

Overfitting, prediction error and trade-offs

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Overfitting



What is overfitting?

We fitted a linear model on our dataset and made predictions; we then measured the “accuracy” of these predictions: **did we do it right?**



What is overfitting?

We fitted a linear model on our dataset and made predictions; we then measured the “accuracy” of these predictions: **did we do it right?**

- short answer: **NO!**
- main reason: **overfitting**



What is overfitting?

Overfitting:

Fitting too well the data: R^2 too large (≈ 1)



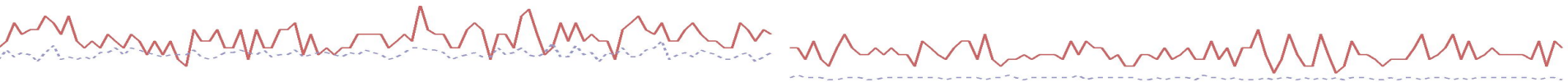
What is overfitting?

Overfitting:

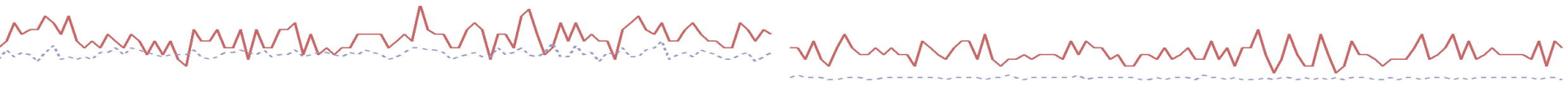
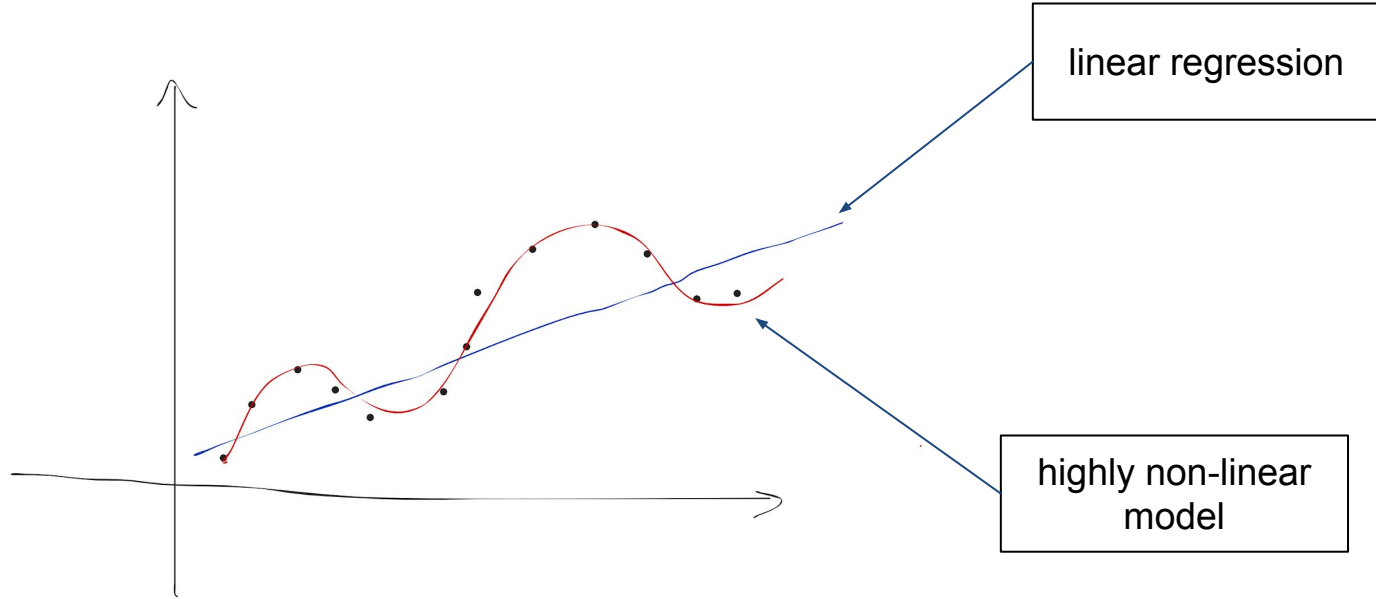
Fitting too well the data: R^2 too large (≈ 1)

overfitting happens with:

- using the same data to fit the model and make predictions
- overparameterization of the model (e.g. too many effects)
- flexible methods (e.g. polynomial functions, splines, classification trees etc.)

