Regression Analysis in ML

Regression analysis is a technique in machine learning which helps in finding the relationship between independent and dependent variable.

Regression Types:

Linear Regression: Linear function is used for uni/multi-variate dataset.

Polynomial Regression: Polynomial function is used for uni/multi-variate dataset.

Logistic Regression: Linear or polynomial function is used followed by sigmoid function. It is used for classification tasks. This regression is evaluated using confusion matrix, accuracy, precision, recall and F1 score.

$$h_{\theta} \text{linear } (x^{(i)}) = \theta_0 + \theta_1 x^{(i)}$$

$$J(\theta) = \min_{\theta} \sum_{i=0}^{m} (y^{(i)} - h_{\theta}^{\text{linear}} (x^{(i)}))^2$$

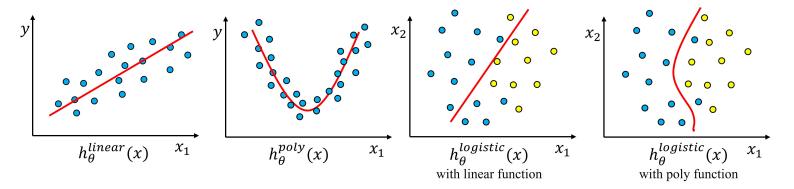
$$h_{\theta}^{\text{poly}} (x^{(i)}) = \theta_0 + \theta_1 x^{(i)} + \theta_2 x^{2(i)} + \dots + \theta_k x^{k(i)}$$

$$J(\theta) = \min_{\theta} \sum_{i=0}^{m} (y^{(i)} - h_{\theta}^{\text{poly}} (x^{(i)}))^2$$

$$f_{\theta} (x^{(i)}) = h_{\theta}^{\text{linear}} (x^{(i)}) \text{ or } h_{\theta}^{\text{poly}} (x^{(i)})$$

$$h_{\theta}^{\text{logistic}} (x^{(i)}) = \frac{1}{1 + exp^{-f_{\theta}}(x^{(i)})}$$

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^{m} y^{(i)} \log h_{\theta} (x^{(i)}) + \dots (1 - y^{(i)}) \log (1 - h_{\theta} (x^{(i)}))$$



Regularized Regression Types:

LASSO Regression: In this regression, we use L1 regularization for model weights. This technique brings sparsity in weights and forcing them to zero.

Ridge Regression:In this regression, we use L2 regularization for model weights. This method is used when all features are useful.

Elastic-Net Regression: It combines LASSO and Ridge regression. It is useful when there are correlation between features.

$$h_{\theta}\left(x^{(i)}\right) = h_{\theta}^{\text{linear}}\left(x^{(i)}\right) \text{ or } h_{\theta}^{\text{poly}}\left(x^{(i)}\right)$$

$$J(\theta) = \min_{\theta} \sum_{i=0}^{m} \left(y^{(i)} - h_{\theta}\left(x^{(i)}\right)\right)^{2} + \lambda_{1} \sum_{j=1}^{k} |\theta_{j}|$$

$$h_{\theta}\left(x^{(i)}\right) = h_{\theta}^{\text{linear}}\left(x^{(i)}\right) \text{ or } h_{\theta}^{\text{poly}}\left(x^{(i)}\right)$$

$$J(\theta) = \min_{\theta} \sum_{i=0}^{m} \left(y^{(i)} - h_{\theta}\left(x^{(i)}\right)\right)^{2} + \lambda_{2} \sum_{j=1}^{k} \theta_{j}^{2}$$

$$h_{\theta}(x^{(i)}) = h_{\theta}^{\text{linear}}(x^{(i)}) \text{ or } h_{\theta}^{\text{poly}}(x^{(i)})$$

$$J(\theta) = \min_{\theta} \sum_{i=0}^{m} (y^{(i)} - h_{\theta}(x^{(i)}))^{2} + \dots \quad \lambda_{1} \sum_{j=1}^{k} |\theta_{j}| + \lambda_{2} \sum_{j=1}^{k} \theta_{j}^{2}$$

Evaluation Metrics for the Regression:

Mean Absolute Error (MAE): $MAE = \frac{1}{m} \sum_{i=1}^{m} |y^{(i)} - h_{\theta} \left(x^{(i)}\right)|$ Mean Squared Error (MSE): $MSE = \frac{1}{m} \sum_{i=1}^{m} (y^{(i)} - h_{\theta} \left(x^{(i)}\right))^{2}$ Root Mean Squared Error (RMSE): $RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} \left(y^{(i)} - h_{\theta} \left(x^{(i)}\right)\right)^{2}}$ R-Squared: $R^{2} = 1 - \frac{SS_{r}}{SS_{m}}$ Adjusted R-Squared: $R^{2}_{a} = 1 - \left[\left(\frac{n-1}{n-k-1}\right) \times (1-R^{2})\right]$ SSr = squared sum error of the regression line; SSm is the squared sum error of the mean line.

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For references and updates: Website, Github