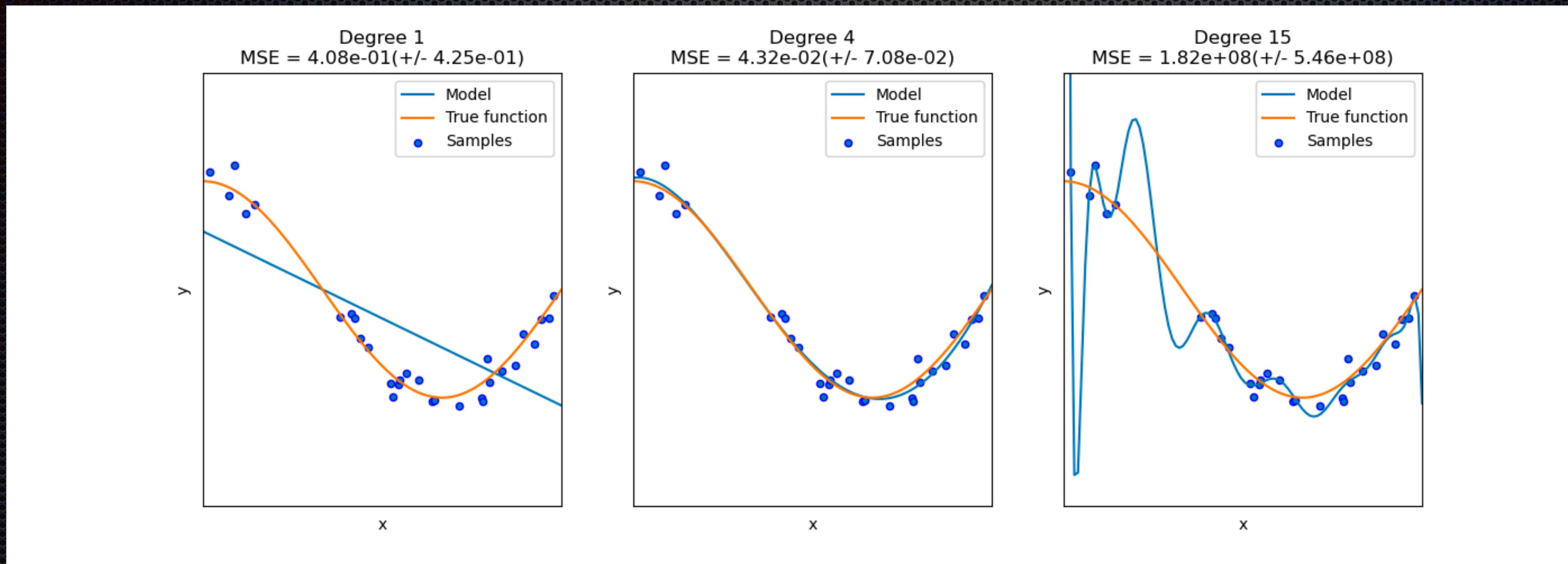


Test set



Regularized regression

The idea is to reconstruct a loss function that penalize the model
If it contains more degrees of freedom than required



We want to construct a loss function that forces the model
to remove the powers above the best fit value