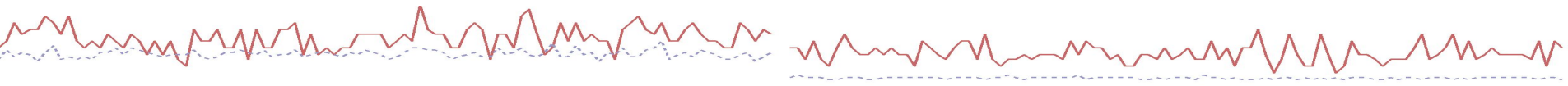
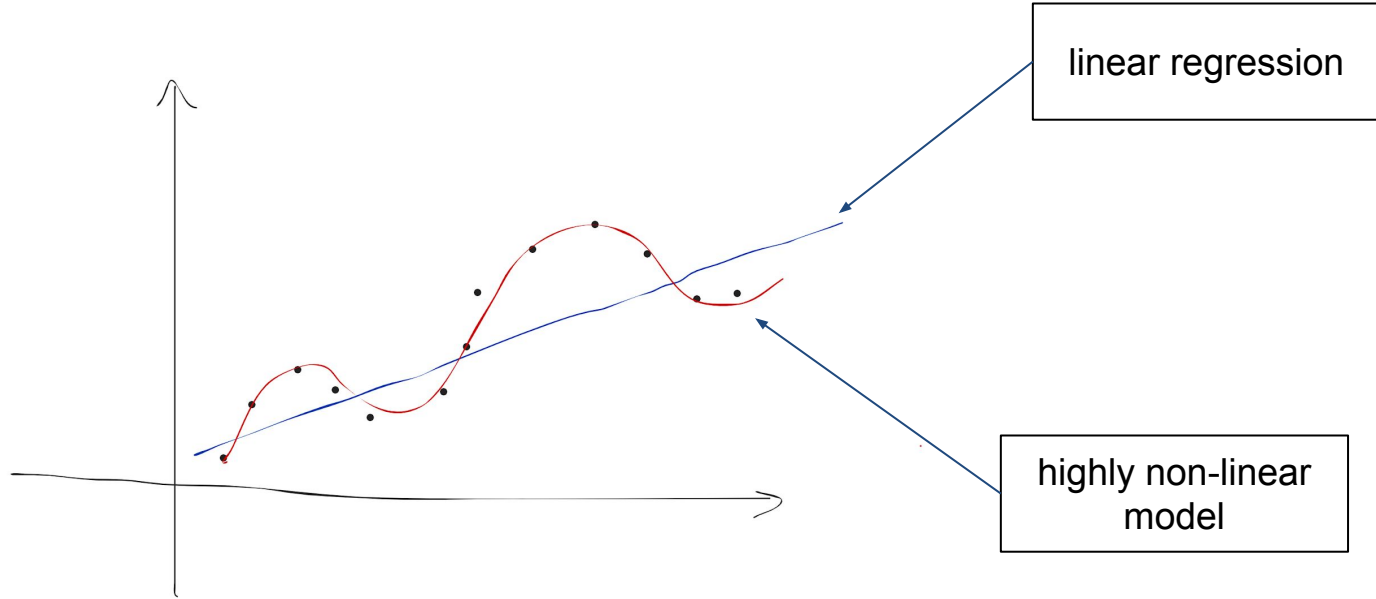


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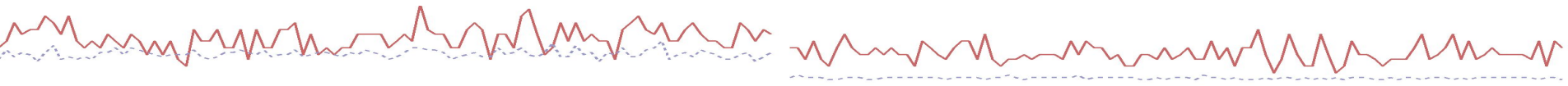


What is overfitting?

Think of KNN
with $k=1$!



