



Model validation

Lecture 8 of “Mathematics and AI”



Outline

1. Why validate models?
2. Single-validation set approach
3. Crossvalidation
4. Bootstrap
5. Data leakage

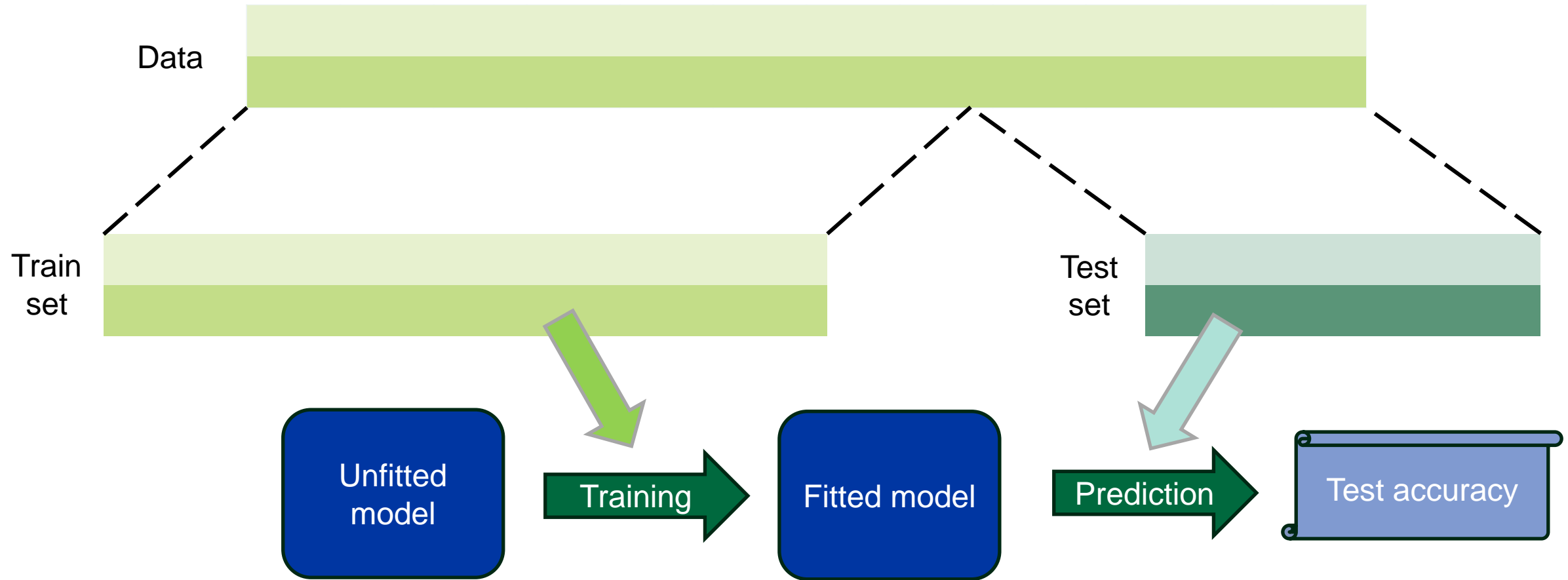


Why validate models?



