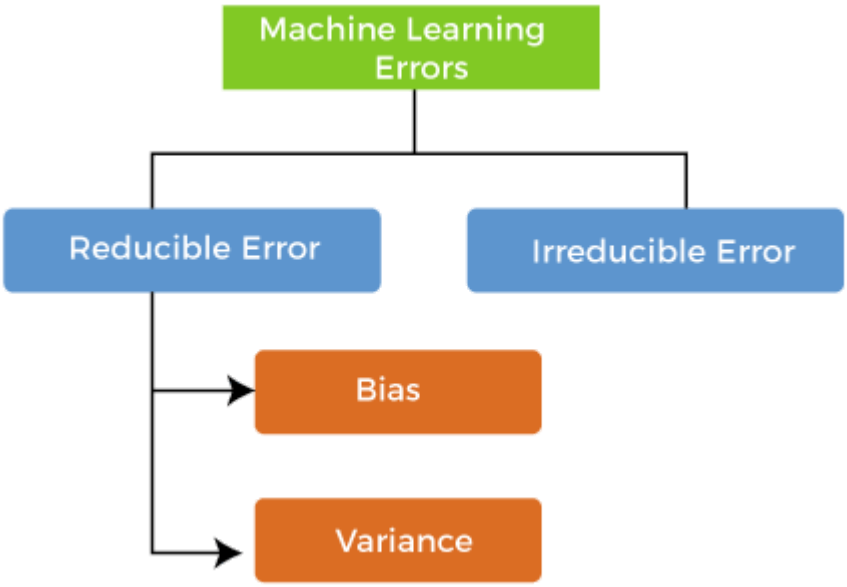
Bias and variance

In machine learning, an error is a measure of how accurately an algorithm can make predictions for the previously unknown dataset. On the basis of these errors, the machine learning model is selected that can perform best on the particular dataset.

- Reducible errors: These errors can be reduced to improve the model accuracy. Such errors can further be classified into bias and Variance.
- Irreducible errors: These errors will always be present in the model



Bias

In general, a machine learning model analyses the data, find patterns in it and make predictions. While **training**, the model learns these patterns in the dataset and applies them to test data for prediction. **While making predictions, a difference occurs between prediction values made by the model and actual values/expected values, and this difference is known as bias errors or Errors due to bias.**

It can be defined as an inability of machine learning algorithms such as Linear Regression to capture the true relationship between the data points. A model has either:

- Low Bias: A low bias model will make fewer assumptions about the form of the target function.
- High Bias: A model with a high bias makes more assumptions, and the model becomes unable to capture the important features of our dataset. A high bias model also cannot perform well on new data.

Generally, a linear algorithm has a high bias, as it makes them learn fast. The simpler the algorithm, the higher the bias it has likely to be introduced. Whereas a nonlinear algorithm often has low bias.

Ways to reduce High Bias:

High bias mainly occurs due to a much simple model. Below are some ways to reduce the high bias:

- Increase the input features as the model is underfitted.
- Decrease the regularization term.
- Use more complex models, such as including some polynomial features.

What is a Variance Error?

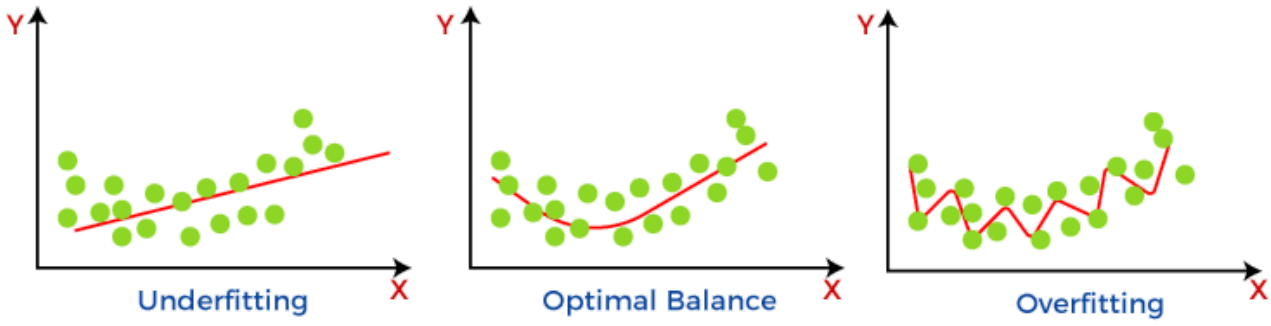
The variance would specify the amount of **variation in the prediction** if the different training data was used. Ideally, a model should not vary too much from one training dataset to another, which means the algorithm should be good in understanding the hidden mapping between inputs and output variables.

