FINTECH 540 - Machine Learning for Fintech

Fall Semester 2024

Third Lecture

Basics Concepts for Machine Learning

Duke

PRATT SCHOOL of ENGINEERING

The Training Process

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Hence, the training procedure differs depending on the machine learning paradigm, i.e., the kind of dataset experienced.

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The **training process** is all about finding the best set of θ for the model.

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We need to organize the available data in a proper way...

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The model does not use the data points included in the test set $\longrightarrow$ a good performance on this set of examples, i.e., a low test error, signals a **good generalization**.

Overfitting-Underfitting

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To summarize: *an ML algorithm aims to reduce the training error while minimizing the test and training error gap.*

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- **High training error** results in **underfitting**: the model cannot capture the information in the data.

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One way to control the **overfitting-underfitting** tradeoff is to change the model capacity, i.e., the possibility to choose the function to represent the model and to fit the data from a broad set of functions. In simple terms, it is the **expressiveness** of a model.

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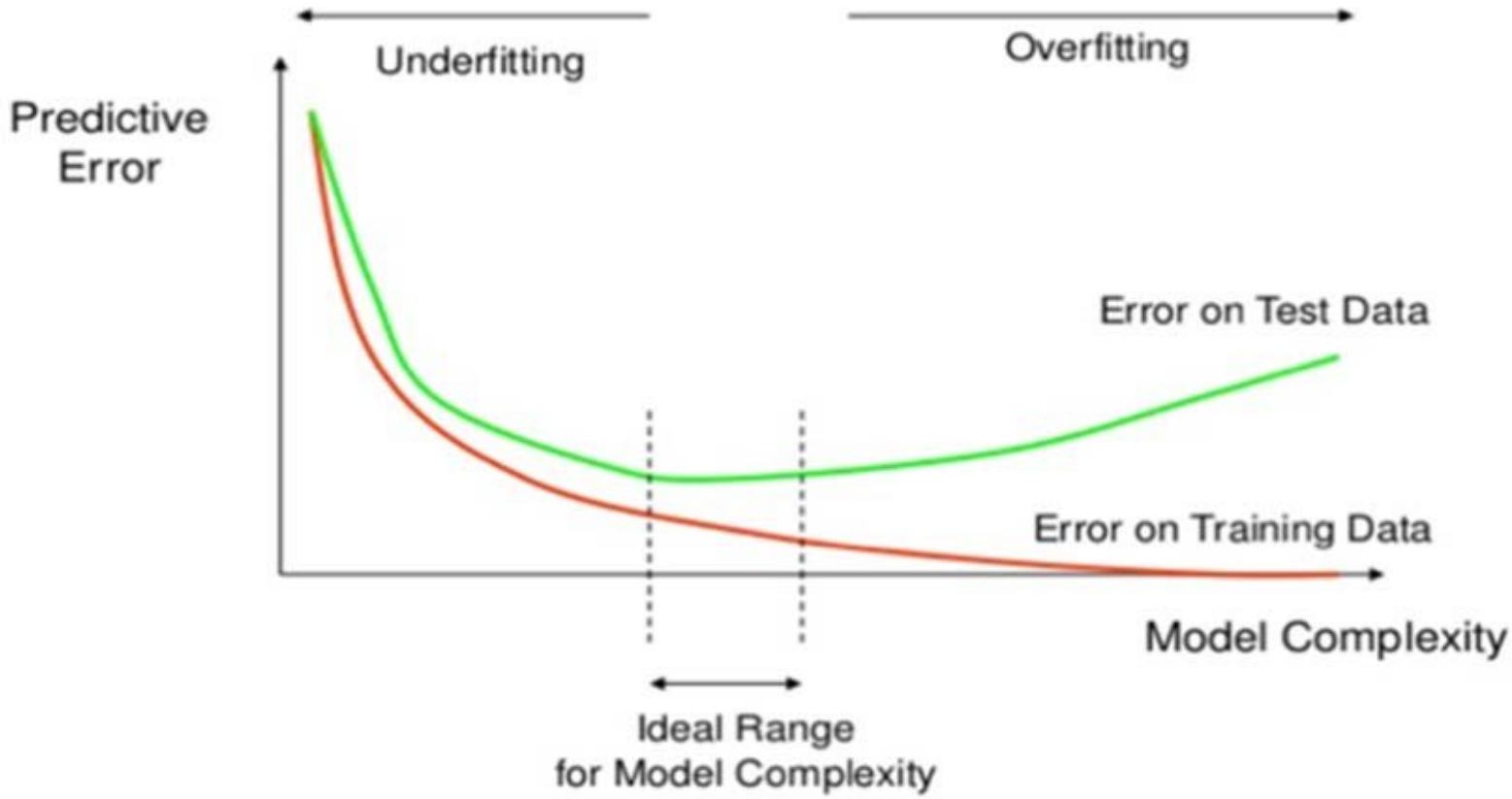
We will see how this applies to more complex algorithms, such as regression trees and neural networks.

