

Overfitting & Underfitting

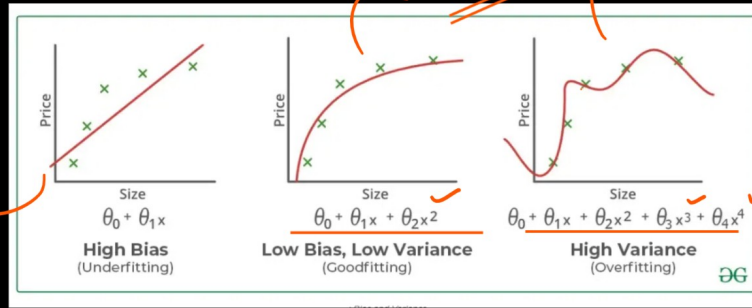
↓ Error = ↓ Bias + ↓ Variance → Variation b/w training set vs test set error

↪ training set error

Residual ≠ 0

Residual = 0

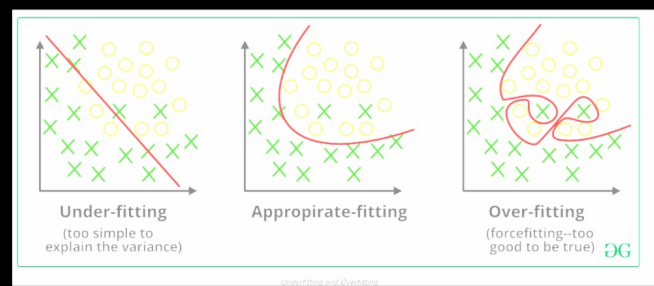
$\hat{y} = mx + c$



underfitting → High Bias + Low Variance

Overfitting → Low Bias + High Variance

≈ 0



$\hat{y} = m_1 x_1 + m_2 x_2 + c$ Regularization Techniques

↪ feature selection

① Lasso Regression (L1 Regularization)

to avoid the issue of overfitting by modifying the cost function of a given model.

new cost function = $MSE + \lambda \sum_{i=1}^n |m_i|$

coefficients

$1+2=3$

hyperparameters

$m_i \approx 0$

$i=1 \text{ to } n$

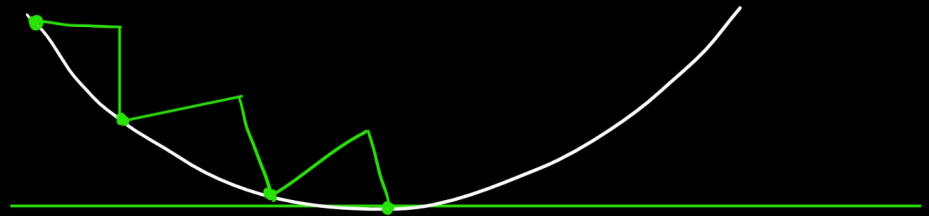
overfitted

$\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$

the feature which belongs to m_i that is irrelevant

② Ridge Regression (L2 Regularisation)

new
cost
function $\Rightarrow \text{MSE} + \lambda \sum_{i=1}^n m_i^2$ ($r^2 + z^2$)



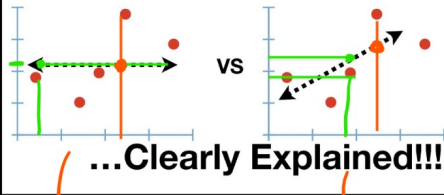
③ Elastic Net Regression \rightarrow Combination $\equiv L1 \& L2$

new
cost
function $\Rightarrow \text{MSE} + \lambda_1 \sum_{i=1}^n |m_i| + \lambda_2 \sum_{i=1}^n m_i^2$

alpha $\left\{ \begin{array}{l} \lambda_1 = 0 \rightarrow \text{Ridge Regression} \\ \lambda_2 = 0 \rightarrow \text{Lasso Regression} \\ 0 < \lambda_1, \lambda_2 < 1 \rightarrow \text{Mix of} \\ \text{both Lasso} \\ \text{\& Ridge} \end{array} \right.$

R-squared

R^2 (R squared)....



...Clearly Explained!!!

Denominator

numerator

$$R^2 = 1 - \frac{SS_{\text{reg}}}{SS_{\text{total}}}$$

Always increased or stays the same

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Numerator ↓

new predictor

↑ Denominator

num > Den → best fit

Line is
not for
now good

Increase → 1 - (small value)

num < Den → ideal

situation

higher the value of R^2 →

better the
performance of
the model

$$(0 < R^2 < 1)$$

Adjusted R-squared

Increases only if the predictor improves fit,
otherwise it should decrease.

new feature \rightarrow location

\rightarrow improved

new feature \rightarrow # children

\rightarrow

$R^2 \approx 1 \rightarrow$ good fit

$R^2 \approx 0 \rightarrow$ poor fit

$$\text{Adjusted } R^2 = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1}$$

Where

R^2 Sample R-Squared

N Total Sample Size

p Number of independent
variable

\leftarrow how irrelevant

features

\rightarrow Adjusted $\downarrow \downarrow$
of ignored