

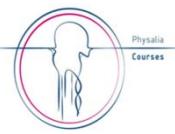


Overfitting, prediction error and trade-offs

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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?**



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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)



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Overfitting:

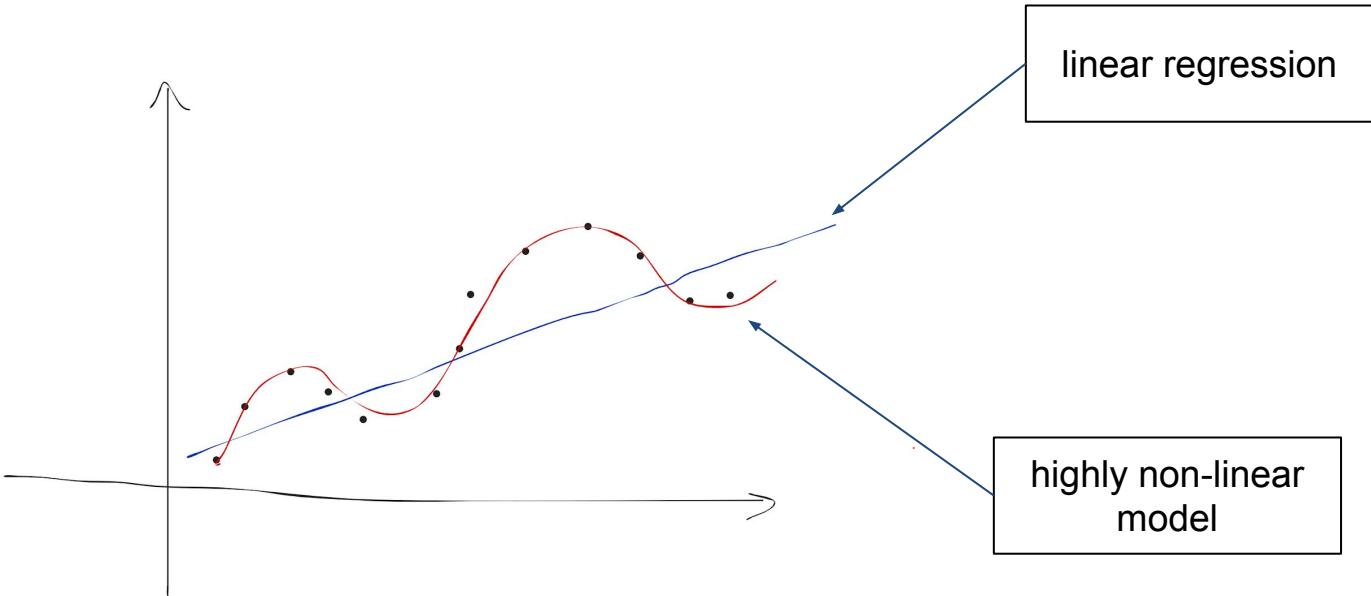
Fitting too well the data: R^2 too large (≈ 1)

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.)

