

# Cross-validation

## Part 1

Jeremy Brown

24 January 2022

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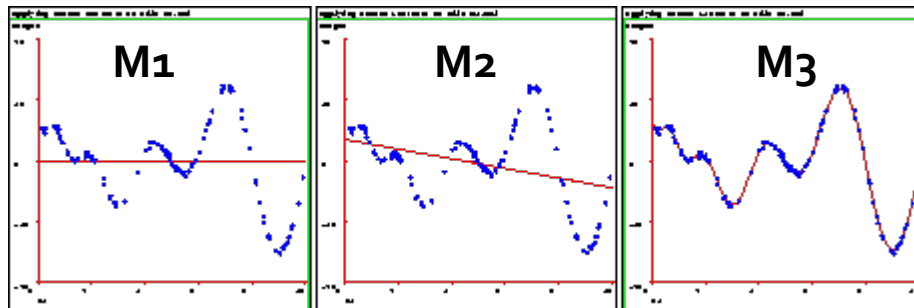


# Breakout room group discussions (5 mins)

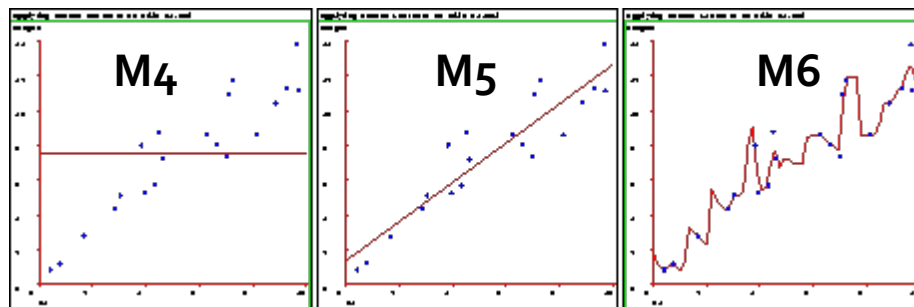
In breakout groups, spend 5 minutes working through one of these discussions:

A. You are fitting a regression model:

1) Which model fits better? Why?



2) Which model fits better? Why?

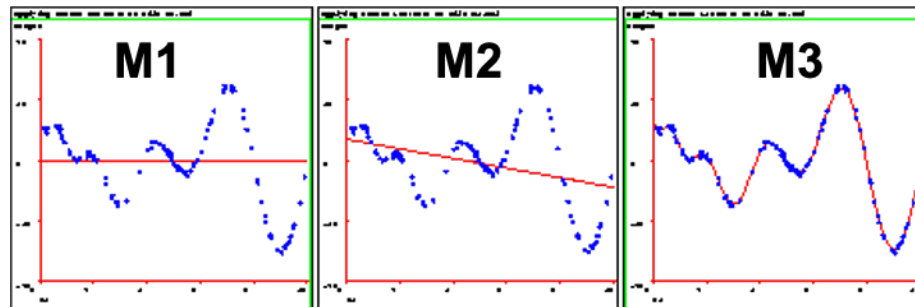


B. Why do you think it is important to do cross-validation?

- Share any experience you might have with cross-validation

# 1) Which model fits better?

One method of assessing the quality of a given model is by *a loss function*.



Very large  
MSE

Large  
MSE

~0 MSE

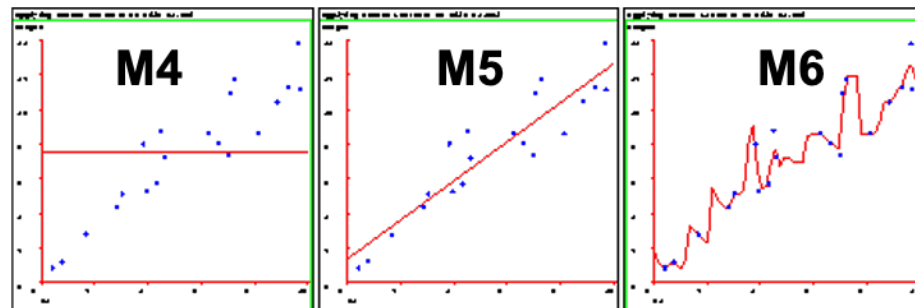


Models with lower error  
are deemed to be better.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2$$

## 2) Which model fits better?

Only looking at *error on training data* can lead us astray



Very large  
MSE

Large  
MSE

$\sim 0$   
MSE

M<sub>4</sub> underfits the data

M<sub>6</sub> overfits the data

### Recap week 1: over-fitting

Test/train error for classification models

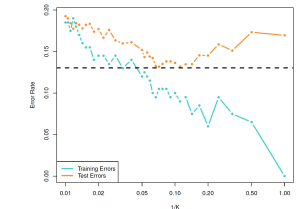
#### Training and Test error

Training error keeps on decreasing as  $K$  decreases.

