

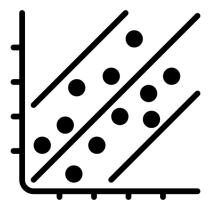
Regression and Variants

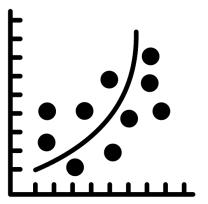
Minh-Hung An - TA Minh-Loi Nguyen - STA

Objectives

Input data Descriptive Statistics Correlation Analysis Hypothesis Testing A/B Testing Train model Evaluation

- ✓ Understand the concept of Regression
- ✓ Understand the variants of Linear Regression
- ✓ Linear Regression & Prompt Engineering





Nguyên lý hoạt động của A/B testing với vai trò feature như sau:

Mỗi dòng dữ liệu được gán ngẫu nhiên vào một trong hai nhóm, nhóm A hoặc nhóm B. Việc ngẫu nhiên hóa này giúp đảm bảo rằng không có sự thiên vị hoặc thành kiến nào trong việc phân nhóm, làm cho kết quả thử nghiệm đáng tin cậy và có thể tổng quát hóa.

Outline

Regression

Linear Regression

Regularization

Other

Outline

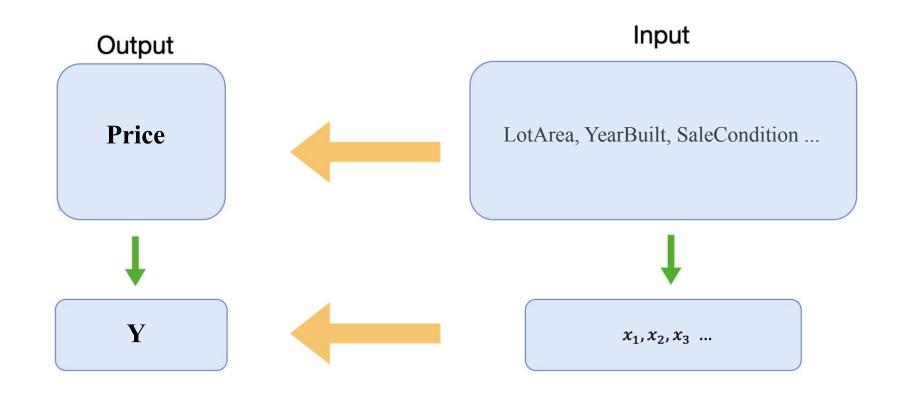
- Regression
- Linear Regression
- Regularization
- 4 Other

Regression Formula

$$Y = a + bX + \in$$

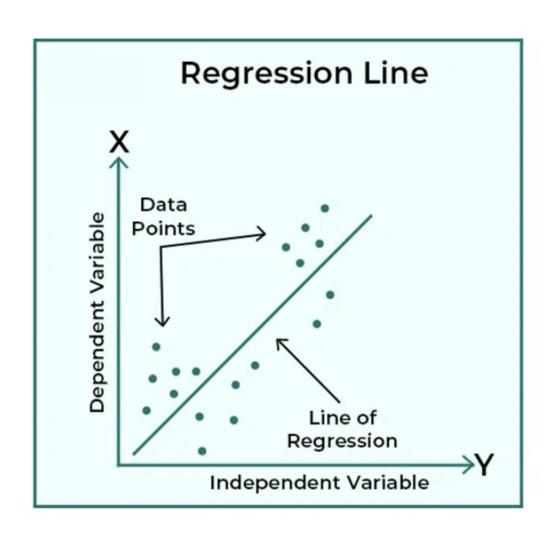


Regression là gì?





Regression là gì?