Data

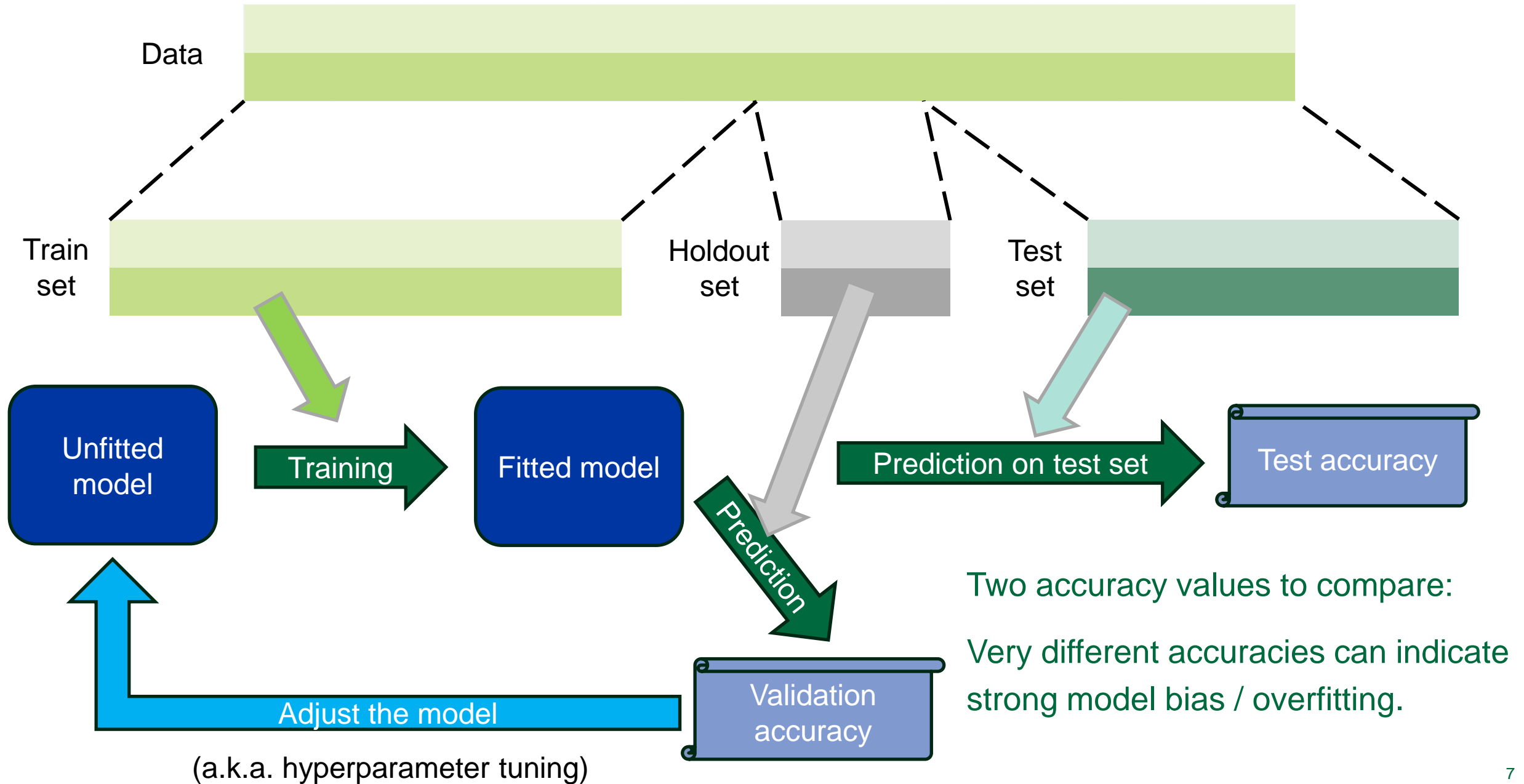
x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	\dots	x_{n-1}	x_n
y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8	y_9	\dots	y_{n-1}	y_n



- High test accuracy: Do we actually have a good model or did we pick a very lucky train-test split?
- Low test accuracy Did we pick a bad model of did we just pick a very unlucky train-test split?



