

# Bootstrap and Splines

DS 6030 | Fall 2022

bootstrap.pdf

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# 1 Introduction to the Bootstrap

## 1.1 Required R Packages

We will be using the R packages of:

- `broom` for tidy extraction of model components
- `splines` for working with B-splines
- `tidyverse` for data manipulation and visualization

```
library(broom)
library(splines)
library(tidyverse)
```

## 1.2 Uncertainty in a test statistic

There is often interest to understand the uncertainty in the estimated value of a test statistic.

- For example, let  $p$  be the actual/true proportion of customers who will use your company's coupon.
- To estimate  $p$ , you decide to take a sample of  $n = 200$  customers and find that  $x = 10$  or  $\hat{p} = 10/200 = 0.05 = 5\%$  redeemed the coupon.

### 1.2.1 Confidence Interval

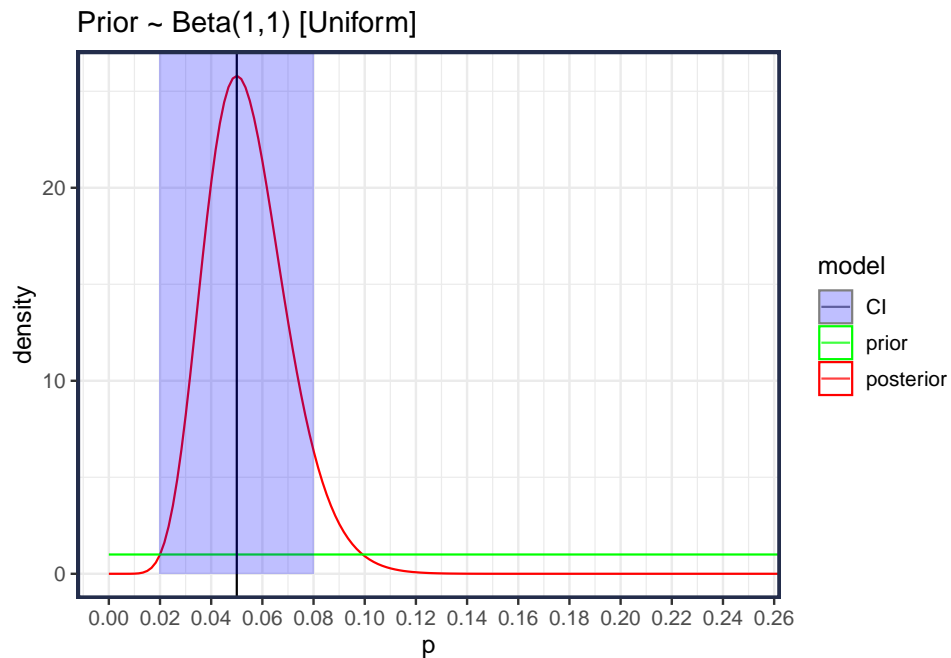
- It is common to calculate the 95% *confidence interval (CI)*

$$\begin{aligned} \text{CI}(p) &= \hat{p} \pm 2 \cdot \text{SE}(\hat{p}) \\ &= \hat{p} \pm 2 \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}} \\ &= 0.05 \pm 0.03 \end{aligned}$$

- This calculation is based on the assumption that  $\hat{p}$  is approximately normally distributed with the mean equal to the *unknown* true  $p$ , i.e.,  $\hat{p} \sim N(p, \sqrt{\frac{p(1-p)}{n}})$ .

