CHAPTER 21

Regularization for Linear Models

Regularization is the technique of adding a parameter, λ, to the loss function of a learning algorithm to improve its ability to generalize to new examples by reducing overfitting. The role of the extra regularization parameter is to shrink or to minimize the measure of the weights (or parameters) of the other features in the model.

Regularization is applied to linear models such as polynomial linear regression and logistic regression which are susceptible to overfitting when high-order polynomial features are added to the set of features.

How Does Regularization Work

During model building, the regularization parameter λ is calibrated to determine how much the magnitude of other features in the model is adjusted when training the model. The higher the value of the regularization, the more the magnitude of the feature weights is reduced.

If the regularization parameter is set too close to zero, it reduces the regularization effect on the feature weights of the model. At zero, the penalty the regularization term imposes is virtually non-existent, and the model is as if the regularization term was never present.

Effects of Regularization on Bias vs. Variance

The higher the value of λ (i.e., the regularization parameter), the more restricted the coefficients (or weights) of the cost function. Hence, if the value of λ is high, the model can result in a learning bias (i.e., it underfits the dataset).

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