Supervised Learning

Predict continous output



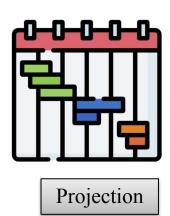
Úng dụng







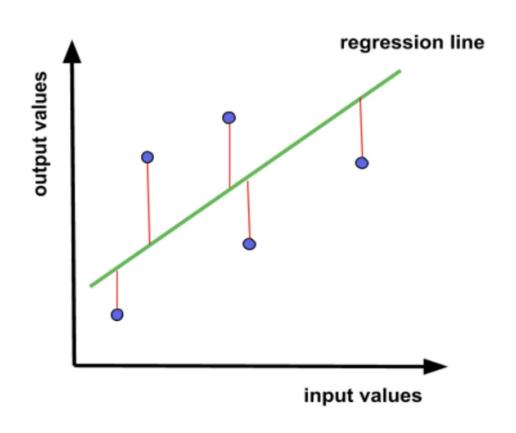


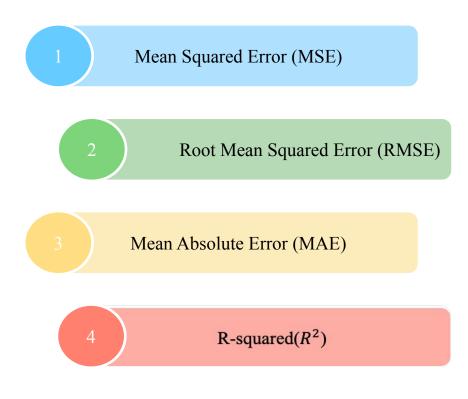






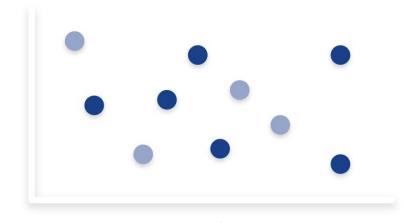
Common Regression Metrics

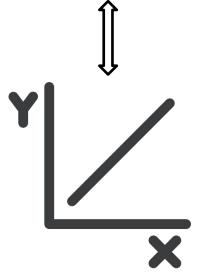




Outline

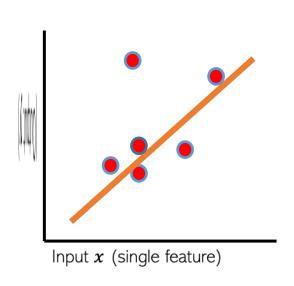
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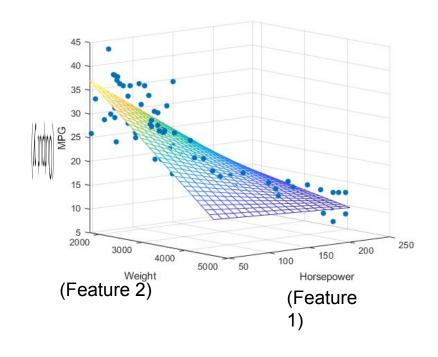






Linear Regression là gì?







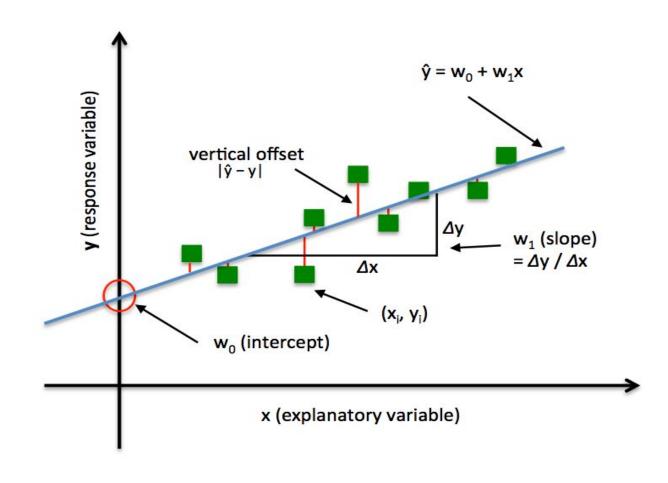
Là việc khớp một đường thẳng hoặc mặt phẳng (siêu) với một tập hợp các điểm.



