

1. Model Performance Evaluation:

This helps you assess whether your model is overfitting, underfitting, or performing well.

If your model performs significantly better on the training data compared to the validation test data, it might be overfitting. Conversely, if the model performs poorly on both, it could be underfitting.

2. Error Analysis:

Identifying whether the errors are due to bias or variance is crucial. This understanding will guide you in making necessary adjustments to your model.

3. Model Complexity:

This aims to explore how model complexity affects the tradeoff b/w bias and variance. More complex models may have lower bias but higher variance, while simpler models might have higher bias and lower variance. Observing performance change with varying complexity will help in finding a good balance.

4. Training vs Validation Error :

This is about monitoring the relationship b/w training and validation errors over different training phases of model configurations. A high training error with a low validation error might indicate underfitting, whereas a low training error with a high validation error often indicates overfitting.

5. Regularization Techniques :

Regularization techniques are used to prevent overfitting. L1 regularization can lead to sparsity, L2 regularization can smooth the model, and dropout can prevent co-adaptation of neurons in neural networks. Analyzing how these techniques affect bias and variance in your model will help in fine-tuning your approach to achieve better generalization.