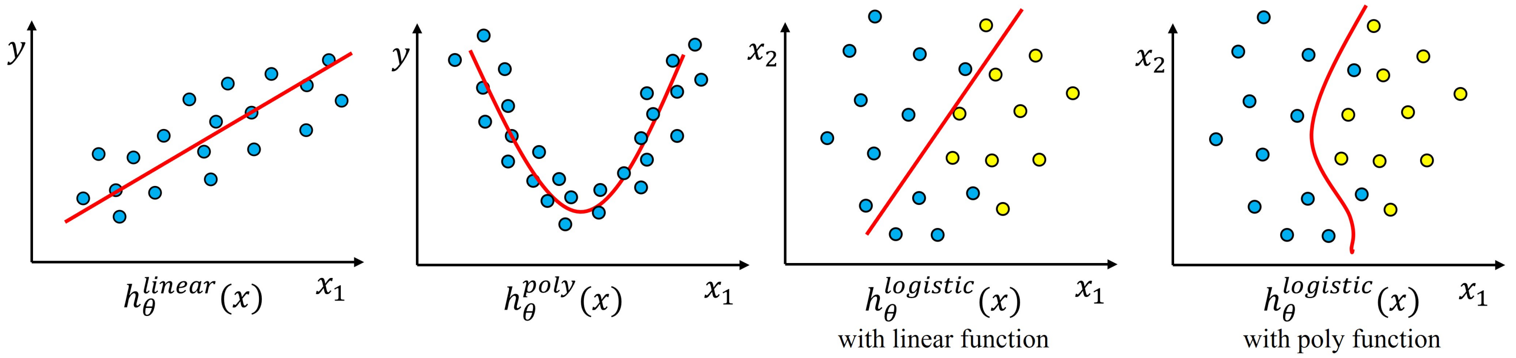
Regression Analysis in ML

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.	$h_\theta \text{linear}\left(x^{(i)}\right) = \theta_0 + \theta_1 x^{(i)}$ $J(\theta) = \min_\theta \sum_{i=0}^{m} \left(y^{(i)} - h_\theta^{\text{linear}}\left(x^{(i)}\right)\right)^2$
Polynomial Regression: Polynomial function is used for uni/multi-variate dataset.	$h_\theta^{\text{poly}}\left(x^{(i)}\right) = \theta_0 + \theta_1 x^{(i)} + \theta_2 x^{2(i)} + \ldots + \theta_k x^{k(i)}$ $J(\theta) = \min_\theta \sum_{i=0}^{m} \left(y^{(i)} - h_\theta^{\text{poly}}\left(x^{(i)}\right)\right)^2$
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.	$f_\theta\left(x^{(i)}\right) = h_\theta^{\text{linear}}\left(x^{(i)}\right)$ or $h_\theta^{\text{poly}}\left(x^{(i)}\right)$ $h_\theta^{\text{logistic}}\left(x^{(i)}\right) = \frac{1}{1+exp^{-f_\theta\left(x^{(i)}\right)}}$ $J(\theta) = -\frac{1}{m}\sum_{i=1}^{m} y^{(i)} \log h_\theta\left(x^{(i)}\right) +$ $\ldots \quad \left(1-y^{(i)}\right)\log\left(1-h_\theta\left(x^{(i)}\right)\right)$



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.	$h_\theta\left(x^{(i)}\right) = h_\theta^{\text{linear}}\left(x^{(i)}\right)$ or $h_\theta^{\text{poly}}\left(x^{(i)}\right)$ $J(\theta) = \min_\theta \sum_{i=0}^{m}\left(y^{(i)} - h_\theta\left(x^{(i)}\right)\right)^2 + \sum_{j=1}^{k}\lvert\theta_j\rvert$
Ridge Regression: In this regression, we use L2 regularization for model weights. This method is used when all features are useful.	$h_\theta\left(x^{(i)}\right) = h_\theta^{\text{linear}}\left(x^{(i)}\right)$ or $h_\theta^{\text{poly}}\left(x^{(i)}\right)$ $J(\theta) = \min_\theta \sum_{i=0}^{m}\left(y^{(i)} - h_\theta\left(x^{(i)}\right)\right)^2 + \sum_{j=1}^{k}\theta_j^2$
Elastic-Net Regression: It combines LASSO and Ridge regression. It is useful when there are correlation between features.	$h_\theta\left(x^{(i)}\right) = h_\theta^{\text{linear}}\left(x^{(i)}\right)$ or $h_\theta^{\text{poly}}\left(x^{(i)}\right)$ $J(\theta) = \min_\theta \sum_{i=0}^{m}\left(y^{(i)} - h_\theta\left(x^{(i)}\right)\right)^2 +$ $\ldots \quad \sum_{j=1}^{k}\lvert\theta_j\rvert + \sum_{j=1}^{k}\theta_j^2$

Evaluation Metrics for the Regression:

Mean Absolute Error (MAE):	$\text{MAE} = \frac{1}{m}\sum_{i=1}^{m}\lvert y^{(i)} - h_\theta\left(x^{(i)}\right)\rvert$
Mean Squared Error (MSE):	$\text{MSE} = \frac{1}{m}\sum_{i=1}^{m}(y^{(i)} - h_\theta\left(x^{(i)}\right))^2$
Root Mean Squared Error (RMSE):	$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)} - h_\theta\left(x^{(i)}\right)\right)^2}$
R-Squared:	$\text{R}^2 = 1 - \frac{SS_r}{SS_m}$
Adjusted R-Squared:	$\text{R}_\text{a}^2 = 1 - \left[\left(\frac{\text{n}-1}{\text{n}-\text{k}-1}\right)\times(1-\text{R}^2)\right]$

SSr = squared sum error of the regression line; SSm is the squared sum error of the mean line.

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