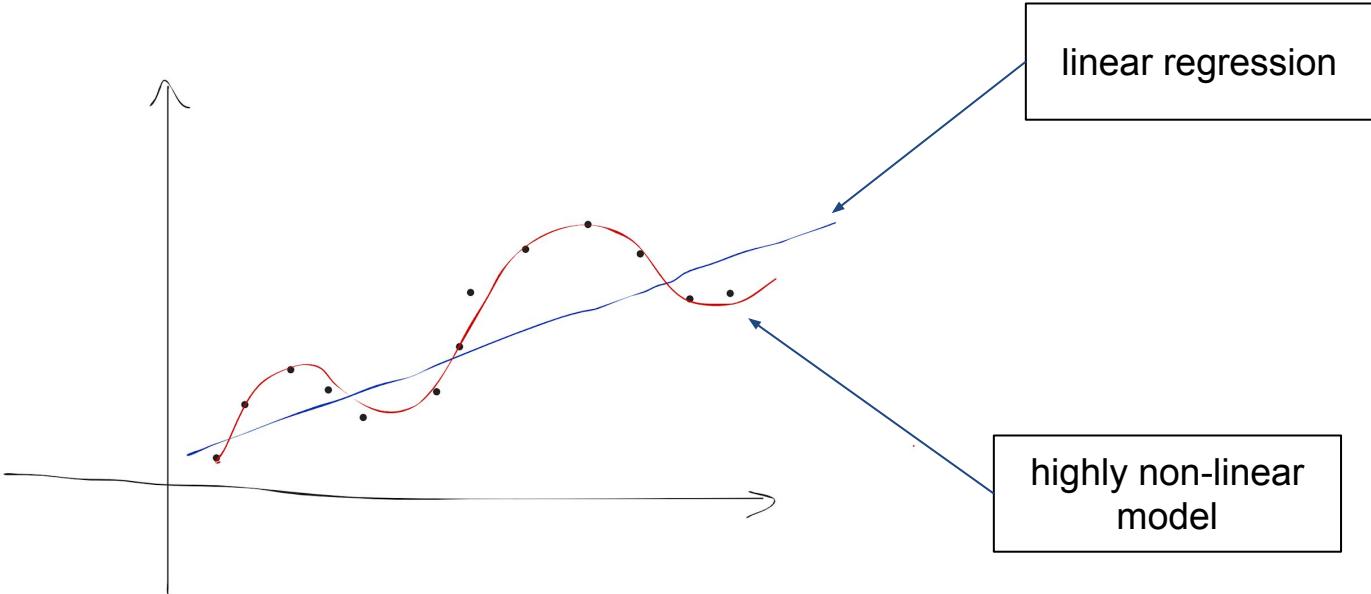


What is overfitting?



What is overfitting?

Think of KNN
with $k=1$!



What is overfitting?

- we want to predict whether a new patient will die or survive from a disease.
- we have 1000 historical patients with that disease and observe that 900 survived and 100 died: probability of survival = 90%



simple, but biased (men/women, old/young, overweight, smokers etc.)



What is overfitting?

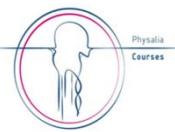
- we want to predict whether a new patient will die or survive from a disease.
- we have 1000 historical patients with that disease and observe that 900 survived and 100 died: probability of survival = 90%
- we refine our estimate to old (> 70 years) men: 300 patients, 100 died and 200 survived
→ prob. surv. = 66.6% (**less biased**)
- we can go on and make a less and less biased comparison: old men that are overweight, who smoke, don't exercise, don't drink alcohol, with high socio-economic status, independent professionals, who live in a residential neighbourhood, with one known comorbidity etc.
- we are left with only three historical patients who all died: shall we say that the probability of survival for our new patient is 0%?



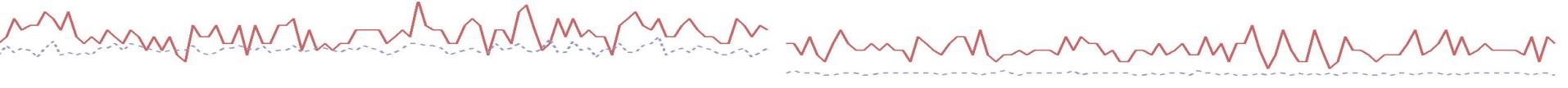
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- **the bias was reduced, but the variability was increased dramatically - the estimate based on only 3 observations has large variance →** $\frac{\sigma^2}{\sqrt{N}}$