Single-validation set approach



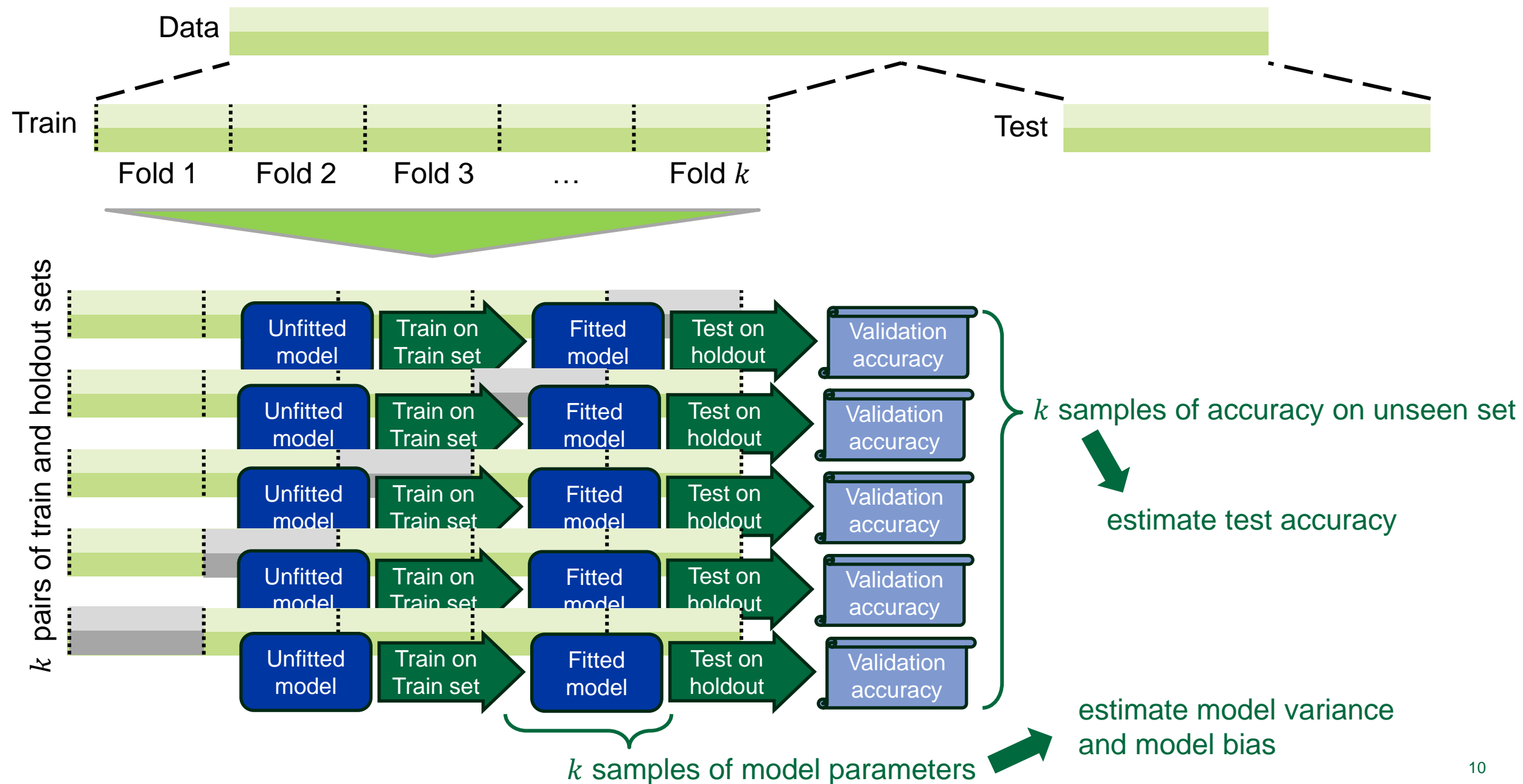


Model validation can be used to assess **model bias**.

It would be nice if we could assess **model variance** too.