Prediction error



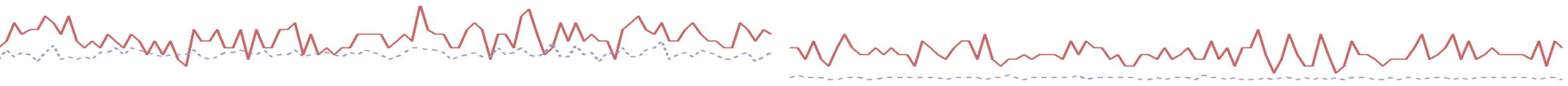
Prediction error

$$E \left(y - \hat{f}(x) \right) = Var \left(\hat{f}(x) \right) + \left[\text{Bias} \left(\hat{f}(x) \right) \right]^2 + Var(\epsilon)$$

variance



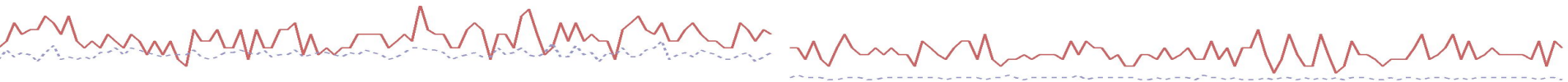
bias²



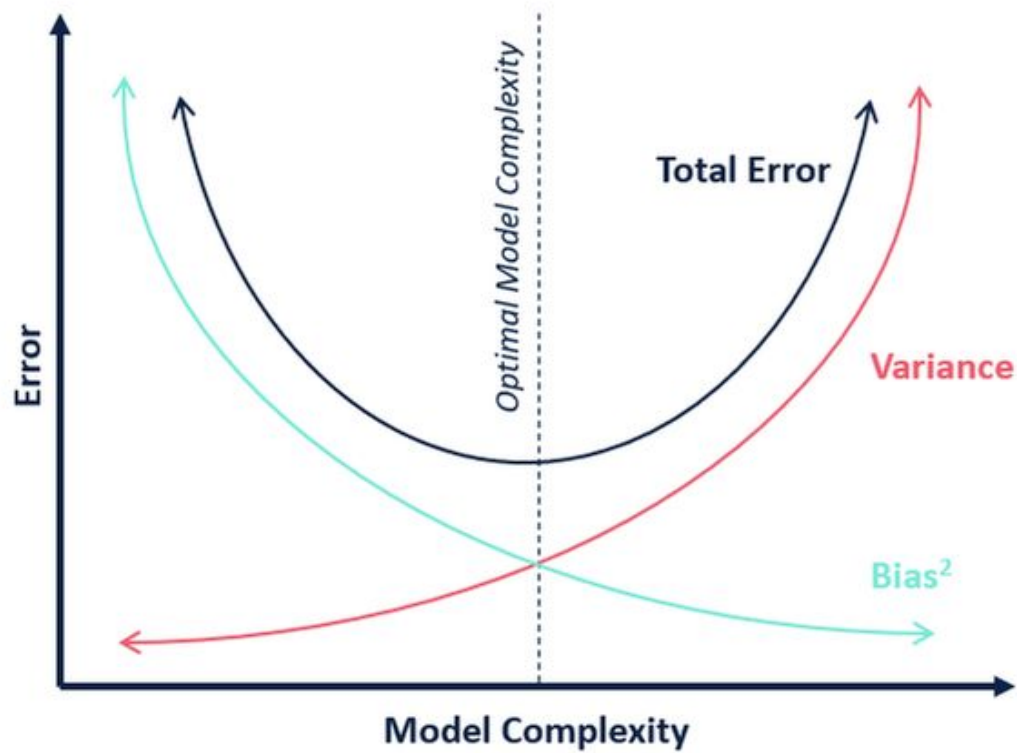
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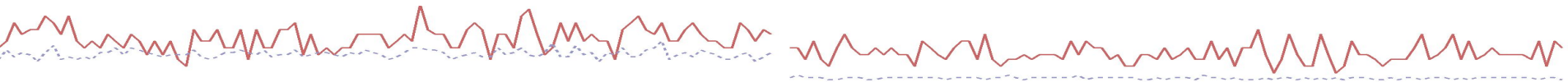
- **variance** refers to the change of the predictor if estimated using different training data
- **bias** refers to the approximation of a real problem by a simpler model



