



← Go Back to Machine Learning

:≡ Course Content

Bias-Variance Trade-off

Let us begin with some key terminologies that will be useful during this lecture:

Training data: The training data is part of the original data used to train the model. Generally, it is taken as the bigger fraction of the data.

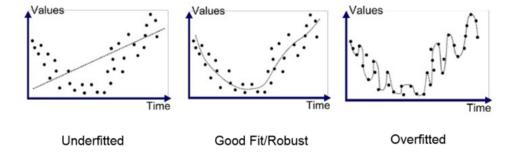
Validation data: This is a **smaller fraction** (in comparison to the training data) of the original data used to **validate** the model. The performance of the model is iteratively validated using the validation data and optimizing the parameters of the model.

Testing/unseen data: The model is finally tested on the testing data which has not been observed by the model, hence called unseen data, to get an understanding of whether the model can replicate the performance from the training data to the new data.

Model Complexity: A model is considered more complex if it has a higher number of parameters that we need to estimate while training the model. The parameters refer to the coefficients associated with the variables in the model.

Overfitting refers to the scenario where a machine learning model can't generalize on the test / unseen dataset. A clear sign of overfitting is that the error on the training set is very small than the error on the test dataset, i.e., the model has fitted very closely to the training data including the noise, and hence cannot give good performance on the testing data.

Underfitting refers to a model that does not fit the training dataset well and fails to identify the pattern in the data, and consequently, gives a poor performance on the training as well the testing dataset. Hence, an underfit machine learning model is not a suitable model.



Bias

In very simple terms, Bias is the amount by which a model's predictions differ from the target values, on the training data, i.e., the **training error**. Every algorithm starts with some level of bias because bias is a result of assumptions of the model that makes the target function easier to learn. A high level of bias can lead to underfitting, which occurs when the algorithm is unable to capture relevant relations between features and target outputs. A high bias model typically includes more assumptions about the target function. A low bias model incorporates fewer assumptions about the target function.

Variance

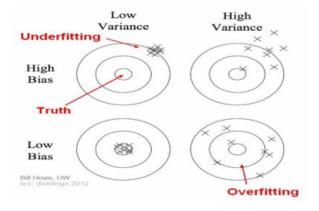
Variance indicates how much the performance of the model would differ if different training data is used. A model with high variance would fit the training data too closely and would result in a significant change in the performance for the small changes in the dataset, i.e., the model will not give a generalized performance, which will lead to overfitting.

A model cannot overfit and underfit at the same time. If it overfits, then it will perform well on the training data but won't be able to reproduce the results on the validation data, and if it underfits, then it will perform poorly on both the training and validation datasets. This creates the possibility of an exchange or tradeoff between bias and variance.

Bias-Variance Trade-off

If we increase the bias of an overfit model, we are making the model simpler and capable of generalizing over the validation set. Its performance on the validation set will improve and, consequently, the variance will decrease. On the other hand, if we decrease the bias of an underfit model, we are making the model more complex and the model will fit the training data more closely and, consequently, the variance will increase. This phenomenon is called the **Bias-Variance tradeoff**.

The below image shows this trade-off between bias and variance. It shows that the model with high bias and low variance will underfit the model and the model with low bias and high variance will overfit the data.



Previous

Next >

Proprietary content. @Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

© 2023 All rights reserved.

Help