Linear Regression

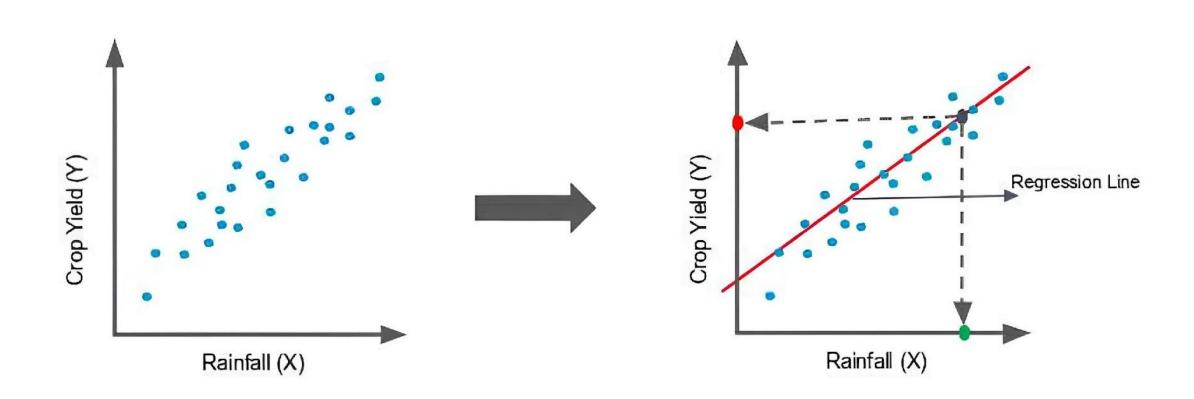
$$\hat{y} = w_0 + w_1 x + \varepsilon$$

- ε: thành phần ngẫu nhiên hoặc thành phần lỗi
- x : feature của biến dữ liệu
- \hat{y} : giá trị mong muốn dự đoán
- w₁: Hệ số góc của đường thẳng
- w₀: Hệ số tự do của đường thẳng



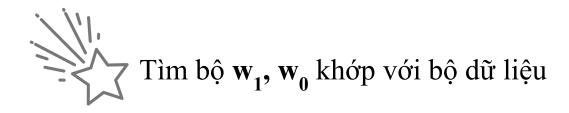


Linear Regression

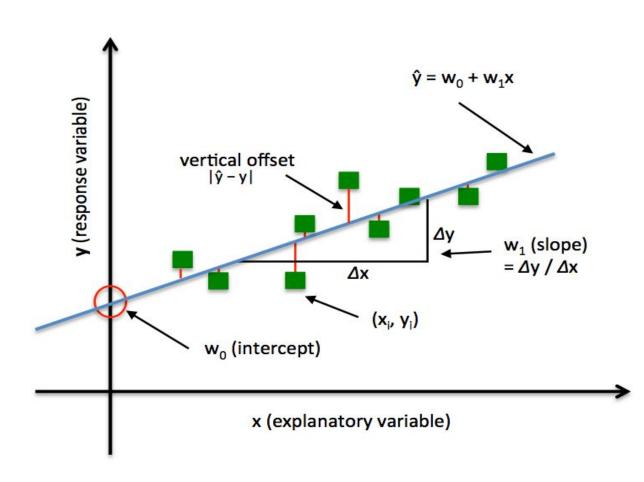




Siải bài toán Regression

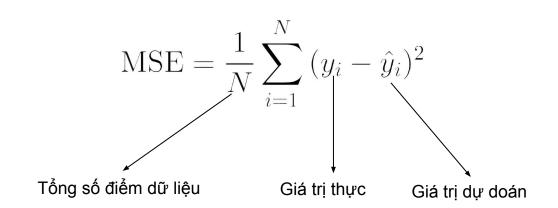


$$\arg\min_{w_0, w_1} \sum_{i=1}^{n} (y_i - w_0 - w_1 x_i)^2$$



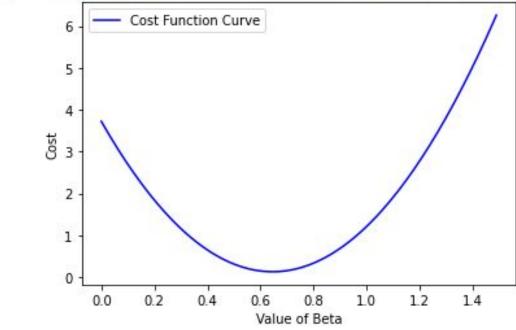


Cost Function











Cost Function

Hypothesis: $h_{\theta}(x) = \theta_0 + \theta_1 x$

Parameters: θ_0, θ_1

Cost Function: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^m \left(h_{\theta}(x^{(i)}) - y^{(i)} \right)^2$

Goal: $\min_{\theta_0,\theta_1} \text{minimize } J(\theta_0,\theta_1)$



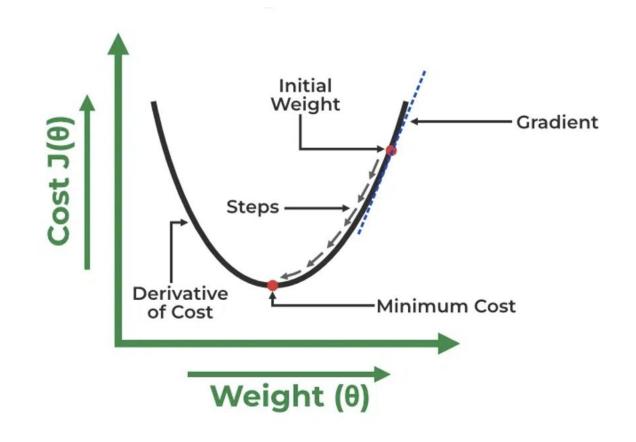
Calculus

$$\frac{\partial \epsilon^2}{\partial w_0} = \sum_{i=0}^{n} -2(y_i - w_0 - w_1 x_i) = 0$$

$$\frac{\partial \epsilon^2}{\partial w_1} = \sum_{i=0}^{n} -2x_i(y_i - w_0 - w_1 x_i) = 0$$

$$w_0 = \bar{y} - w_1 \bar{x}$$

$$w_1 = \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n \sum_{i=1}^{n} x_i x_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} x_i}$$