Overfitting-Underfitting relationship (IV)



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How do we evaluate the goodness of an estimator?

We should look at two important properties: **bias** and **variance**.

- The bias for an estimator $\hat{\theta}_N$ is defined as:

$$\text{Bias}(f(\mathbf{x};\hat{\theta})) = \mathbb{E}(f(\mathbf{x};\hat{\theta})) - f(\mathbf{x};\theta)$$

  where the expectation is computed over the set of training samples of length M.

  An estimator is **unbiased** if $\mathbb{E}(f(\mathbf{x};\hat{\theta})) = f(\mathbf{x};\theta)$ or **asymptotically unbiased** if $\lim_{M\to\infty} \mathbb{E}[f(\mathbf{x};\hat{\theta})] = f(\mathbf{x};\theta)$.

  The bias reflects how well the estimator approximates the actual value on average.

Bias and Variance (II)

- The variance of an estimator is simply the variance of the estimated function

$$\text{Var}(f(\mathbf{x};\hat{\theta})) = \mathbb{E}\left[(f(\mathbf{x};\hat{\theta}) - \mathbb{E}[f(\mathbf{x};\theta)])^2\right]$$

The variance measures how much one would expect the estimator to vary if one computes it over another sample of the data from the same DGP.

Since the number of data is finite, the variance measures how much one would expect the estimate to vary when independently sampling the dataset multiple times from the same DGP.

Bias and **Variance** represent two different sources of error in the estimate

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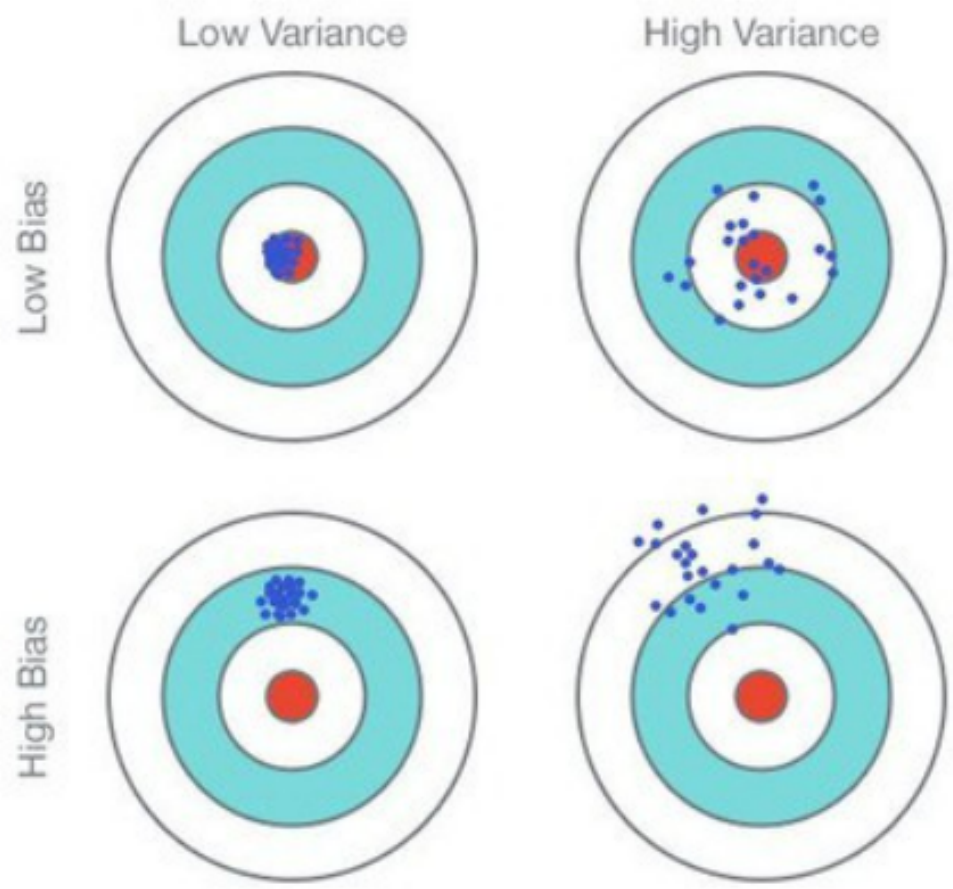
Remember that *bias measures the expected deviation from the actual value to be estimated. Conversely, variance calculates the deviation from the expected estimation, likely to occur if one changes the training examples.*