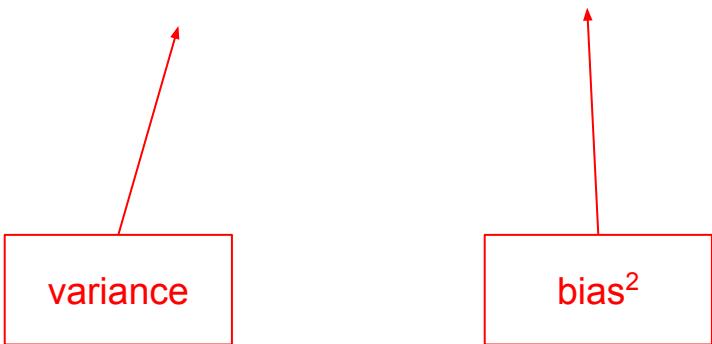


Prediction error



Prediction error

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



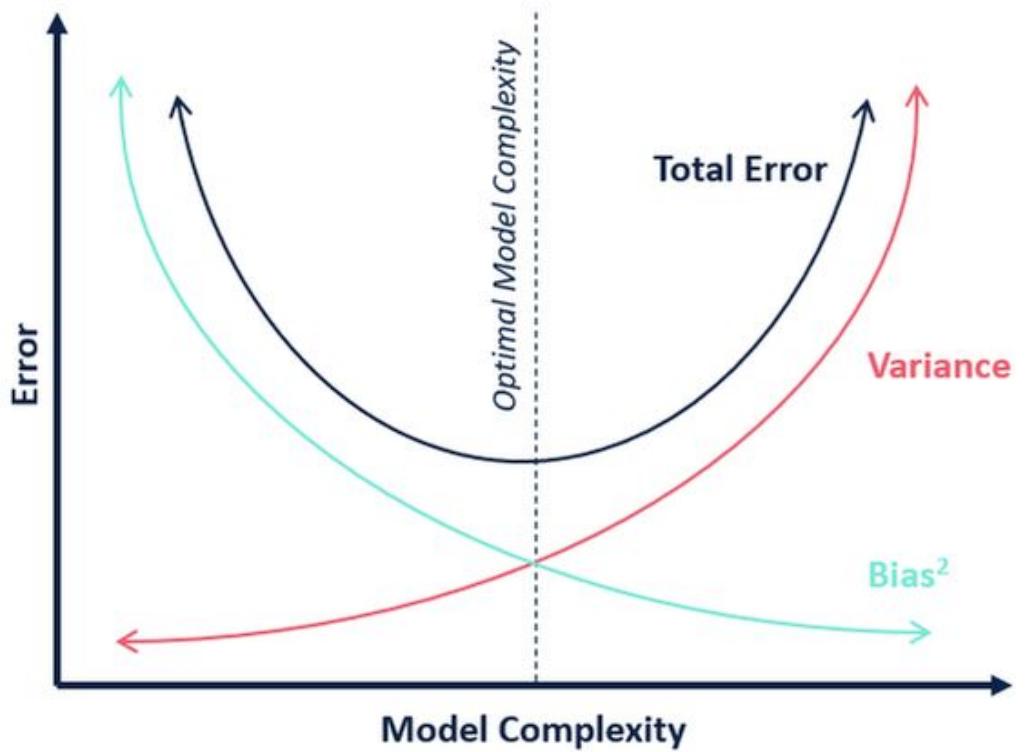
Prediction error

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

- **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

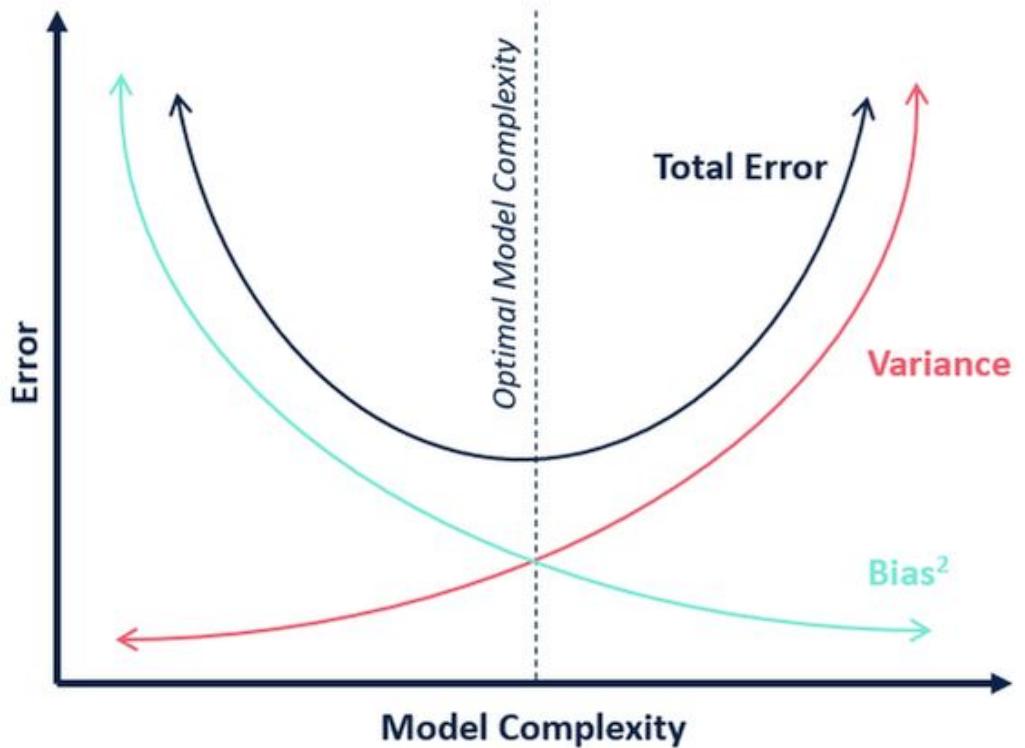


Bias-variance trade-off



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

Bias-variance trade-off



- models/methods with low bias and high variance (e.g. KNN with $k=1$)
