Random forest

Bias: Bias describes how well a model matches the training set. A model with high bias won't match the data set closely, while a model with low bias will match the data set very closely. Bias comes from models that are overly simple and fail to capture the trends present in the data set

In his 1980 paper entitled “The need for bias in learning generalizations”, Tom Mitchell introduced the first use of the word “bias” in machine learning. He defined it to mean that a learning algorithm will not generalize unless it introduces some form of preference or restriction over the space of possible functions. Without any limitation or preference, the learning algorithm can memorize any data set without generalizing. This was later formalized in terms of the VC dimension (for a fixed-complexity function space), the No Free Lunch theorem, and structural risk minimization (for nested families of function spaces of increasing complexity.

This use of “bias” is closely related to the bias-variance tradeoff, because a learning algorithm with no bias (in the Mitchell sense) will have low bias and high variance in the bias-variance sense.

The most common interpretation of bias is with regards to the [bias–variance tradeoff](https://en.wikipedia.org/wiki/Bias%E2%80%93variance_tradeoff). Essentially, bias here is a source of error in your model that causes it to over-generalize and underfit your data. In contrast, variance is sensitivity to noise in the data that causes your model to overfit. We call it a tradeoff because improving one will often make the other metric worse.