

# ML

## LECTURE-8

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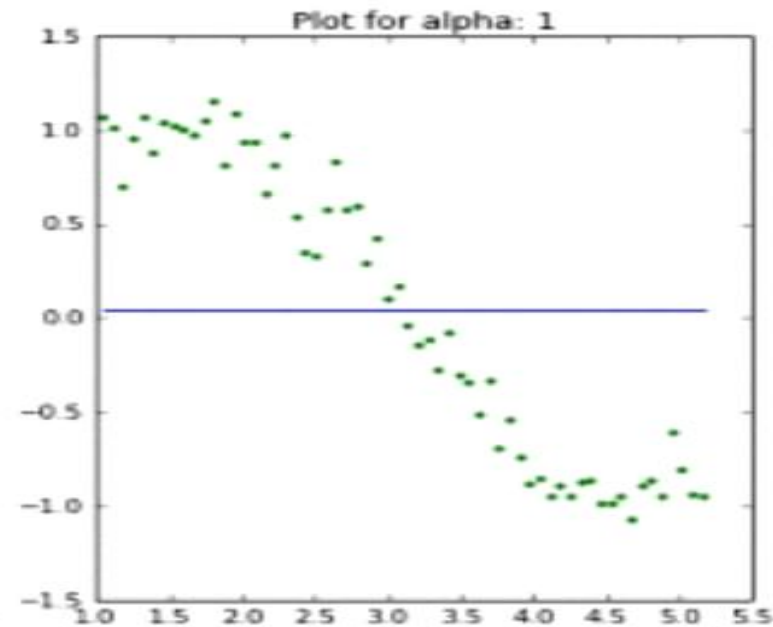
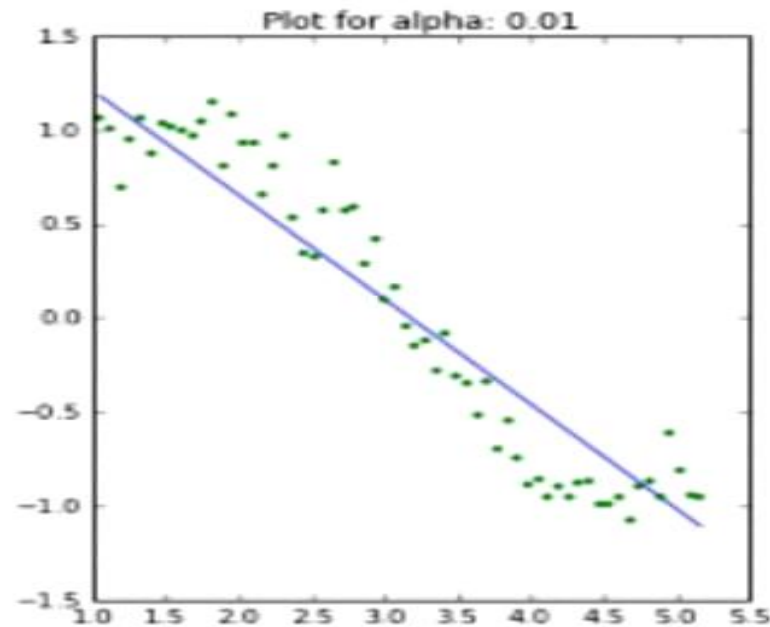