Test error decreases at first: this shows model is getting better at fitting the test data.

When  $K$  gets too small, test error increases: the training data is not representative of the test data - this is **over-fitting**.

- Blue: training error,
- Orange: test error
- $K$  decreases to the right



Alex Lewin (LSHTM)

K-NN

Spring 2021 14 / 16

# What is cross-validation (CV)?

*Previously...*

**Goal:** build a generalisable model that can **make good predictions**: low test error rate

## Training error rate

- Can be calculated on the data used to train the model
- Often can underestimate the test error rate

## Test error rates

- Requires a separate set of data or cross-validation

**Cross-validation** refers to a set of methods for measuring the performance of a given predictive model on new data.

# What is cross-validation (CV)?

A **resampling method** because it involves fitting the same algorithm multiple times using different subsets of the data.

## Basic recipe of cross-validation techniques:

1. Divide the data into **two sets**:
  - a. the **training data set**, used to train or build the model; and
  - b. the **testing set**
2. Train the model using the **training set**
3. Use the testing set to test the model by estimating the prediction error. This will help you in gauging the effectiveness of your model's performance.

There are different cross-validation methods.

# Minimising error or expected loss

**Data:**  $D = ((x_1, y_1), \dots, (x_n, y_n))$

**Model:**  $M \in (1, \dots, C)$

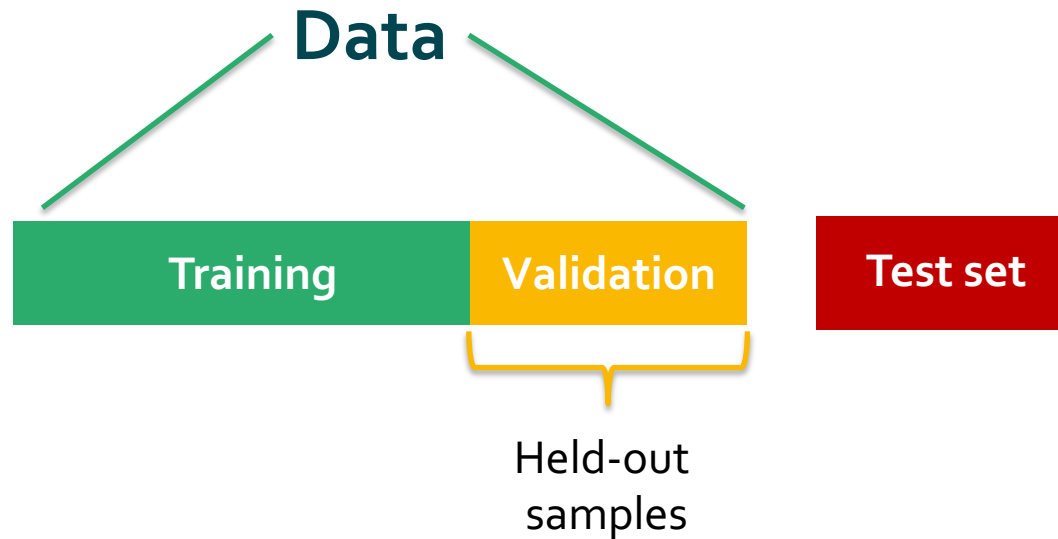
**Expected loss:**  $\text{Err} = \mathbb{E}[L(Y, f_m(X))]$

**True distribution of the data:**  $(X, Y) \sim p$

$D = ((x_1, y_1), \dots, (x_n, y_n))$  and  $T = ((x'_1, y'_1), \dots, (x'_t, y'_t))$  i.i.d. of  $p$



# Validation set approach



**Validation set approach** is the most straightforward kind of cross-validation

1. Split **Data** into two sets:
  - training set
  - validation set
2. Use the **training data** to build the model
  - Train for each of the M models
3. Use **validation data** to evaluate performance
4. Choose the model with the smallest empirical error on the validation set

The validation set approach is also known as the **hold-out method**.