Low variance means there is a small variation in the prediction of the target function with changes in the training data set. At the same time, High variance shows a large variation in the prediction of the target function with changes in the training dataset.

A model that shows high variance learns a lot and perform well with the training dataset, and does not generalize well with the unseen dataset. As a result, such a model gives good results with the training dataset but shows high error rates on the test dataset.

Since, with high variance, the model learns too much from the dataset, it leads to overfitting of the model. A model with high variance has the below problems:

- A high variance model leads to overfitting.
- Increase model complexities.
- Usually, nonlinear algorithms have a lot of flexibility to fit the model, have high variance.



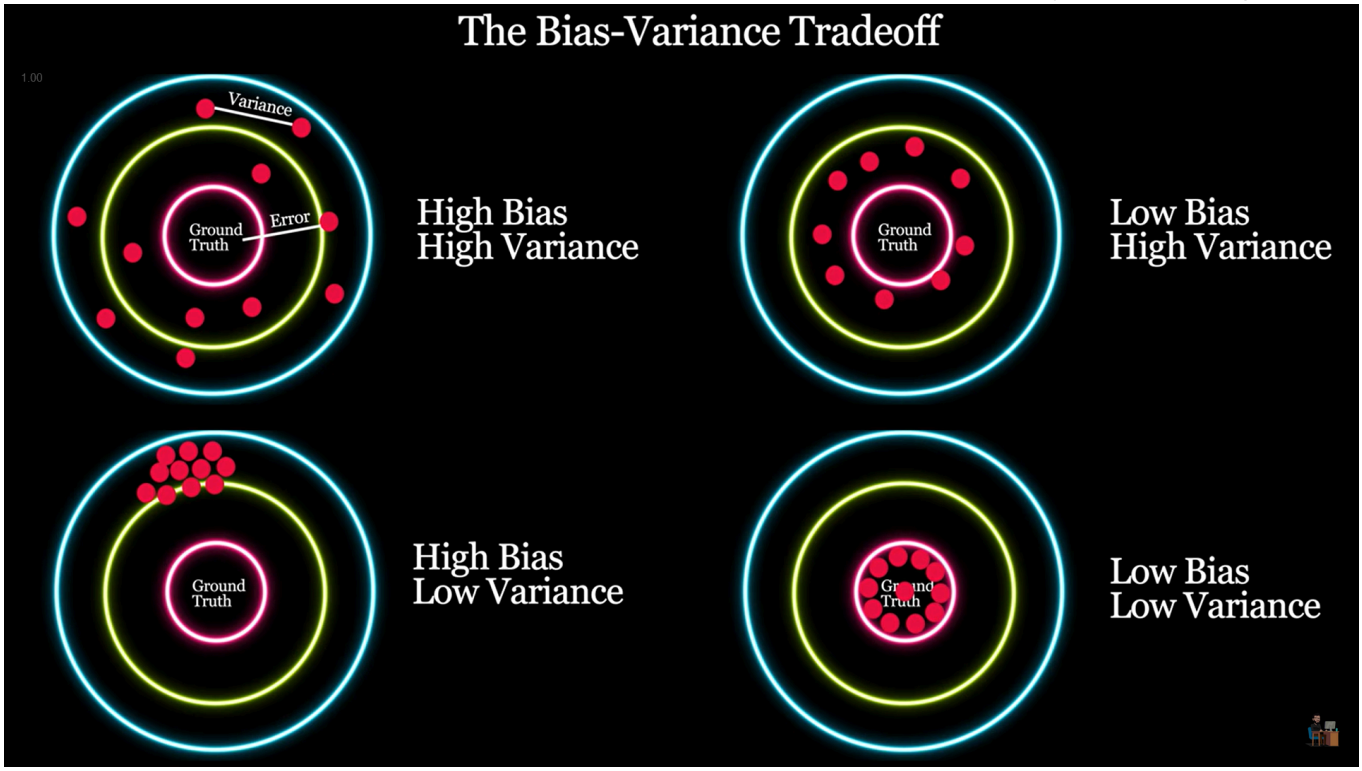
Some examples of machine learning algorithms with low variance are, Linear Regression, Logistic Regression, and Linear discriminant analysis. At the same time, algorithms with high variance are decision tree, Support Vector Machine, and K-nearest neighbours.