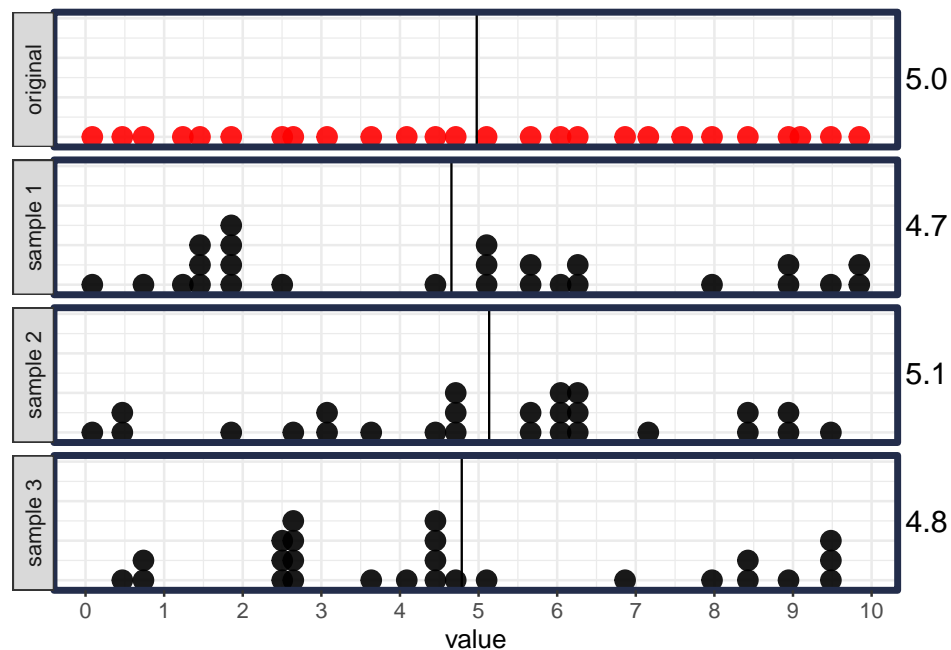
### 1.2.2 Bayesian Posterior Distribution

In the Bayesian world, you'd probably specify a Beta *prior* for  $p$ , i.e.,  $p \sim \text{Beta}(a, b)$  and calculate the *posterior* distribution  $p \mid x = 10 \sim \text{Beta}(a + x, b + n - x)$  which would fully characterize the uncertainty.



### 1.2.3 The Bootstrap

- The Bootstrap is a way to assess the uncertainty in a test statistic using *resampling*.
- The idea is to simulate the data from the *empirical distribution*, which puts a point mass of  $1/n$  at each observed data point (i.e., sample the original data **with replacement**).
  - It is important to simulate  $n$  observations (same size as original data) because the uncertainty in the test statistic is a function of  $n$



- Then, calculate the test statistic for each bootstrap sample. The variability in the collection of bootstrap test statistics should be similar to the variability in the test statistic.

**Algorithm: Nonparametric/Empirical Bootstrap**

Observe data  $D = [X_1, X_2, \dots, X_n]$  ( $n$  observations).

Calculate a test statistic  $\hat{\theta} = \hat{\theta}(D)$ , which is a function of  $D$ .

Repeat steps 1 and 2  $M$  times:

1. Simulate  $D^*$ , a new data set of  $n$  observations by sampling from  $D$  with replacement.
2. Calculate the bootstrap test statistic  $\hat{\theta}^* = \hat{\theta}(D^*)$

The bootstrapped samples  $\hat{\theta}_1^*, \hat{\theta}_2^*, \dots, \hat{\theta}_M^*$  can be used to estimate the distribution of  $\hat{\theta}$ .

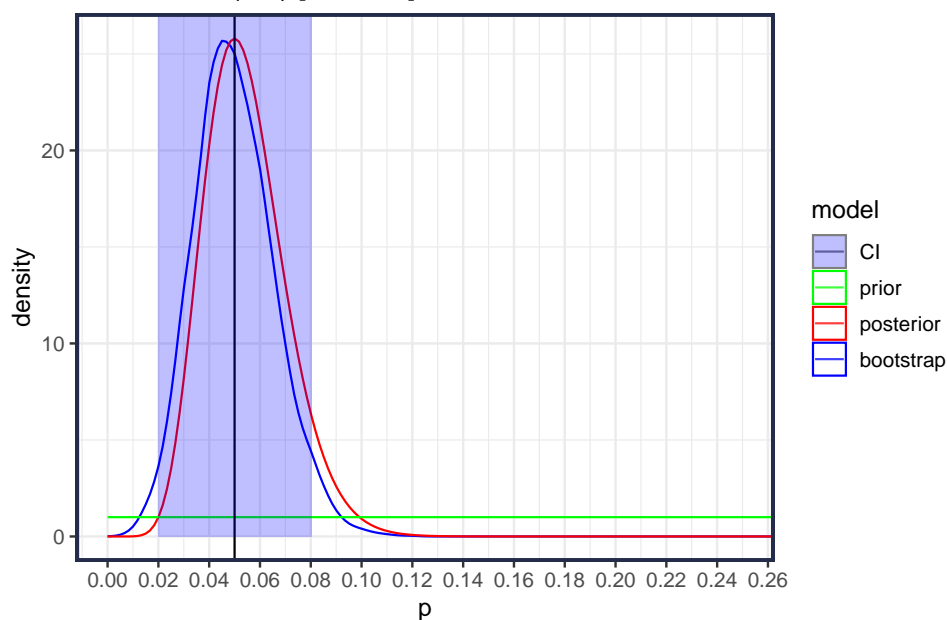
- Or properties of the distribution, like standard deviation (standard error), percentiles, etc.

```
#: Original Data
x = c(rep(1, 10), rep(0, 190))      # 10 successes, 190 failures
n = length(x)                       # length of observed data

#: Bootstrap Distribution
M = 5000                            # number of bootstrap samples
p = numeric(M)                     # initialize vector for test statistic
set.seed(201910)                   # set random seed
for(m in 1:M) {
  #- sample from empirical distribution
  ind = sample(n, replace=TRUE)      # sample indices with replacement
  xboot = x[ind]                    # bootstrap sample
  #- calculate proportion of successes
  p[m] = mean(xboot)                # calculate test statistic
}

#: Bootstrap Percentile based confidence Intervals
quantile(p, probs=c(.025, .975))    # 95% bootstrap interval
#> 2.5% 97.5%
#> 0.020 0.085
```