## Out of sample prediction

- Let's split the *kyphosis* data set in two

```
library(caret)
set.seed(21)
kyph_folds <-
  createFolds(y = kyphosis$Kyphosis,
             k = 2) %>%
  setNames(c('Train', 'Test'))

kyph_train <-
  kyphosis[kyph_folds$Train, ]
kyph_test <-
  kyphosis[kyph_folds$Test, ]

kyph_glm_train <- glm(
  data = kyph_train,
  formula = y ~ Age * Start * Number,
  family = binomial())
```

## 1.3 Deciding on a good value of k

Loop over different values of k.

Here we calculate the predictions for both training and test data the error rates so that we can plot them later.

```
#kValues <- c(1,2,5,10,30,50,100,200,400)
#kValues <- 1:200
kValues <- seq(10,400,by=10)
#kValues <- 30

TestErrorArray.KNN <- rep(NA,length(kValues))
TrainErrorArray.KNN <- rep(NA,length(kValues))
TestPrecisionArray.KNN <- rep(NA,length(kValues))
TrainPrecisionArray.KNN <- rep(NA,length(kValues))
TestRecallArray.KNN <- rep(NA,length(kValues))
TrainRecallArray.KNN <- rep(NA,length(kValues))
```



# k-fold cross-validation

1. Randomly permute (or shuffle) the data



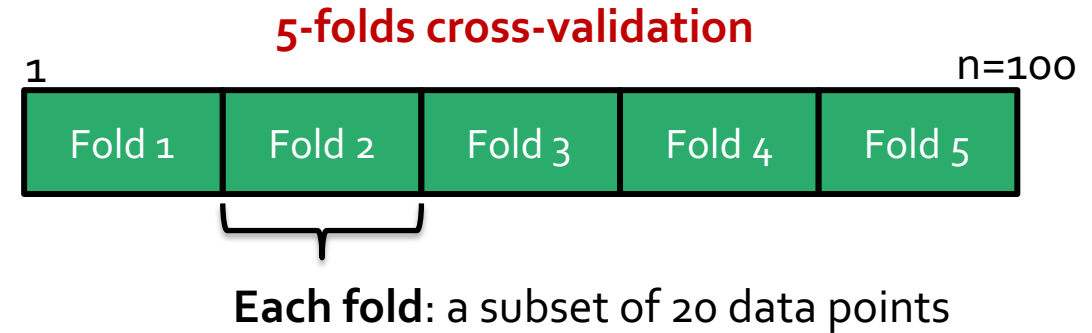
# k-fold cross-validation

1. Randomly permute (or shuffle) the data
2. **Split the data into equally sized  $k$ -folds**
  - Choose a value for the parameter  $k$