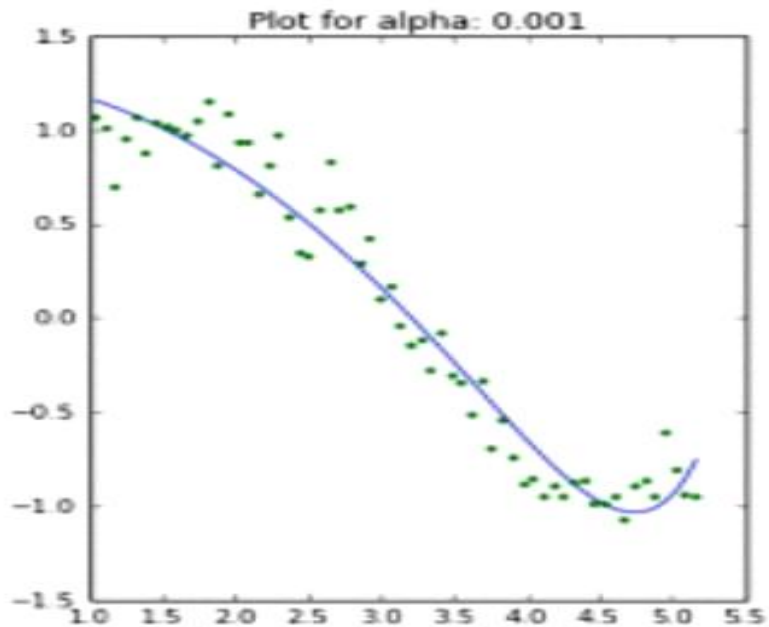
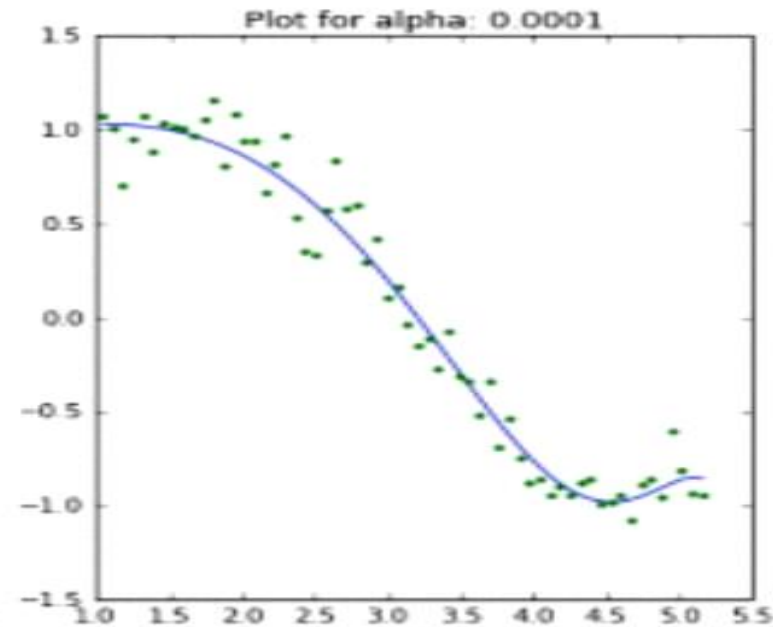
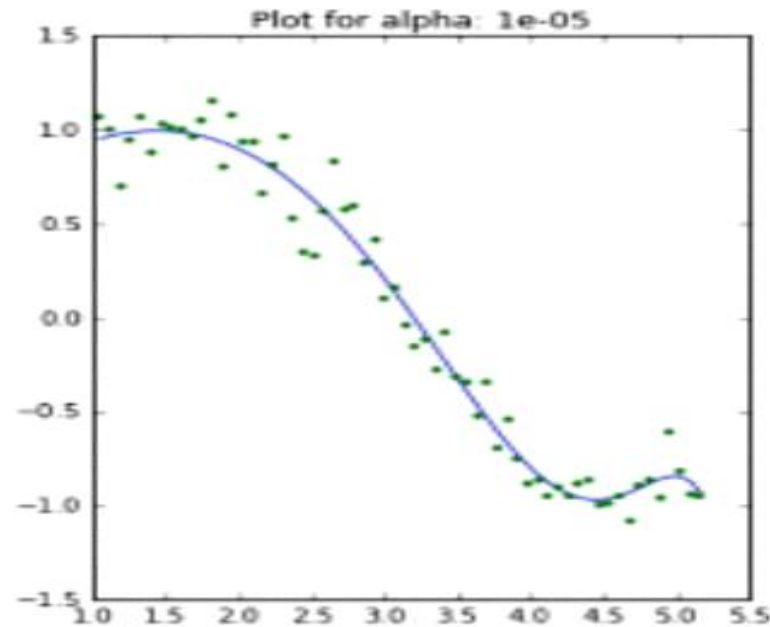
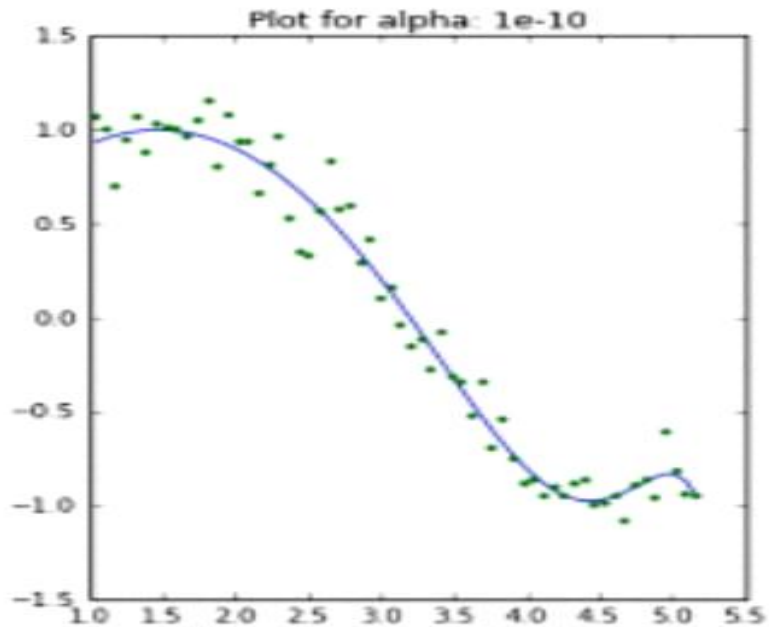
# Regularization