Ways to Reduce High Variance:

- Reduce the input features or number of parameters as a model is overfitted.
- Do not use a much complex model.
- Increase the training data.
- Increase the Regularization term.

Different Combinations of Bias-Variance

There are four possible combinations of bias and variances, which are represented by the below diagram:



Note: In the above plot one can think green circle area as idealistic modeled situation and red dots are the data points.

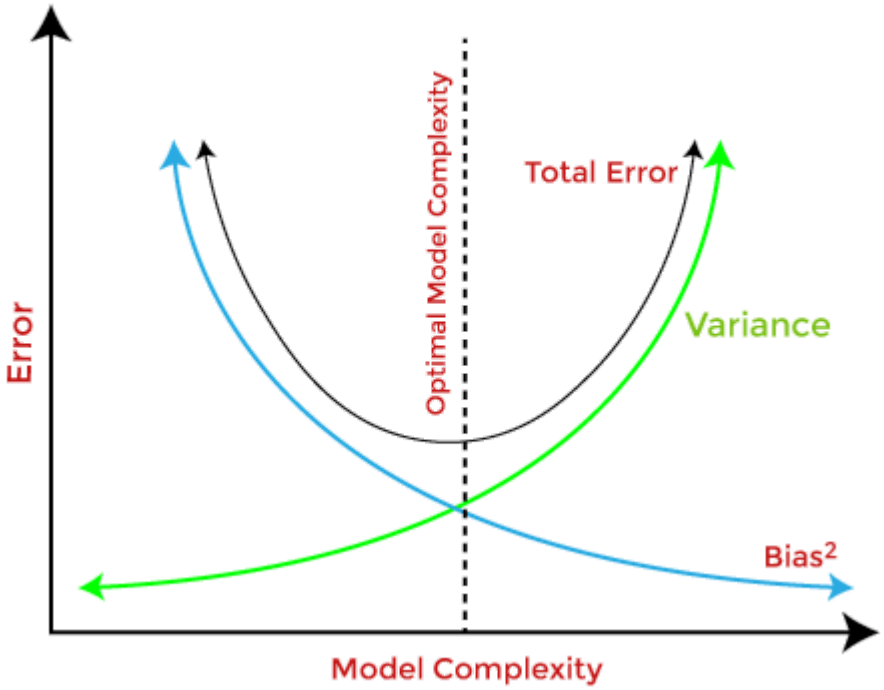
- Low-Bias, Low-Variance: The combination of low bias and low variance shows an ideal machine learning model. However, it is not possible practically.
- Low-Bias, High-Variance: With low bias and high variance, model predictions are inconsistent and accurate on average. This case occurs when the model learns with a large number of parameters and hence leads to an overfitting
- High-Bias, Low-Variance: With High bias and low variance, predictions are consistent but inaccurate on average. This case occurs when a model does not learn well with the training dataset or uses few numbers of the parameter. It leads to underfitting problems in the model.
- High-Bias, High-Variance: With high bias and high variance, predictions are inconsistent and also inaccurate on average.