Gradient Descent

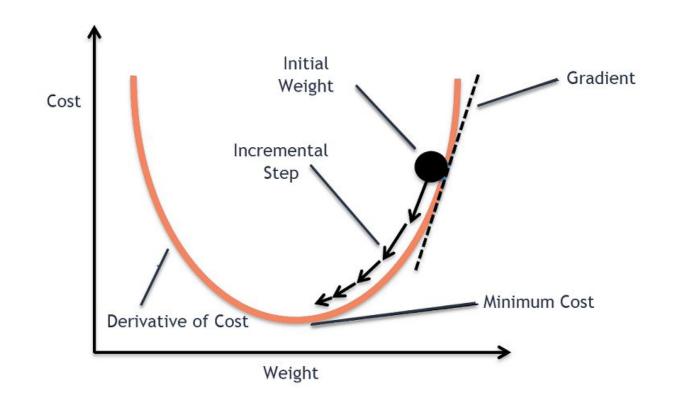
Gradient descent algorithm

repeat until convergence {

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

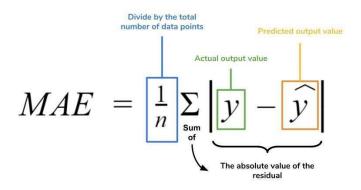
(for
$$j = 1$$
 and $j = 0$)

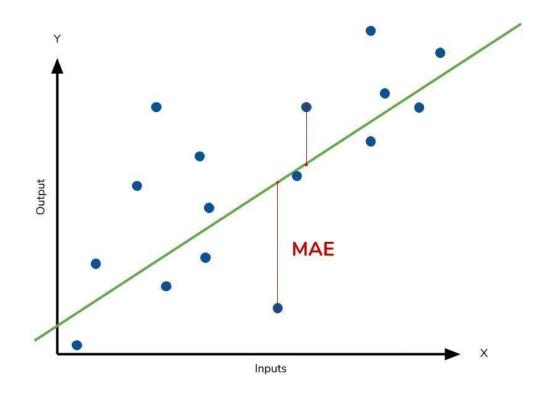






Dánh giá mô hình Linear Regression

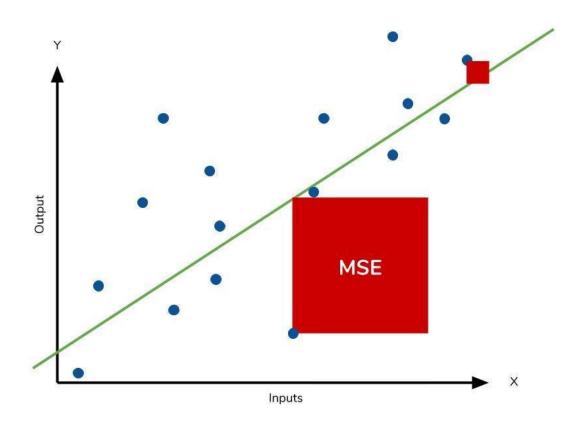






♦ Đánh giá mô hình Linear Regression

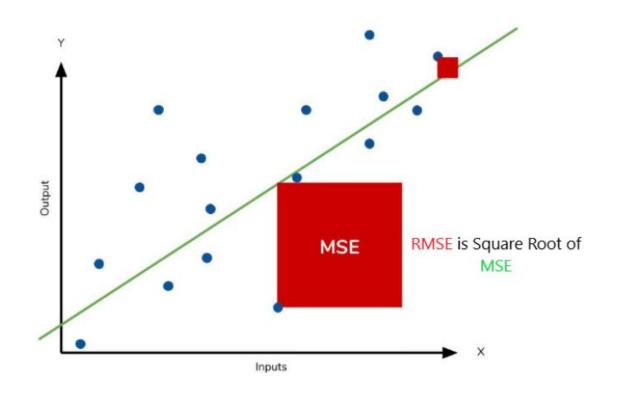
$$MSE = \frac{1}{n} \sum \left(y - \hat{y} \right)^{2}$$
The square of the difference between actual and predicted