- ❖ Regularization is a technique used in machine learning and statistical modelling to **prevent overfitting and improve the generalization ability of models.**
- ❖ When a model is **overfitting**, it has **learned the training data too well and may not perform well on new, unseen data.**
- ❖ Regularization introduces additional constraints or penalties to the model during the training process, aiming to control the complexity of the model and avoid over-reliance on specific features or patterns in the training data.
- ❖ By doing so, **regularization helps to strike a balance between fitting the training data well and generalizing it well to new data.**
- ❖ The most common regularization techniques used are **L1 regularization (Lasso), L2 regularization (Ridge), and Elastic Net regularization.**
- ❖ **L1 regularization adds the sum of the absolute values of the model's coefficients to the loss function, encouraging sparsity and feature selection.**
- ❖ **L2 regularization adds the sum of the squared values of the model's coefficients, which enables smaller but non-zero coefficients.**
- ❖ Finally, **Elastic Net regularization combines both L1 and L2 regularization.**

# L1 - Regularization (Lasso)

- ❖ L1 regularization, also known as **Lasso (Least Absolute Shrinkage and Selection Operator)** regularization, **adds the sum of the absolute values of the model's coefficients to the loss function.**
- ❖ It encourages sparsity in the model by **shrinking some coefficients to precisely zero.**
- ❖ This has the effect of performing **feature selection**, as the model can effectively ignore irrelevant or **less important features.**
- ❖ L1 regularization is particularly useful when dealing with **high-dimensional datasets with desired feature selection.**
- ❖ Mathematically, the L1 regularization term can be written as:
- ❖ 
$$\text{L1 regularization} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda * \sum |\beta_i|$$
- ❖ Here,  $\lambda$  is the regularization parameter that controls the strength of regularization,  $\beta_i$  represents the **individual model coefficients** and the sum is taken over all coefficients.