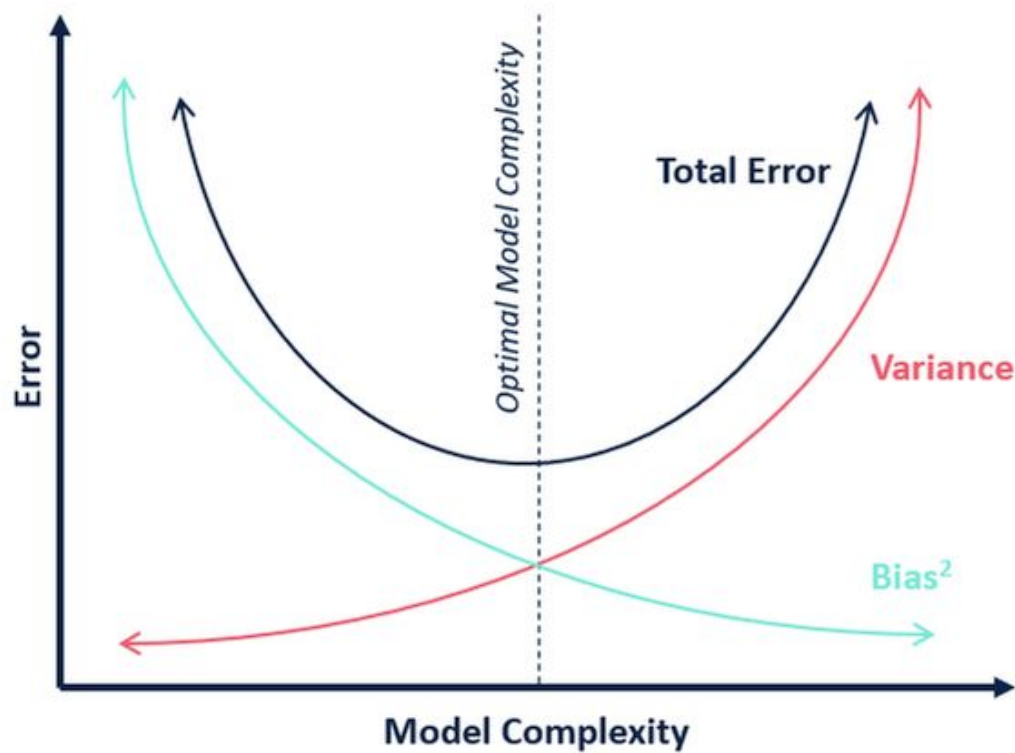
Bias-variance trade-off



Source: <https://ai-pool.com/a/s/bias-variance-tradeoff-in-machine-learning>

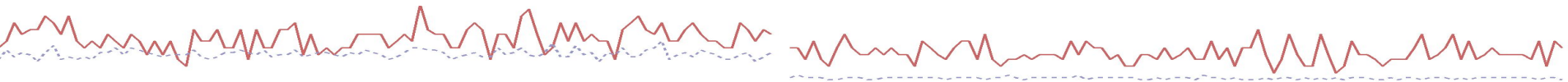


Bias-variance trade-off



- models with low bias and high variance (e.g. KNN with $k=1$)
- models with high bias and low variance (e.g. horizontal line crossing the data)
- → find models/methods with both low variance and low bias

Source: <https://ai-pool.com/a/s/bias-variance-tradeoff-in-machine-learning>



Bias-variance trade-off

Related trade-offs

1. Prediction accuracy vs model interpretability:
 - e.g. linear regression is easy to interpret, splines are not
2. Parsimony vs black-box:
 - e.g. variable selection, all-variable models (e.g. RF), Occam's razor



Bias-variance trade-off

Important for:

1. Correctly estimating the performance of a predictive machine
2. Correctly estimating model parameters
3. Selecting between models



Bias-variance trade-off

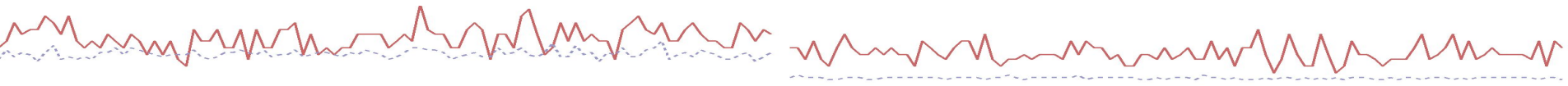
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So, how do we control for overfitting and the bias-variance trade-off?