Regularized regression

Error function with regularization

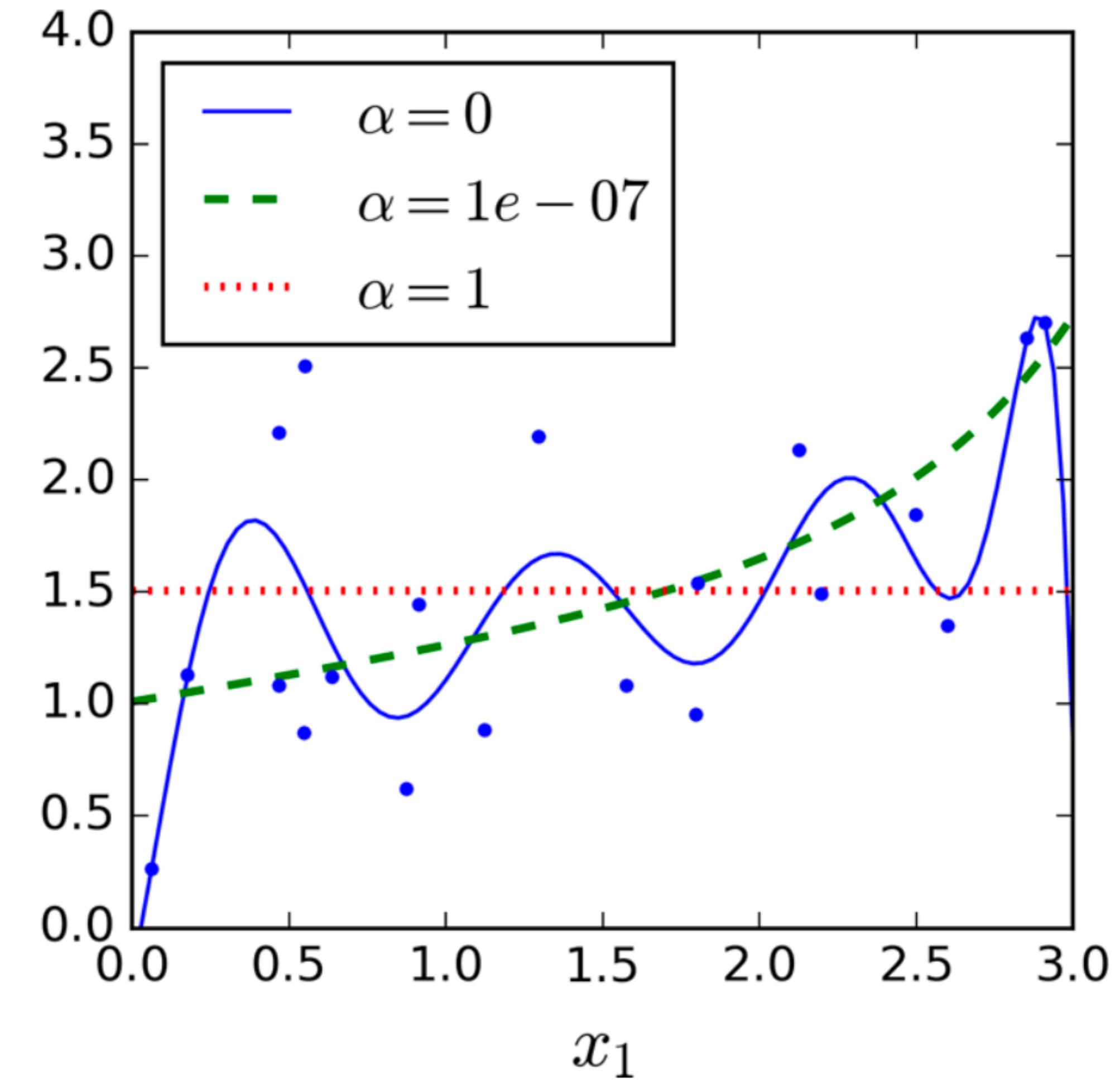