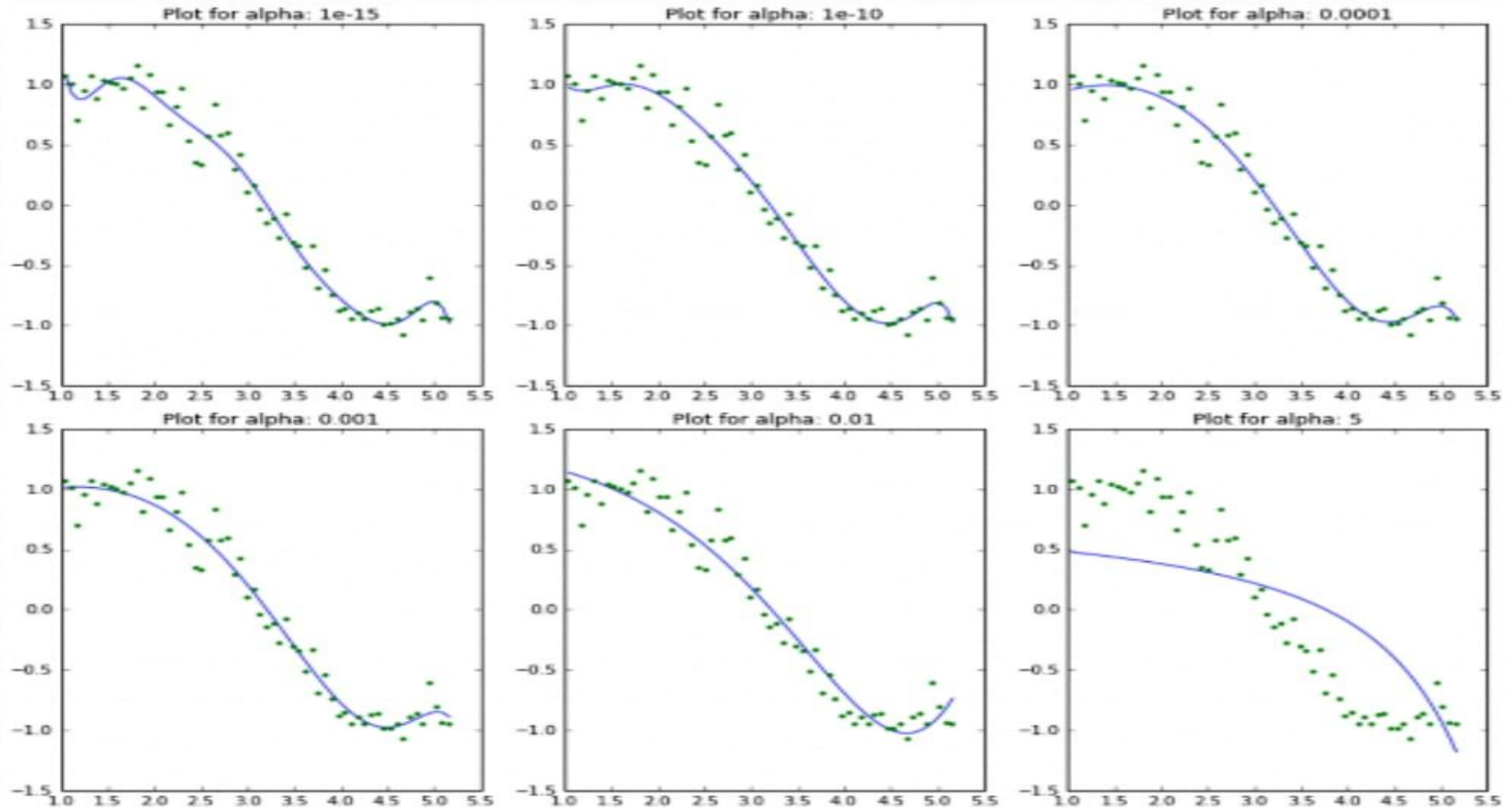
# L1 - Regularization (Lasso)