Training and test sets



Training and testing sets



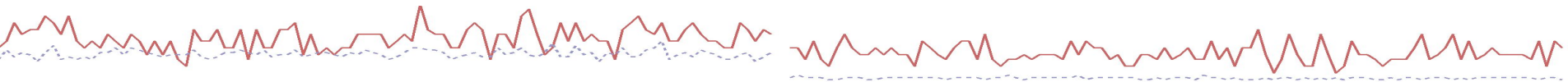
Training data

the predictive model is **trained here**



Test data

the predictive model is **evaluated here**

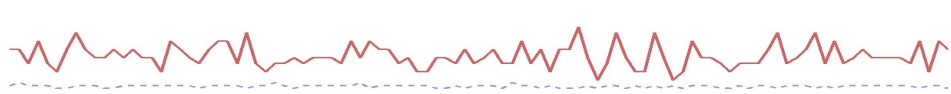
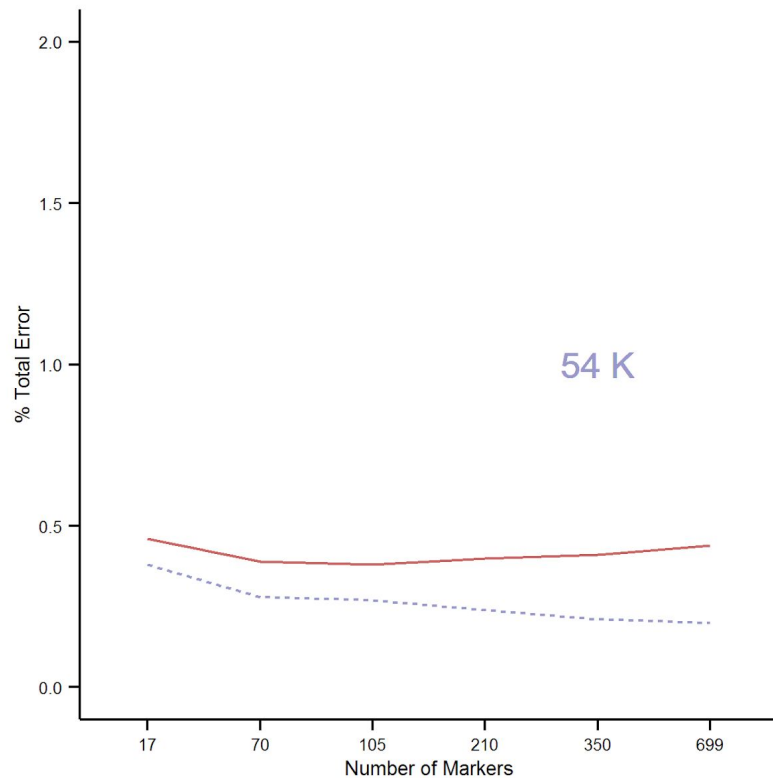
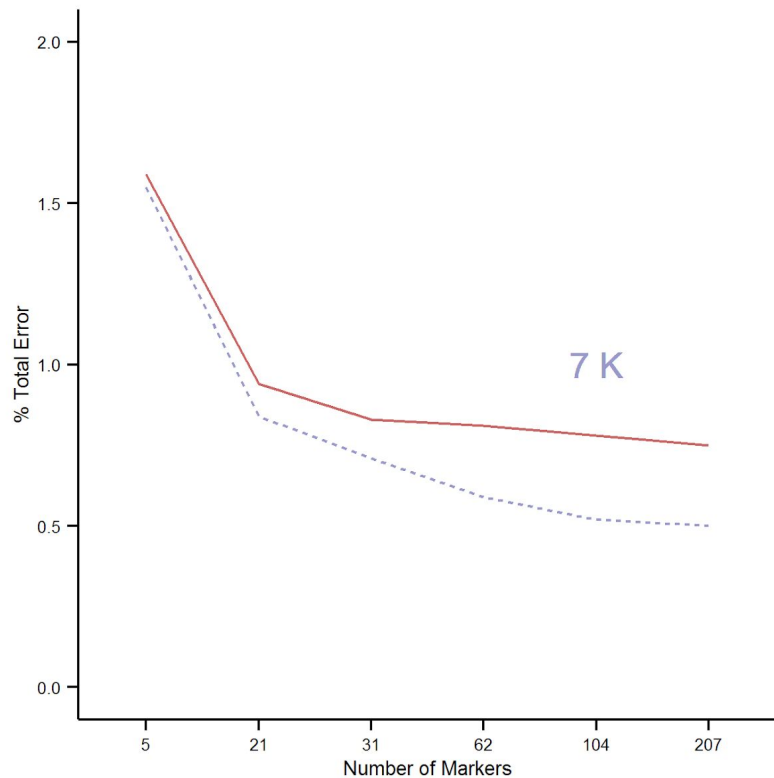