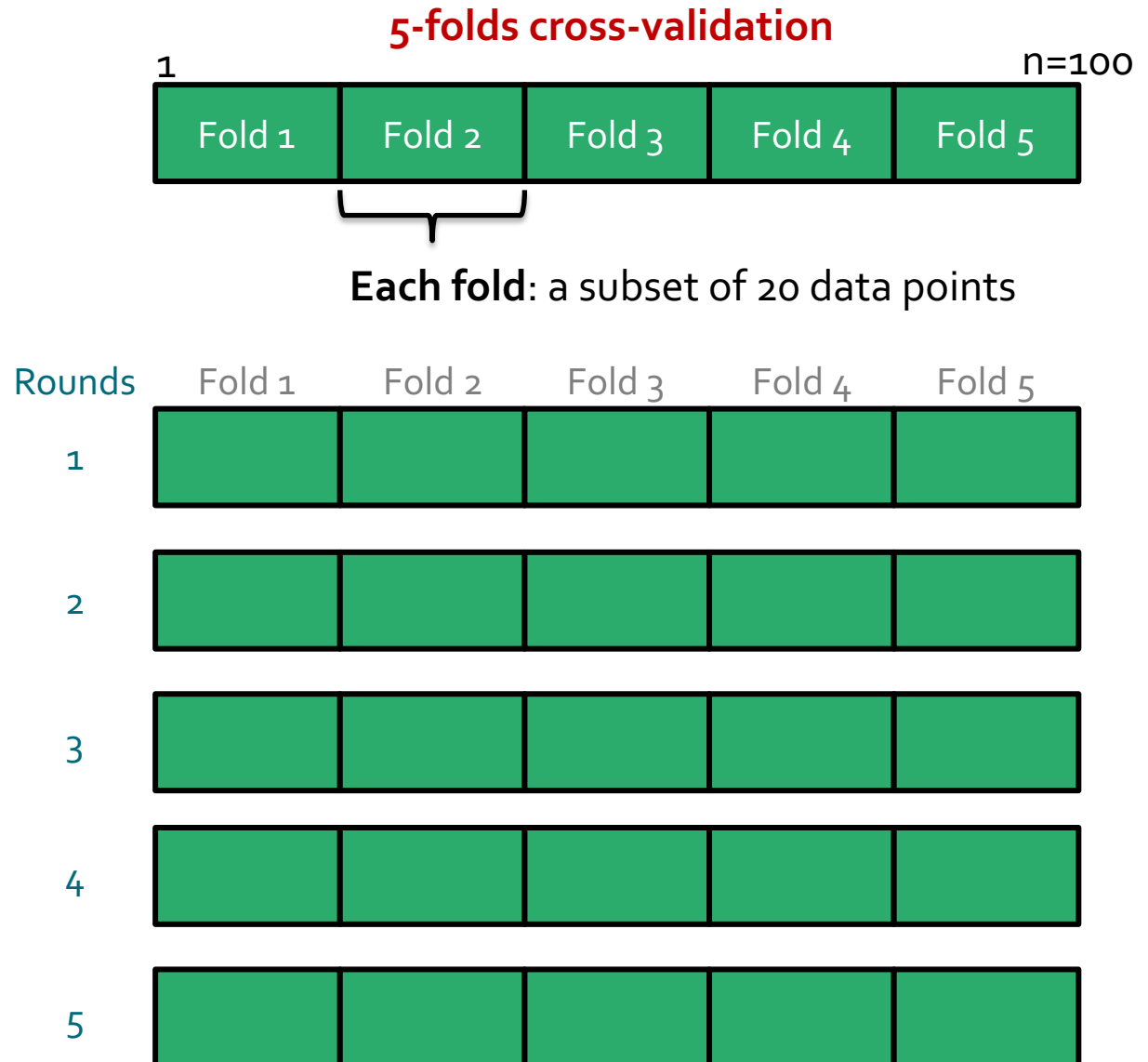
# k-fold cross-validation

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# k-fold cross-validation

1. Randomly permute (or shuffle) the data
2. **Split the data into equally sized  $k$ -folds**
  - Choose a value for the parameter  $k$
3. **Validation!**
  - #rounds = #folds
  - For each round, there will be a different fold that is the validation set