- models/methods 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

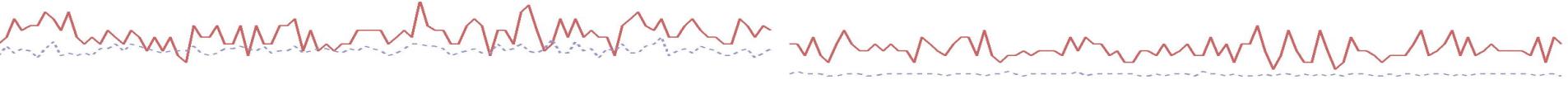
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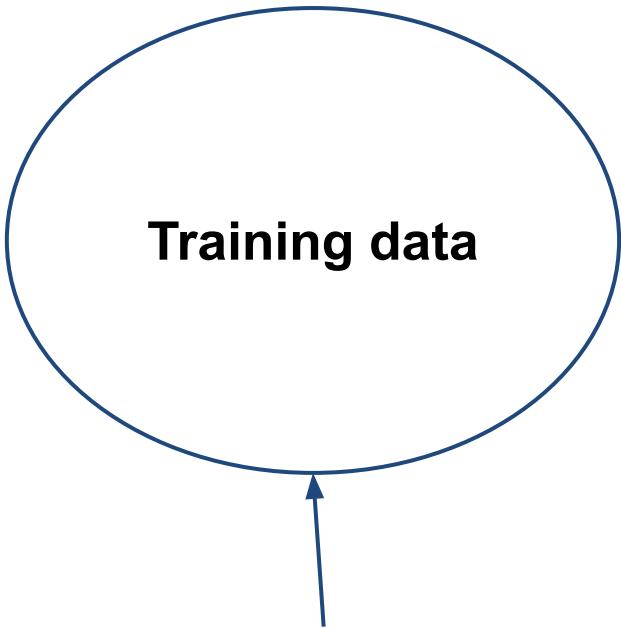
So, how do we control for overfitting and the bias-variance trade-off?



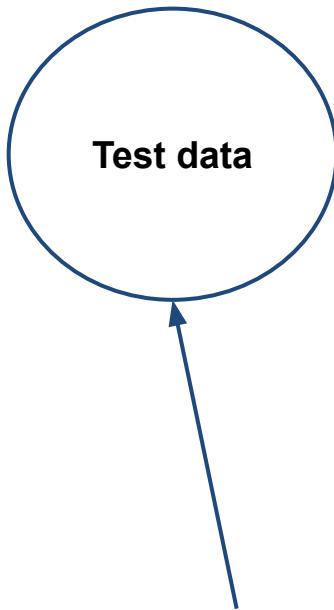
Training and test sets



Training and testing sets



the predictive model is **trained here**



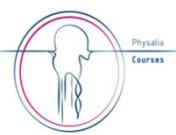
the predictive model is **evaluated here**