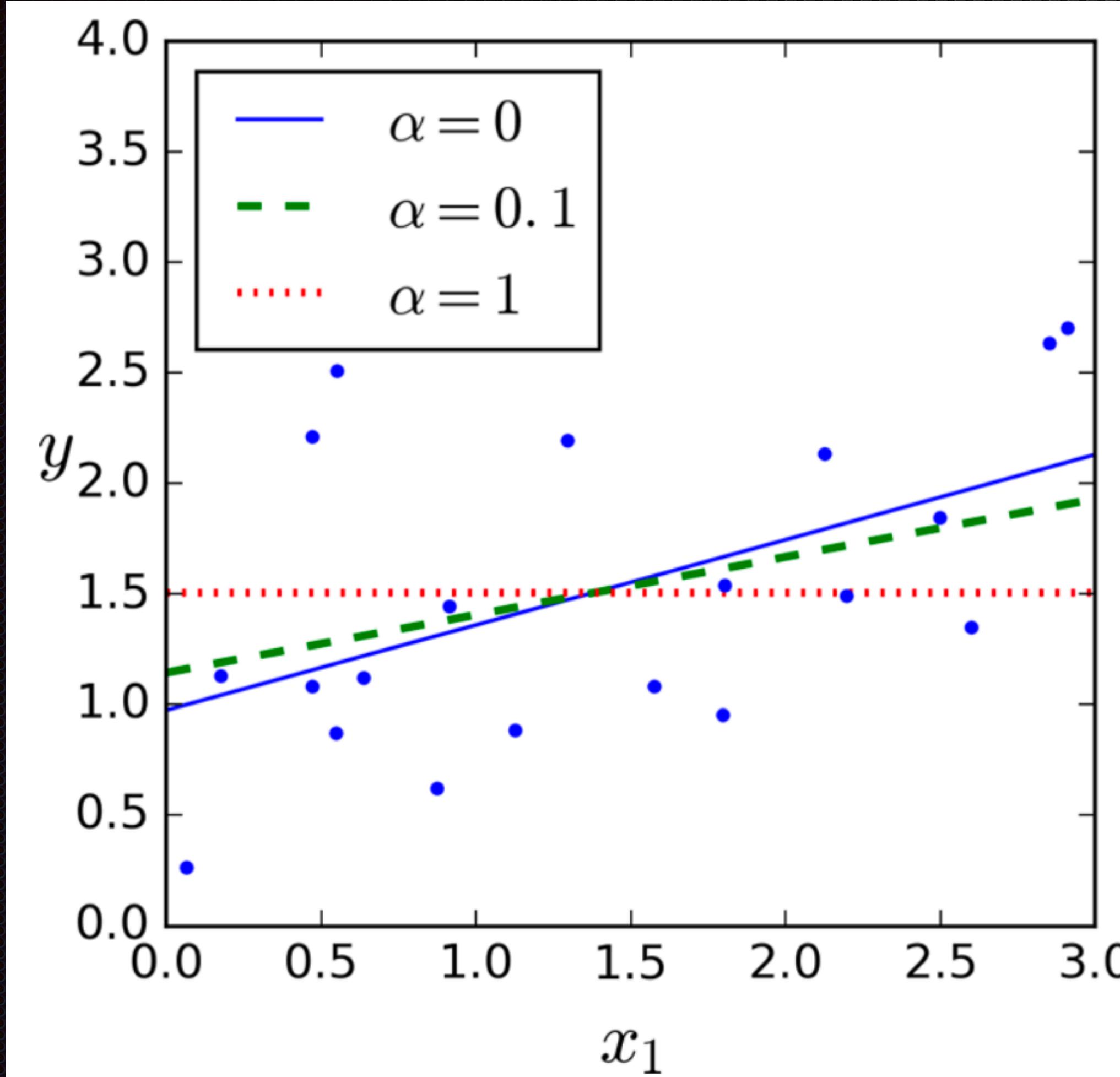
$$\hat{Y} = \omega_1 x + \omega_2 x^2 + \dots + \omega_n x^n + B_0$$