Dánh giá mô hình Linear Regression

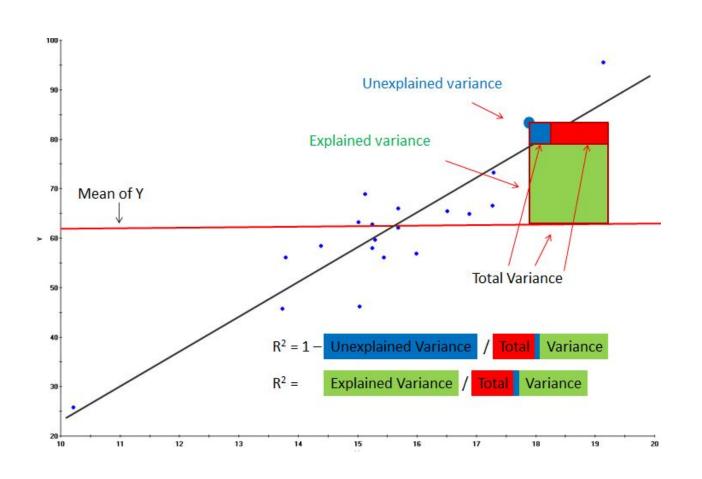
$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_{i} - Actual_{i})^{2}}{N}}$$