# k-fold cross-validation

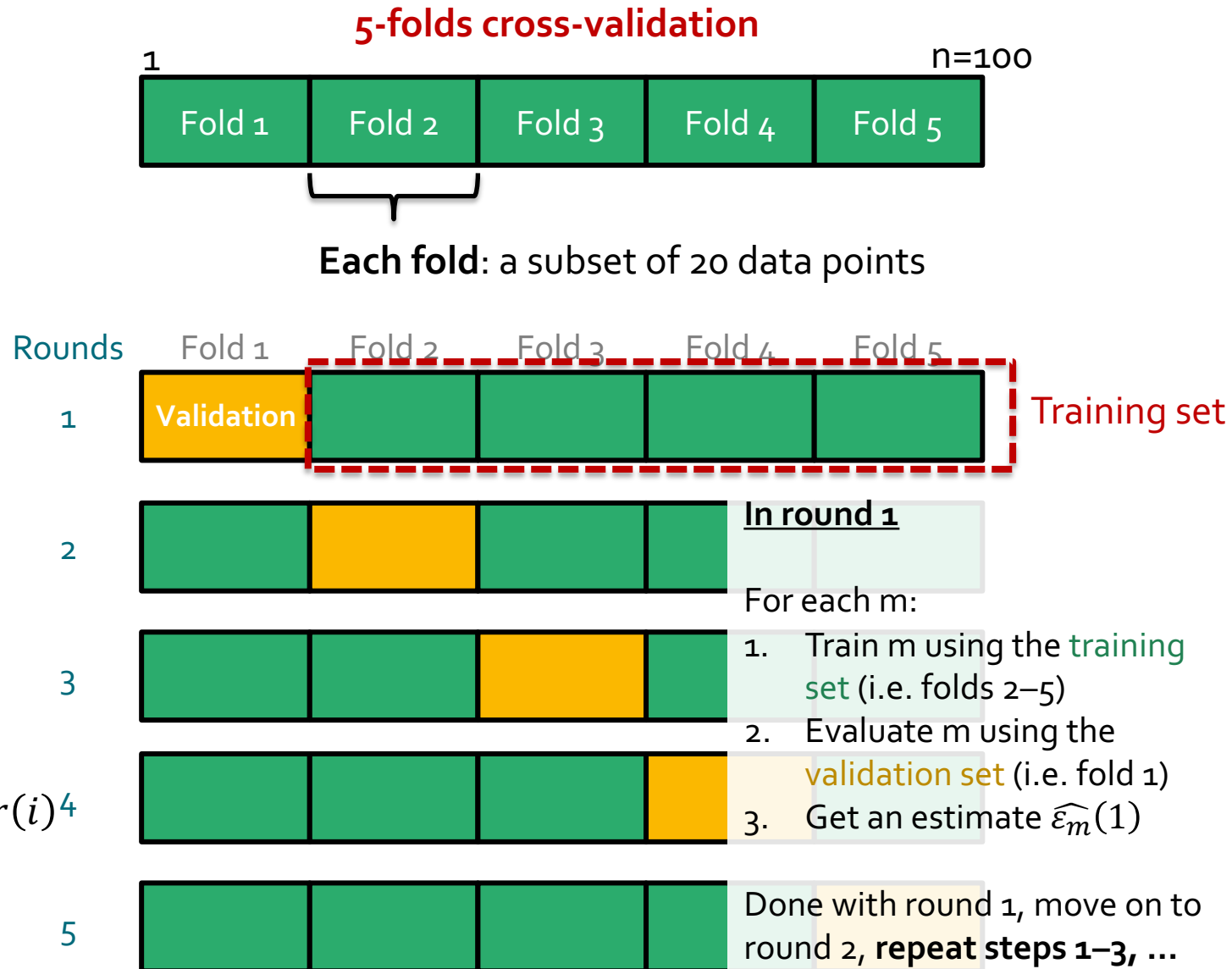
1. Randomly permute (or shuffle) the data
2. **Split the data into equally sized  $k$ -folds**
  - Choose a value for the parameter  $k$

## 3. Validation!

- #rounds = #folds
- For each round, there will be a different fold that is the validation set

- Calculate  $\widehat{Err}$  across the rounds
- $$\widehat{Err} = \frac{1}{k} \sum_{i=1}^{k=5} \widehat{Err}(i)$$

4. Choose  $m^*$  to minimise  $\widehat{Err}_m$
5. Retrain using  $m^*$  on all of  $D$



# Leave-one-out cross-validation (LOOCV)

LOOCV is a **special case** of the  $k$ -fold cross-validation

- $K = n$  : the number of data points in the training set
- there will be  $n$  rounds (you don't really need to permute the data: Step 1 for  $k$ -fold cv)

- **In round 1**

For each  $m$ :

1. Train  $m$  using the **training set** (i.e. folds 2– $n$ )
2. Evaluate  $m$  using the **validation set** (i.e. fold 1)
3. Get an estimate  $\widehat{Err}_m(1)$

Done with round 1, move on to round 2, **repeat steps 1–3, ...**

# Cross-validation

## Part 2

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# Breakout room group discussions (20 mins)

**In breakout groups, spend 20 minutes to review k-fold cross-validation.**

**1. What are the advantages and disadvantages of k-fold cross-validation relative to:**

- i. the validation set approach?
- ii. the leave-one-out cross-validation (LOOCV)?