Lasso Model: $L1 = \frac{1}{m} \sum_{i=1}^m (Y_i - \hat{Y}_i) + \lambda \sum_{n=1}^N |\omega_n|$

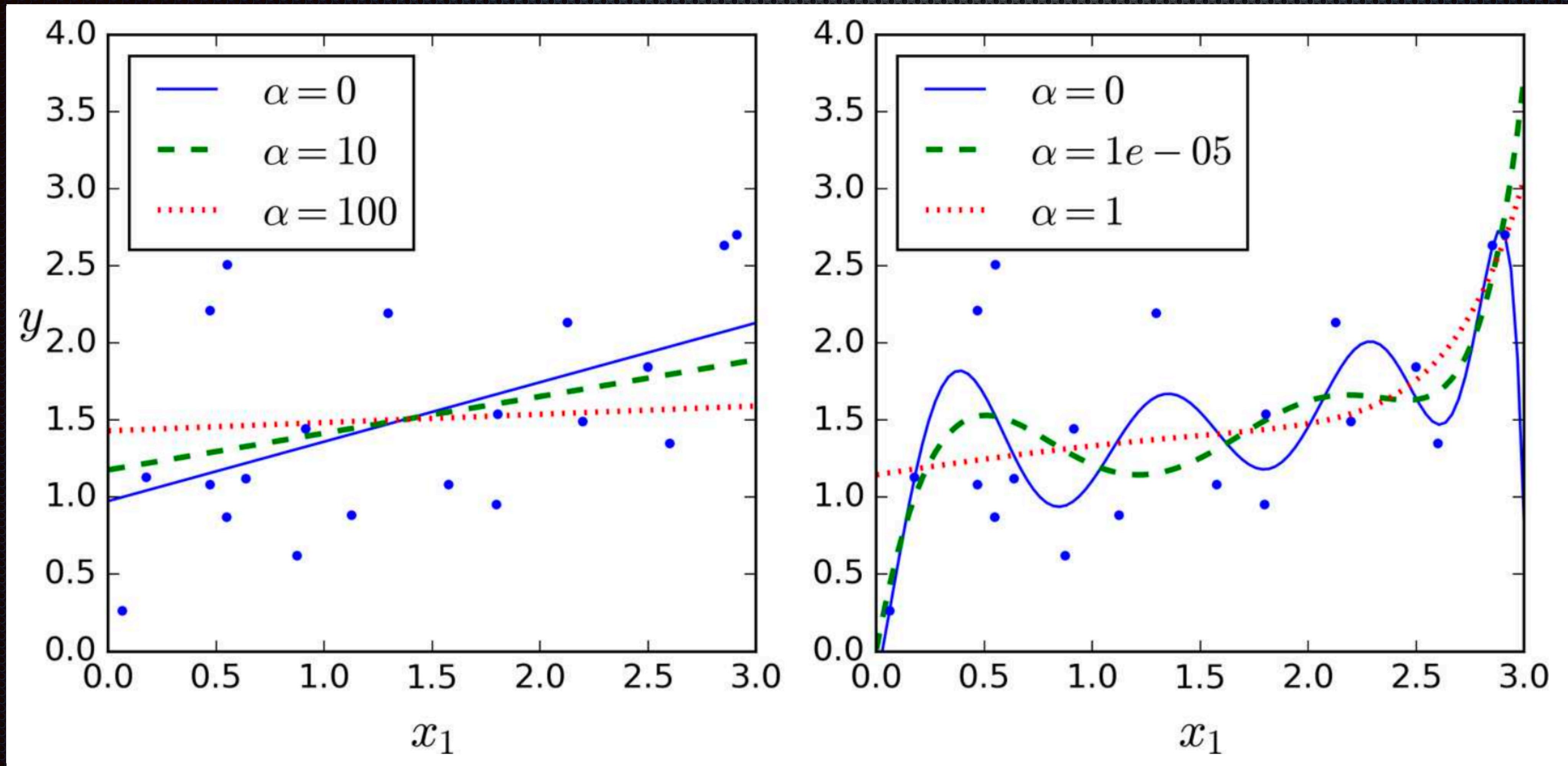
Ridge Model: $L2 = \frac{1}{m} \sum_{i=1}^m (Y_i - \hat{Y}_i) + \lambda \sum_{n=1}^N (\omega_n)^2$

Hyper-parameter to be optimized

Lasso Model



Ridge Model



Question

In which analysis problems we need to use Lasso over Ridge regression ?

To be continued...