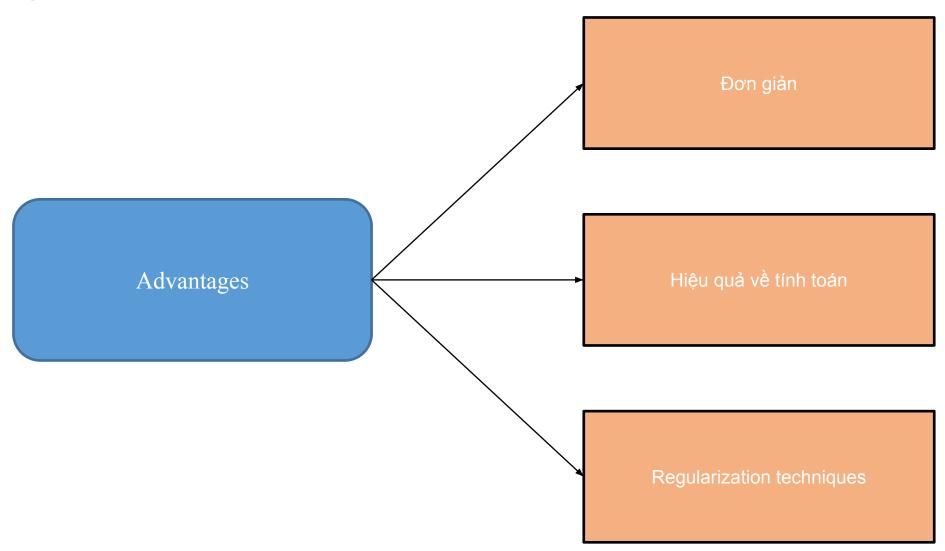
♦ Đánh giá mô hình Linear Regression

$$R^2 = 1 - \frac{\text{MSE(model)}}{\text{MSE(baseline)}}$$



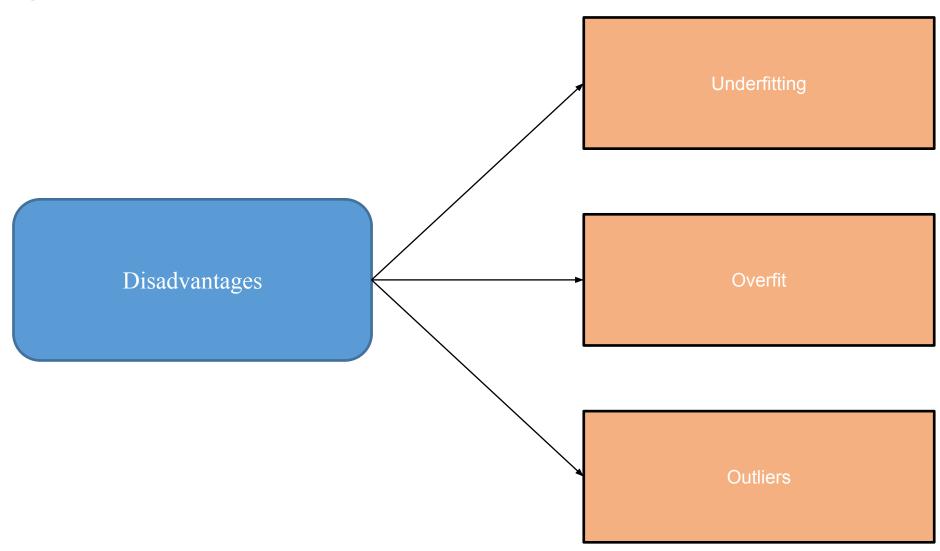


Linear Regression





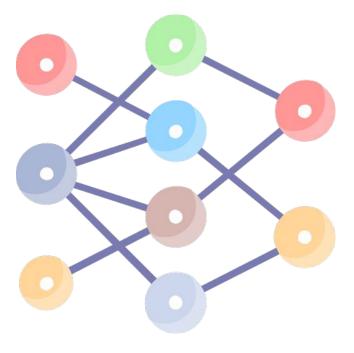
Linear Regression



Outline

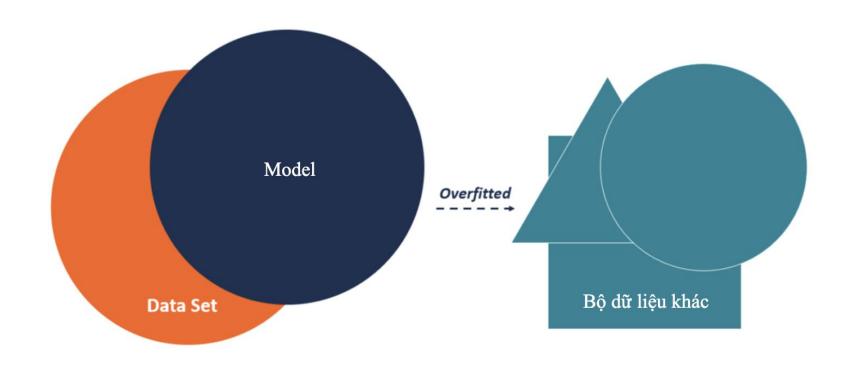
- Regression

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Overfitting





Không khớp trên bộ dữ liệu khác



Linear Regression

- Problem: Overfitting xảy ra vì chỉ giảm thiểu loss được xác định trên training dataset
- Weights $\mathbf{w} = [w_1, w_2, ..., w_D]$ trở nên quá lớn để fit trên training dataset
 - Weights sẽ hoạt động không tốt trên test dataset

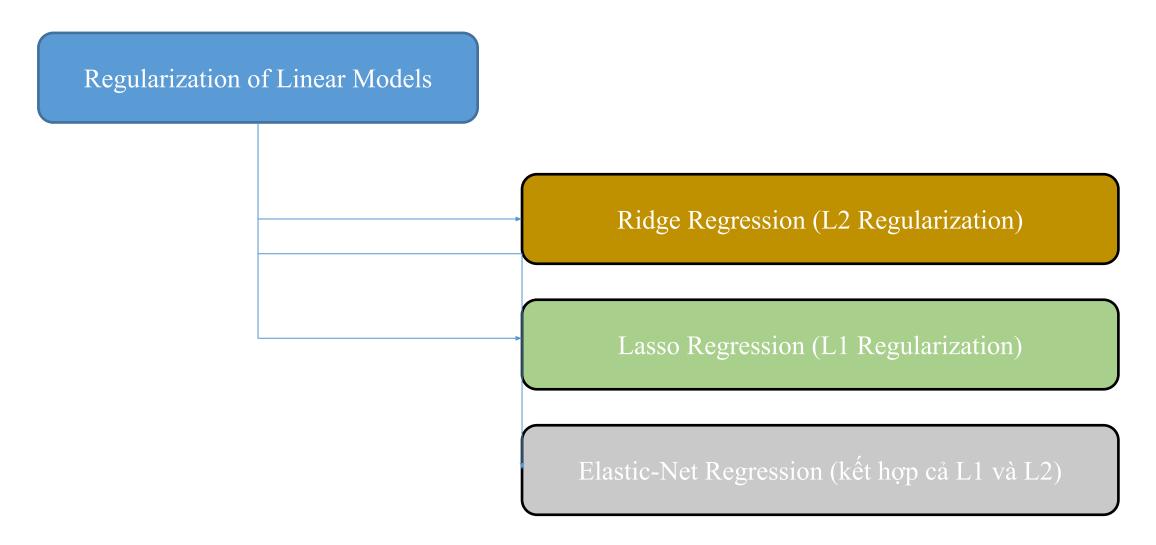
R(w): Regularizer

- Solution: Minimize a regularized objective $L(w) + \lambda R(w)$
 - Ngăn chặn Weights w trở nên quá lớn
 - Giải thích : Minimize trên cả training error + magnitude of vector

