universität freiburg

# Assignment 03



# **Assignment 03 Solution**

- 1. Bias-Variance Trade-off
- 2. Overfitting and Underfitting in Linear Regression

$$E_{x,y,D}\left[\left(\hat{f}(x;D)-y\right)^{2}\right] = E_{x,D}\left[\left(\hat{f}(x;D)-\bar{f}(x)\right)^{2}\right] + E_{x,y}\left[\left(\bar{f}(x)-\bar{y}(x)\right)^{2}\right] + E_{x,y}\left[\left(\bar{y}(x)-y\right)^{2}\right]$$
Variance

Noise

where  $\hat{f}(\cdot)$  is the prediction model,

 $\bar{f}(\cdot)$  is the expected prediction model,

y is the target,

and  $\bar{y}(x)$  is the expected target.

$$E_{x,y,D}\left[\left(\hat{f}(x;D)-y\right)^{2}\right] = E_{x,D}\left[\left(\hat{f}(x;D)-\bar{f}(x)\right)^{2}\right] + E_{x,y}\left[\left(\bar{f}(x)-\bar{y}(x)\right)^{2}\right] + E_{x,y}\left[\left(\bar{y}(x)-y\right)^{2}\right]$$
Variance

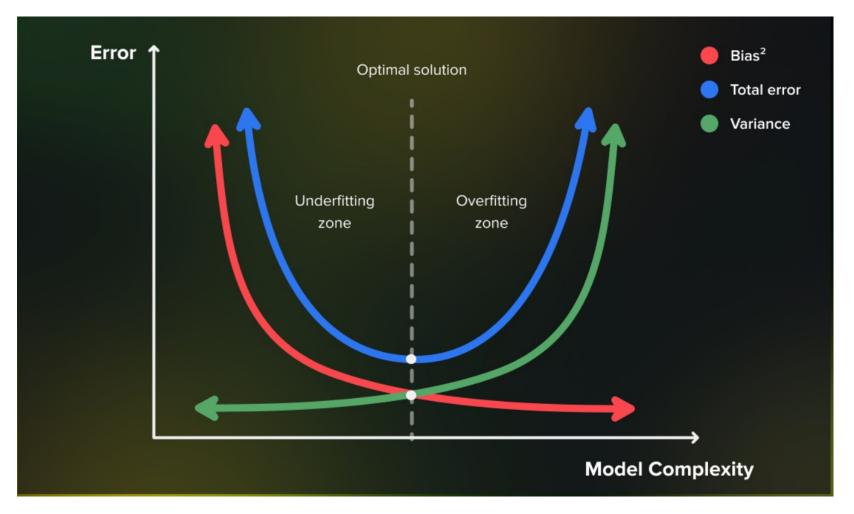
Noise

**Variance** – measures how much a model's predictions **vary** across different training datasets. High variance suggests the model heavily depends on its training data and may not perform well on new, unseen data. This is often seen in **complex**, nonlinear models which, while fitting training data well, can struggle with new data due to **overfitting**, i.e. interpolating the data and not learning the underlying relationship in the data. Cross-validation can help measure this by showing the model's consistency across various training subsets.

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Variance

Noise

**Bias** – measures how a model's predictions differ from the actual distribution of the value it tries to predict. High-bias models, which tend to oversimplify, result in noticeable errors during training and testing, indicative of **underfitting** — the model's failure to capture the true patterns and variations in the data.



Source: https://serokell.io/blog/bias-variance-tradeoff

How does regularization prevent overfitting?

Regularization is a technique that penalizes more complex models to prevent overfitting. By adding a constraint to the model parameters, typically by shrinking them towards zero, regularization reduces model complexity. This discourages the model from fitting the noise in the training data, leading to improved generalization on unseen data.

Let us say now you have 500 MRI images and you have tested 4 different machine learning models whose error metrics are as follows:

	Model 1	Model 2	Model 3	Model 4
Train error [%]	0.1	25	15	0.2
Test error [%]	13	19	40	3

	Model 1	Model 2	Model 3	Model 4
Train error [%]	0.1	25	15	0.2
Test error [%]	13	19	40	3
Bias	Low	High	High	Low

	Model 1	Model 2	Model 3	Model 4
Train error [%]	0.1	25	15	0.2
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Variance	High	High	High	Low

	Model 1	Model 2	Model 3	Model 4
Train error [%]	0.1	25	15	0.2
Test error [%]	13	19	40	3
Bias	Low	High	High	Low
Variance	High	High	High	Low
Fitting	Overfitting	Underfitting	Underfitting	Good fit

In the case of model 2, what could be the reason that the test error is lower than the training error?

	Model 2
Train error [%]	25
Test error [%]	19

In the case of model 2, what could be the reason that the test error is lower than the training error?

- There could be complex instances to learn in the training set.
- The samples in the test dataset could be from a different source than the training dataset and have easier instances.

	Model 2
Train error [%]	25
Test error [%]	19