What would be the ideal case for our estimator?

Low bias and low variance are not always achievable.

Bias-Variance tradeoff.

Bias-Variance Tradeoff (II)



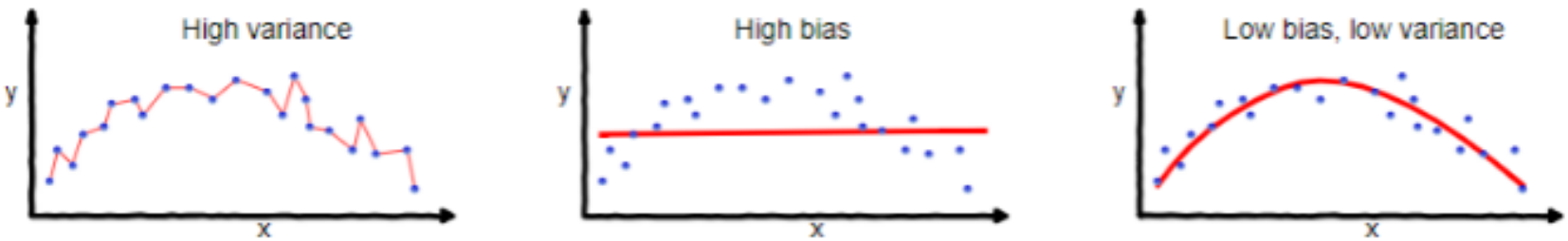
Source: Understanding Bias Variance tradeoff

Bias-Variance Tradeoff (III)

One can show that in estimating $f(\mathbf{x}; \hat{\theta})$, the expected mean square error (MSE) on the test set is

$$\mathbb{E}[f(\mathbf{x}; \hat{\theta}) - y]^2 = \text{Var}(f(\mathbf{x}; \hat{\theta})) + [\text{Bias}(f(\mathbf{x}; \hat{\theta}))]^2$$

In general, a model with **many parameters** can obtain estimates with lower bias and high variance. Could you tell why?



The first case shows a lack of generalization, the second offers a lack of fitting. The challenge in ML is to keep both measures low.