Crossvalidation



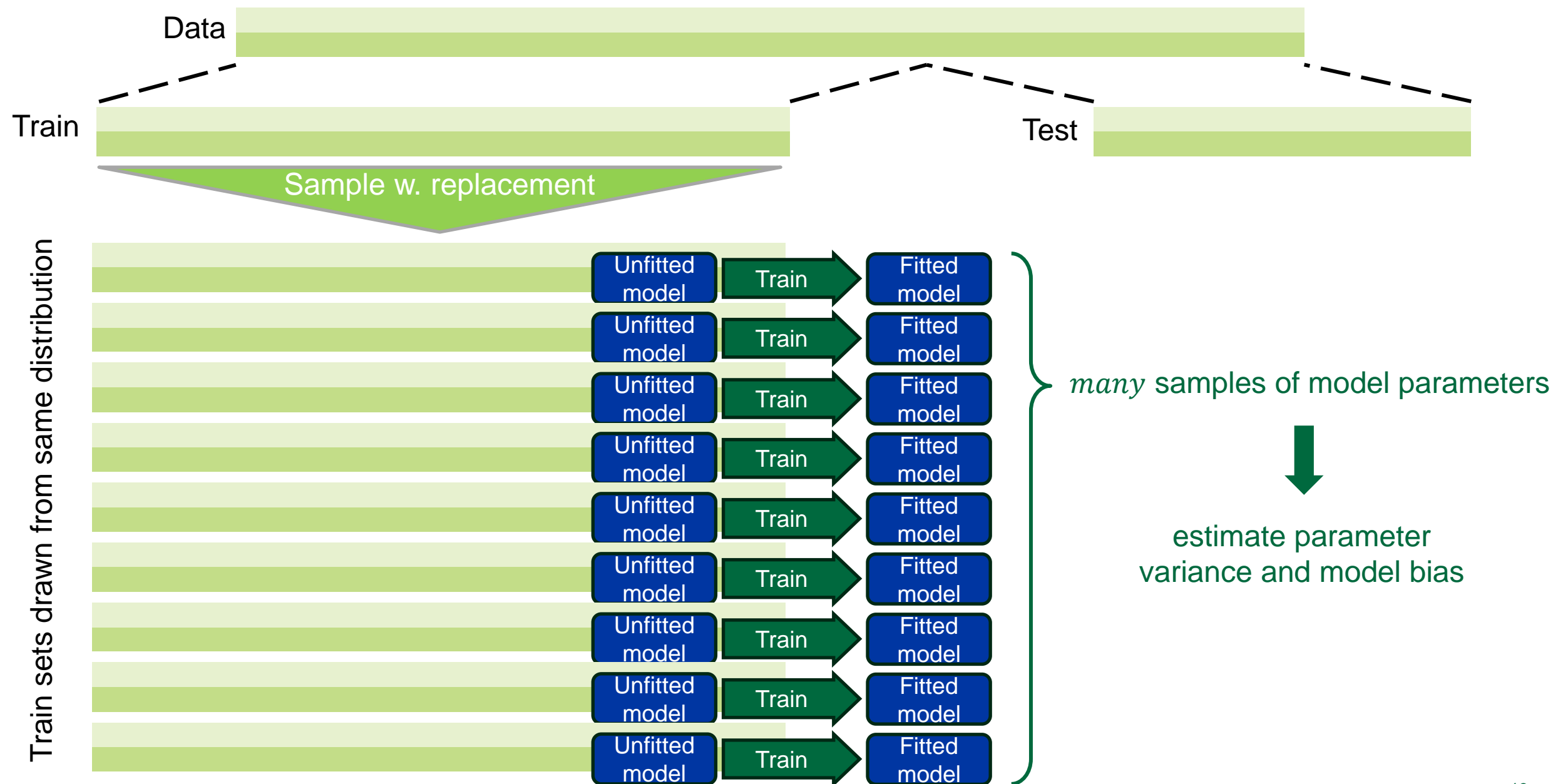


k -fold Crossvalidation

- Leave-one-out crossvalidation (LOOCV) = n -fold validation
- Benefits of large k :
 - Improved estimate of model variance and bias through large number of samples
- Benefits of small k :
 - Greater independence among the k train sets
 - Fewer models to train



Bootstrap





Bootstrap

Useful when:

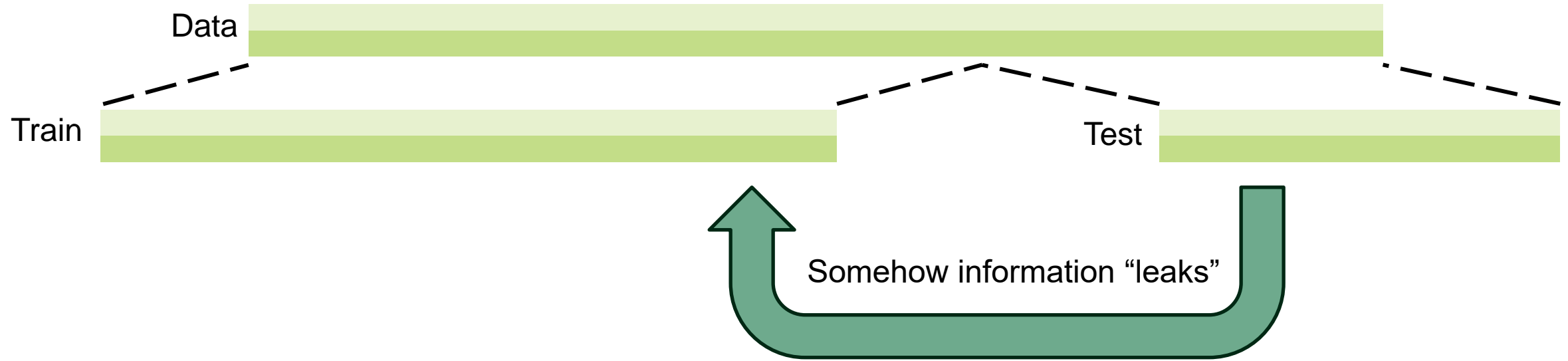
- Accurate assessment of parameter variance is necessary
- Too few training samples for good crossvalidation



Data leakage

“Data leakage can be [a] multi-million dollar mistake in many data science applications.”

Dan Becker (Kaggle Instructor)



Examples:

- Observations of the same test subject in train and test set (compare “eigenfaces” example)
- Conducted feature selection or data imputation on the full data set