**What is the optimal number of folds in k-folds cross-validation?**

A recommended value for  $k$  is 10

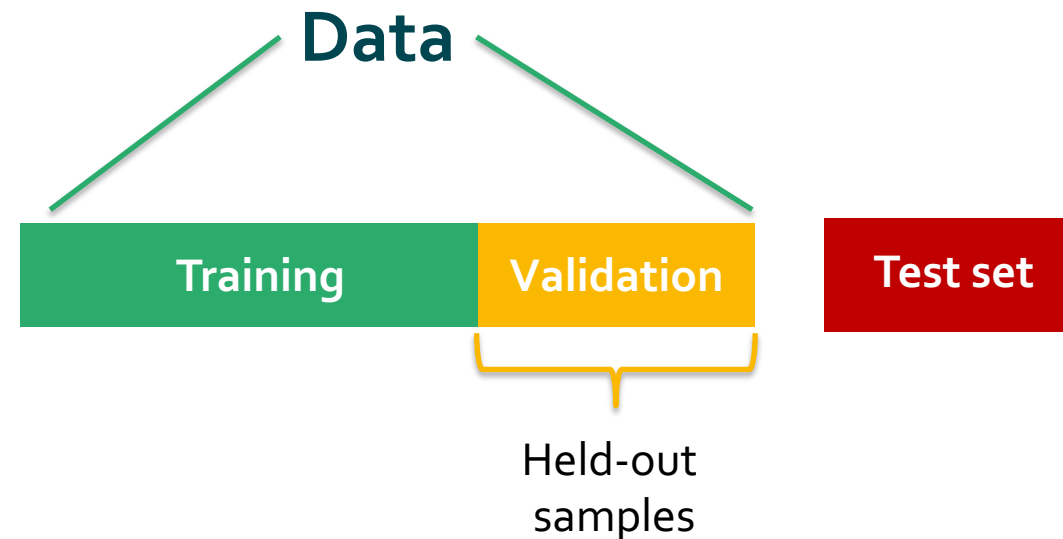
How do we know that this configuration is appropriate for our dataset and our algorithms?



# Validation set approach vs k-folds cross-validation

Model evaluation may depend heavily on which data points end up in the training set and which end up in the test set

- may be significantly different depending on how you divide the data



# Optimal number of folds in k-folds cross-validation

*It depends.*

**During cross-validation, you were averaging over independent estimates**

- **LOOCV** → lower bias

**What happens when training sets are highly correlated?**

Correlation may increase with  $k$  (LOOCV is when  $k = n$ )

**Model performance also depends on the training size.**

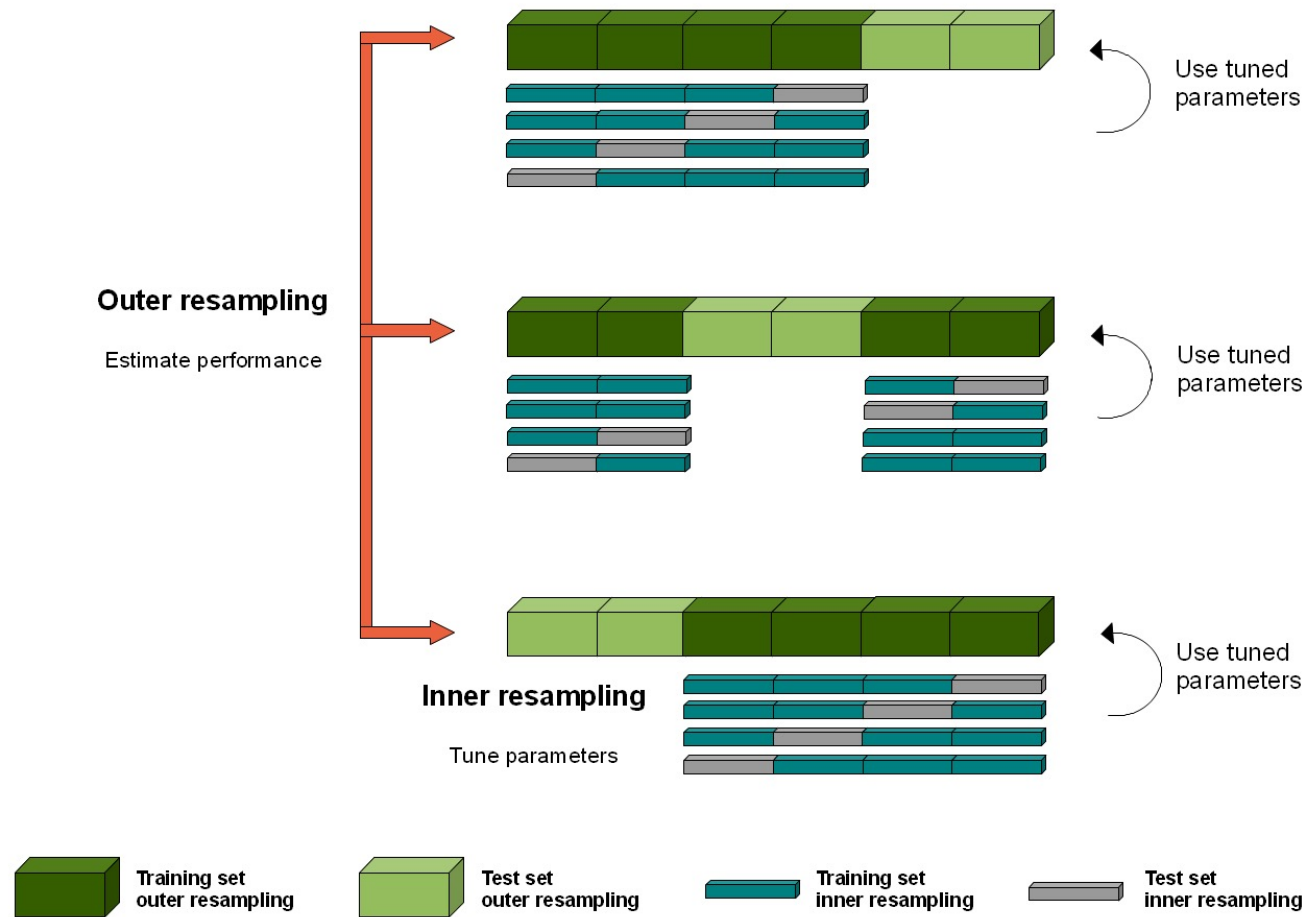
1. If there were **100 observations** in the training set
2. If there were **50 observations** in the training data set