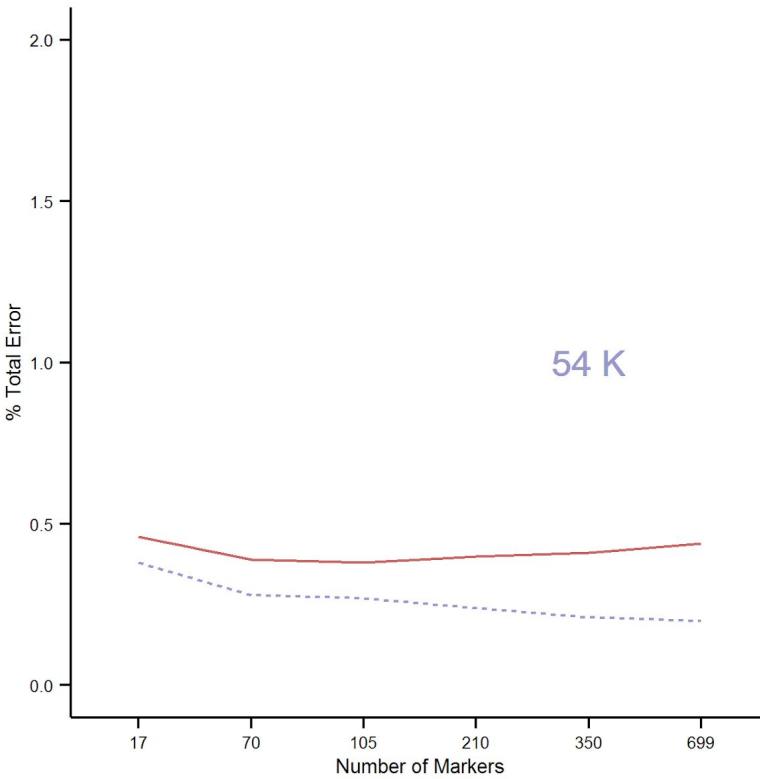
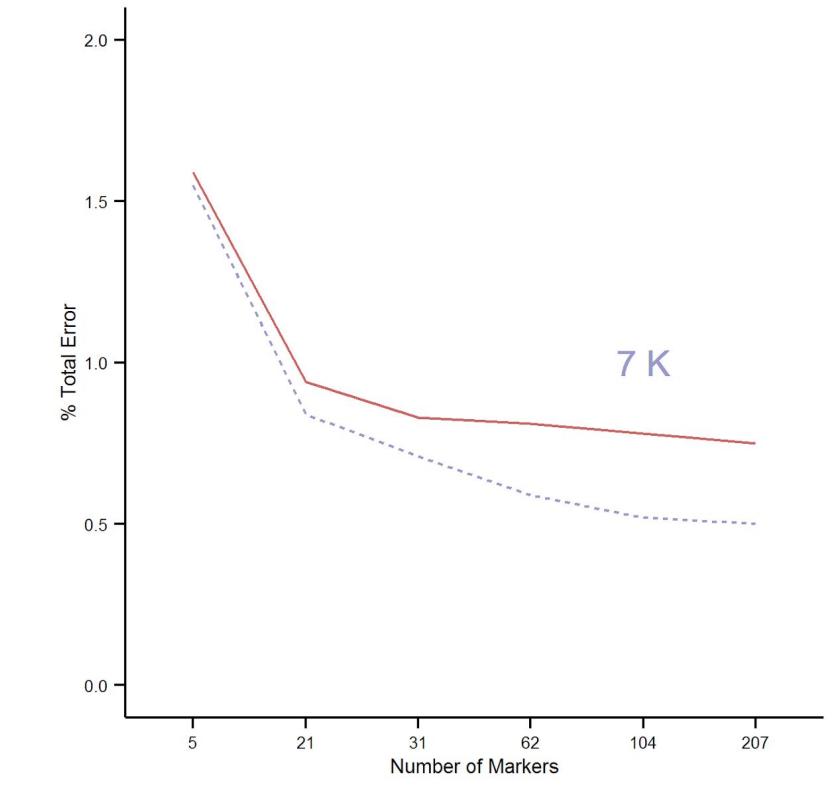
Training and testing sets