 $\lambda \geq 0$



Linear Regression





Ridge Regression

$$L_{reg}(\mathbf{w}) = L(\mathbf{w}) + \lambda R(\mathbf{w})$$

$$R(\mathbf{w}) = ||\mathbf{w}||_2^2 = \mathbf{w}^{\mathsf{T}} \mathbf{w}$$

$$w_{ridge} = \arg\min_{w} L(w) + \lambda R(w)$$

$$= \arg\min_{w} \sum_{n=1}^{N} (y_n - w^{\mathsf{T}} x_n)^2 + \lambda w^{\mathsf{T}} w$$

$$w_{rid,ge} = (\sum_{n=1}^{N} x_n x_n^{T} + \lambda I_D)^{-1} (\sum_{n=1}^{N} y_n x_n)$$
 (the optimal w)



Lasso Regression

$$L_{reg}(w) = L(w) + \lambda R(w)$$

$$R(w) = ||w||_1 = \sum_{d=1}^{D} |w_d|$$

$$w_{lasso} = \arg\min_{\mathbf{w}} L(\mathbf{w}) + \lambda R(\mathbf{w})$$

$$= \arg\min_{\mathbf{w}} \sum_{n=1}^{N} (y_n - \mathbf{w}^{\mathsf{T}} \mathbf{x}_n)^2 + \lambda ||\mathbf{w}||_1$$



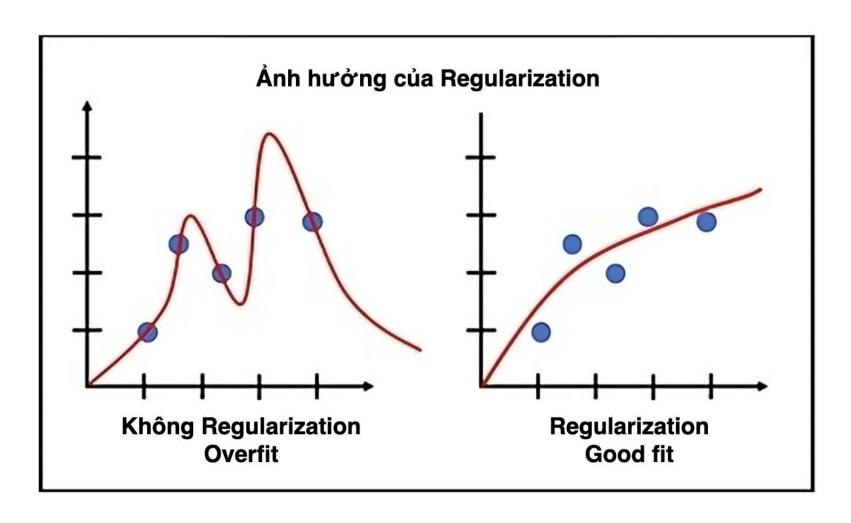
Elastic-Net Regression

$$L_{reg}(\mathbf{w}) = L(\mathbf{w}) + \lambda_1 R_1(\mathbf{w}) + \lambda_2 R_2(\mathbf{w})$$

$$R_1(\mathbf{w}) = ||\mathbf{w}||_1 = \sum_{d=1}^{D} |w_d| \qquad \qquad R_2(\mathbf{w}) = ||\mathbf{w}||_2^2 = \mathbf{w}^{\mathsf{T}} \mathbf{w}$$