Training and testing sets

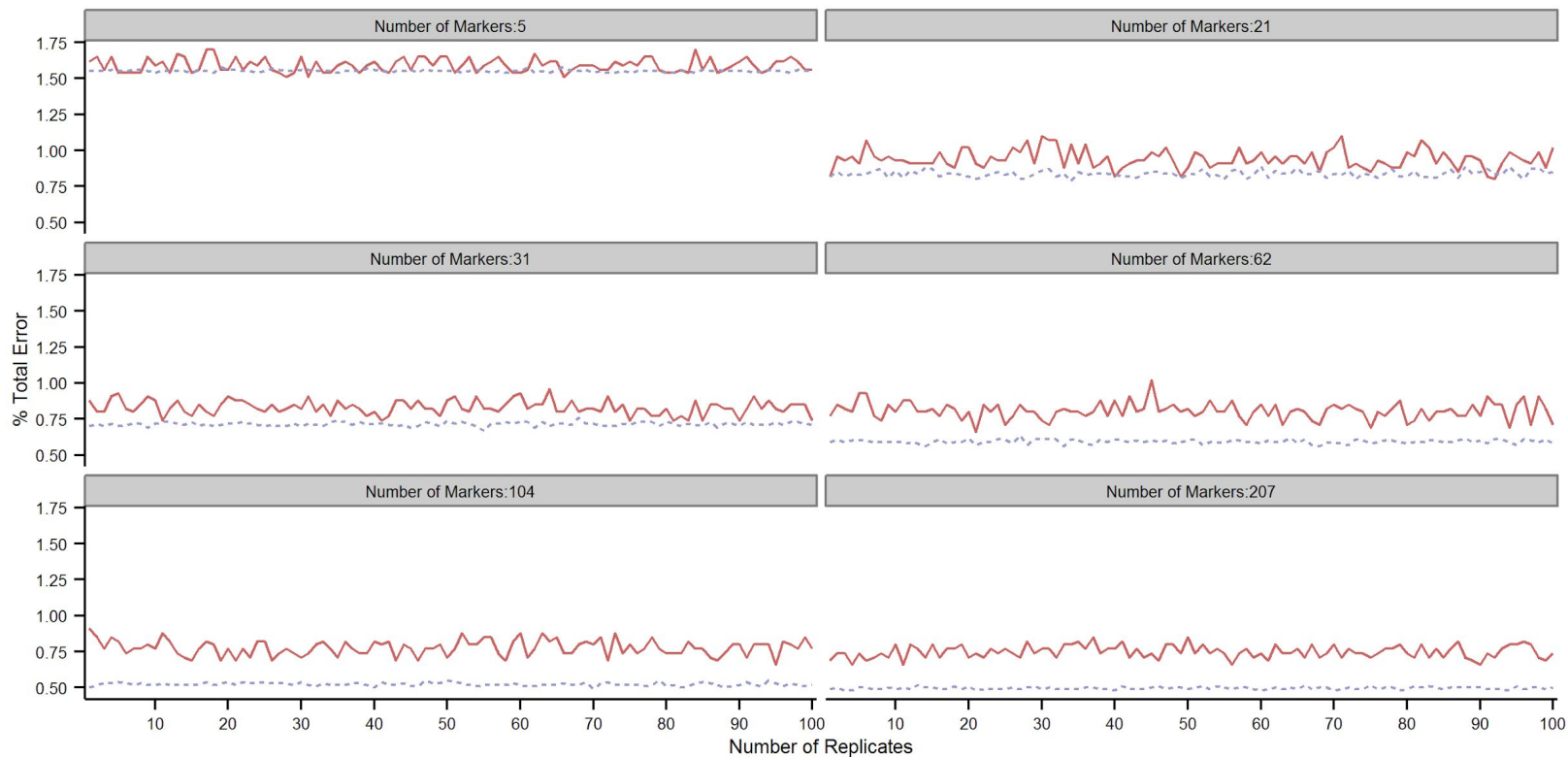
- accuracy (model performance) on the training set is “optimistic” (biased upward ← *overfitting*)
- a better estimate of model performance can be obtained from independent test data
- usually we are interested in the predictive performance on new data
- accuracy in the test set is usually lower than in the training set



Training and testing sets



Training and testing sets



Overfitting - hands on!

→ 3.training_testing.ipynb
Exercise 3.1