- 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

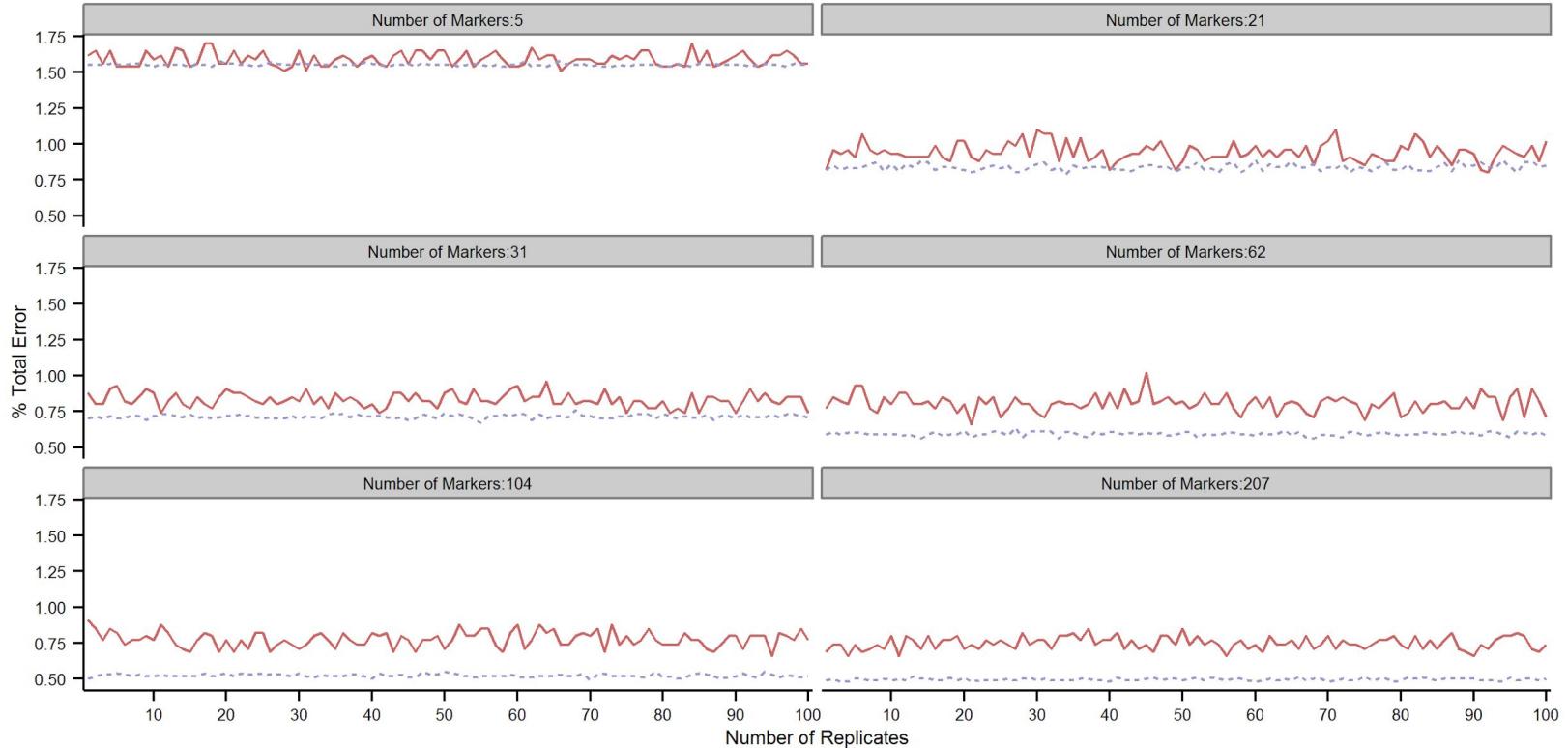




Training and testing sets



Training and testing sets





Overfitting - hands on!

→ 3.training_testing.Rmd
Exercise 3.1