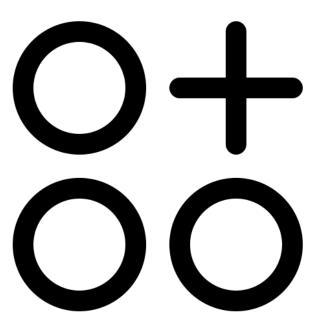


Linear Regression



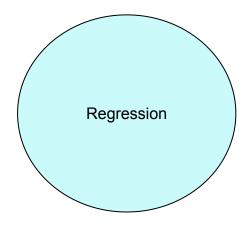
Outline

Regression **Linear Regression** Regulariation Other





Types of Regression



Linear Regression

Lasso Regression

Ridge Regression

Support Vector Regression

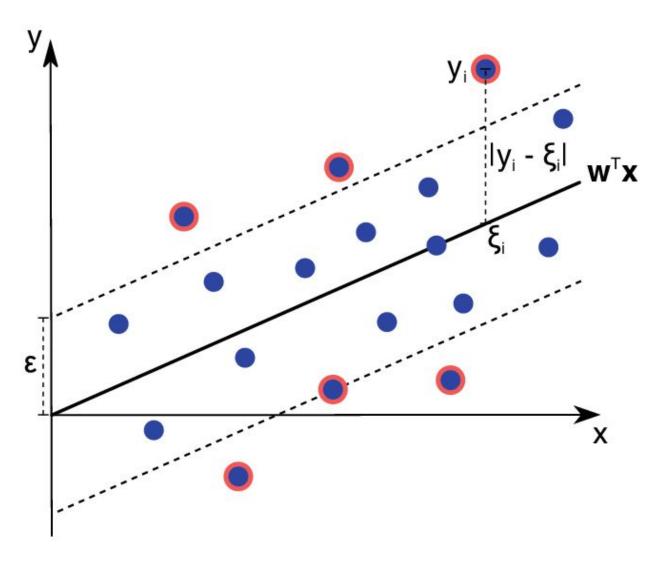
Decision Tree Regression

Random Forest Regression

Logistic Regression

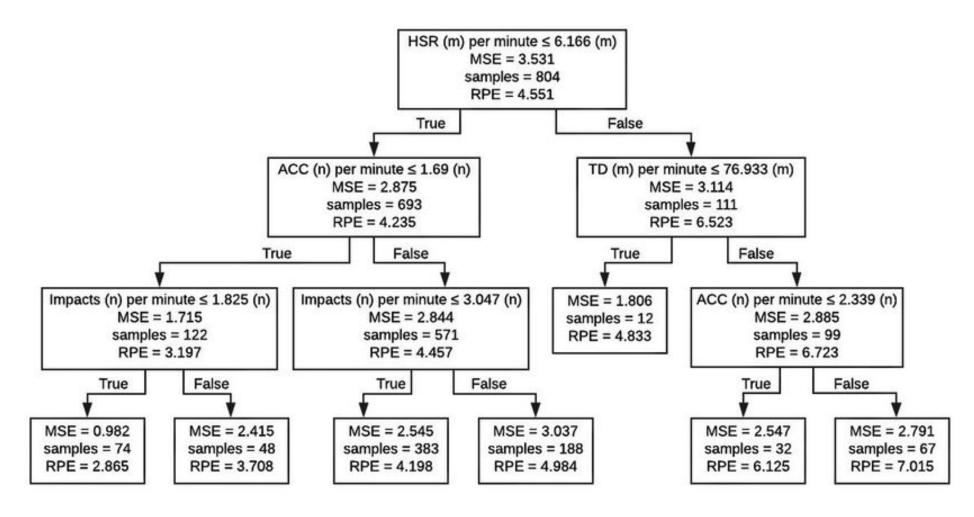


♦ Support Vector Regression



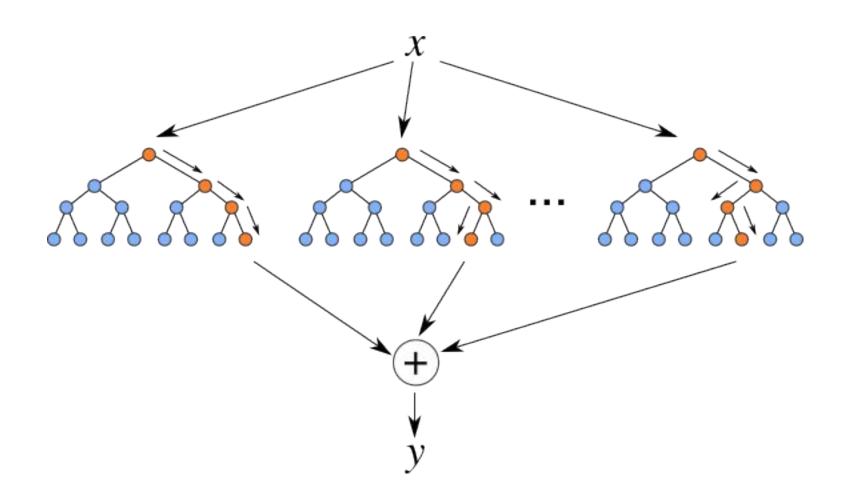


Decision Tree Regression





Random Forest Regression





♦ Logistic Regression