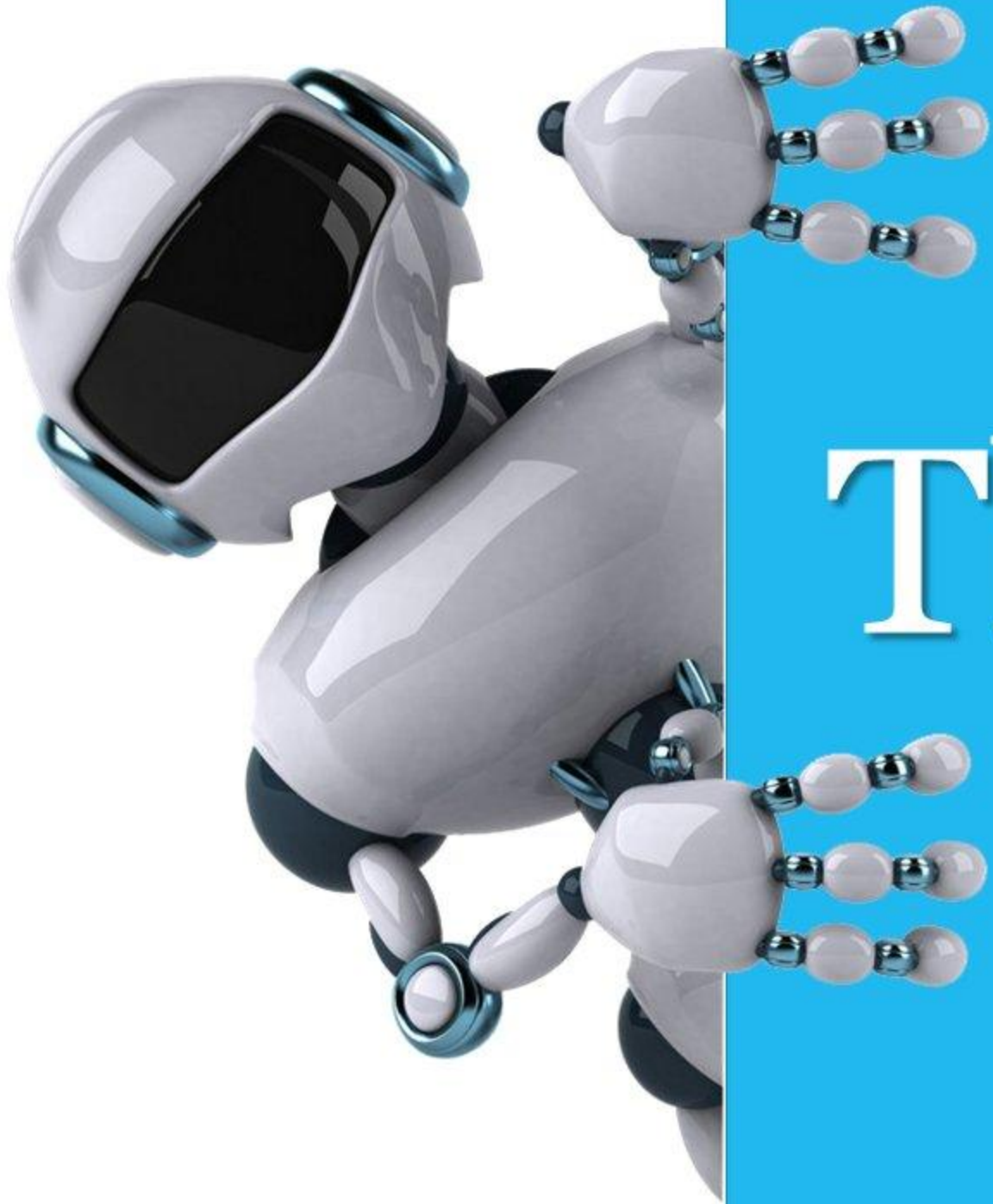
# L2 - Regularization (Ridge)

- ❖ L2 regularization, also known as **Ridge regularization**, adds the **sum of the squared values of the model's coefficients to the loss function**.
- ❖ Unlike L1 regularization, L2 regularization does not force the coefficients to be exactly zero but instead **encourages them to be small**.
- ❖ L2 regularization can **prevent overfitting** by spreading the influence of a single feature across multiple features.
- ❖ It is **advantageous when there are correlations between the input features**.
- ❖ Mathematically, the L2 regularization term can be written as:
- ❖ 
$$\text{L2 regularization} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda * \sum (\beta_i^2)$$
- ❖ Similar to L1 regularization,  $\lambda$  is the **regularization parameter**, and  $\beta_i$  represents the **model coefficients**.
- ❖ The sum is taken over all coefficients, and the squares of the coefficients are summed.

# L2 - Regularization (Ridge)







Thank you