Flexibility vs. Interpretability

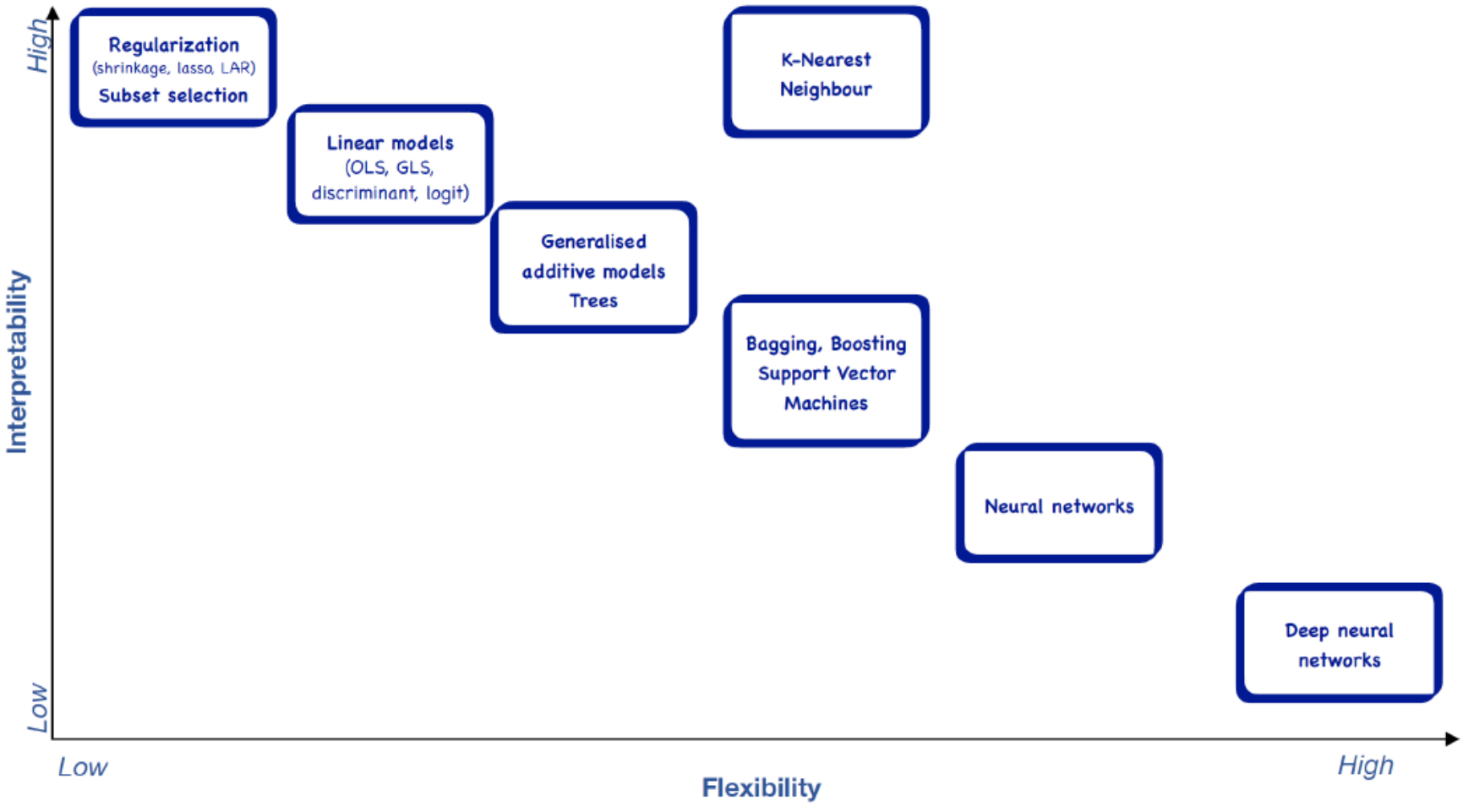
When trading off bias for variance, an aspect to consider is the interpretability of the **machine learning** model.

Being able to **explain** a model is crucial, even more in finance. Look at this hedge fund story.

There are specific frameworks to interpret even complex machine learning models. We are going to use them during the coming classes.

Remember that *the best model is not always the complex one.* Sometimes simple is better.

Flexibility vs. Interpretability (II)



Source: AIFI bootcamp

A question for you

Do you know the difference between linear regression and machine learning regression?

Linear Regression vs. Machine Learning Regression

Linear Regression:

- Fits a linear equation to data.
- Assumes a linear relationship between variables.
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Machine learning regression captures complex patterns in data

Questions? Comments?