# Breakout room group discussions (10 mins)

**In breakout groups, spend 10 minutes**

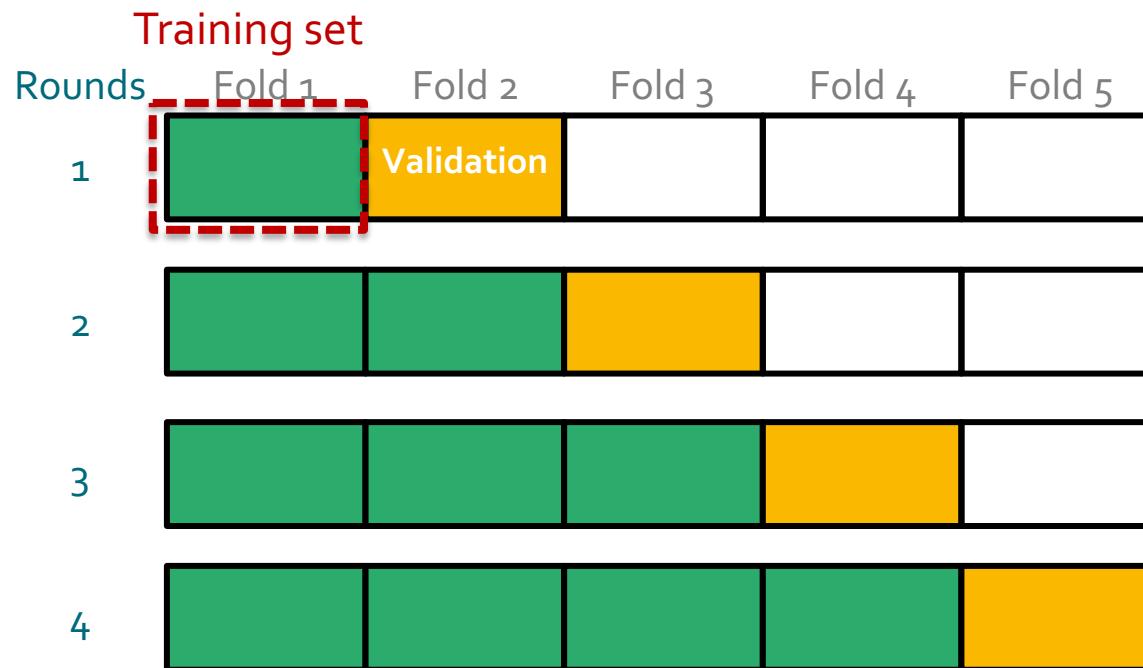
1. What is data leakage when training a model?
2. Why it is a problem?
3. How can you minimize data leakage?

# Nested cross-validation



# Time series cross-validation

How to implement time series (or other intrinsically ordered data) cross-validation in R ?



Cross-validation on a rolling basis

<https://github.com/robjhyndman/forecast>

<https://robjhyndman.com/hyndsight/tscv/>