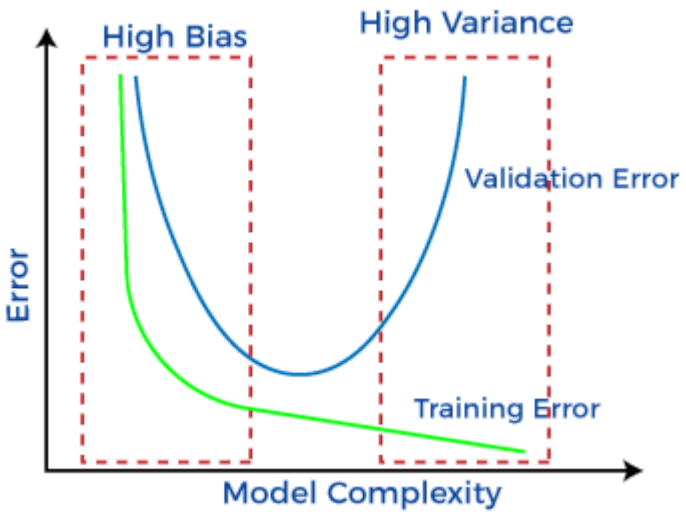
Identification of High variance or High Bias:

- High variance: Low training error and high test error.
- High Bias: High training error and the test error is almost similar to training error.

Bias-Variance Trade-Off

While building the machine learning model, it is really important to take care of bias and variance in order to avoid overfitting and underfitting in the model. If the model is very simple with fewer parameters, it may have low variance and high bias. Whereas, if the model has a large number of parameters, it will have high variance and low bias. So, it is required to make a balance between bias and variance errors, and this balance between the bias error and variance error is known as the Bias-Variance trade-off.





Bias-Variance trade-off is a central issue in supervised learning. A high variance algorithm may perform well with training data, but it may lead to overfitting to noisy data. Whereas, high bias algorithm generates a much simple model that may not even capture important regularities in the data.

Hence, the Bias-Variance trade-off is about finding the sweet spot to make a balance between bias and variance errors.

Key Points on Bias and Variance

1. **Bias**
    - Measures how much the predicted values deviate from actual values.
    - High bias → Underfitting (model is too simple, fails to capture patterns).
    - Example: Linear regression on a complex dataset.
    - **Solution:** Use more complex models, add relevant features, or reduce assumptions.
2. **Variance**
    - Measures the model's sensitivity to small fluctuations in the training data.
    - High variance → Overfitting (model learns noise, performs poorly on new data).
    - Example: Deep neural networks with too many parameters.
    - **Solution:** Regularization (L1/L2), more data, or simpler models.
3. **Bias-Variance Tradeoff**
    - Low bias, high variance → Overfitting.
    - High bias, low variance → Underfitting.
    - **Ideal model balances both for optimal generalization.**
    - The **Bias-Variance Tradeoff Curve** is typically an **inverse U-shaped curve** where the test error decreases first and then increases.
4. **Impact of Increasing Training & Testing Data**
    - **Reducing Variance:** More training data helps the model generalize better, reducing overfitting and high variance.
    - **Minimal Effect on Bias:** If a model is too simple (e.g., linear regression on a nonlinear problem), adding more data **won't** reduce bias. The model itself needs improvement.
    - **Improved Generalization:** More training data provides better feature representation, leading to lower variance.
    - **Testing Data Helps Estimate True Error:** A larger test set gives a more reliable estimate of the model's real-world performance.
5. **Techniques to Control Bias & Variance**
    - **Regularization (Lasso/Ridge)** reduces variance by preventing overfitting.
    - **Cross-validation** helps detect bias-variance issues.
    - **Ensemble methods (Bagging, Boosting)** improve stability and generalization.
    - **Increasing Training Data** helps reduce variance and improve model robustness.

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