Prior ~ Beta(1,1) [Uniform]



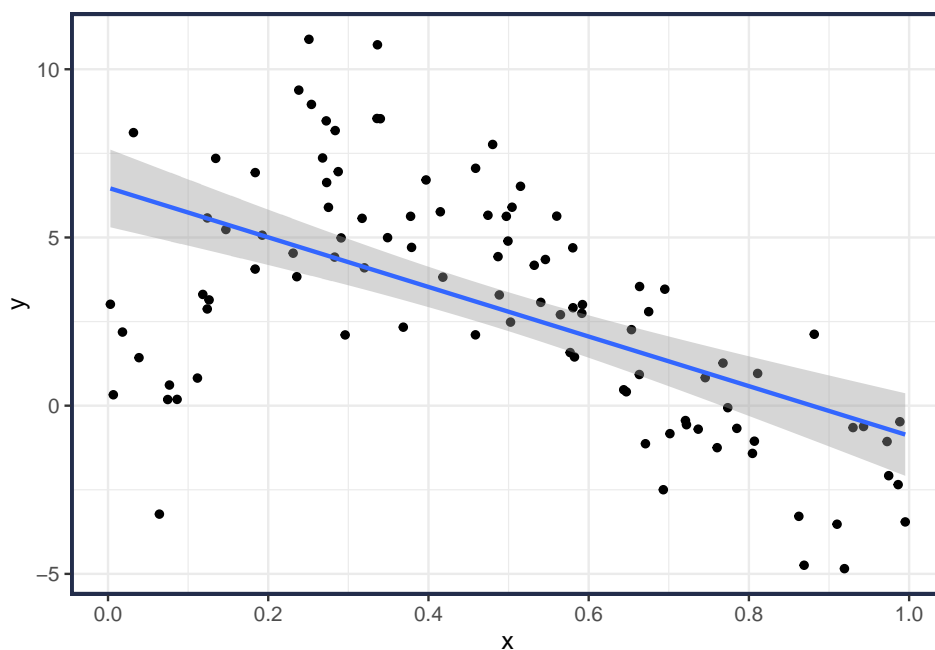
**Note**

- Notice that in the above example the bootstrap distribution is close to the Bayesian posterior distribution (using the uninformative Uniform prior).
- This is no accident, it turns out there is a close correspondence between the bootstrap derived distribution and the Bayesian posterior distribution under *uninformative priors*
  - See ESL 8.4 for more details

## 2 Bootstrapping Regression Parameters

The bootstrap is not limited to univariate test statistics. It can be used on multivariate test statistics.

Consider the uncertainty in estimates of the parameters (i.e.,  $\beta$  coefficients) of a regression model.



```
m1 = lm(y~x, data=data_train) # fit simple OLS
broom::tidy(m1, conf.int=TRUE) # OLS estimated coefficients
#> # A tibble: 2 x 7
#>   term      estimate std.error statistic  p.value conf.low conf.high
#>   <chr>      <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
#> 1 (Intercept)  6.48    0.584    11.1 5.39e-19  5.32    7.64
#> 2 x          -7.37    1.06    -6.97 3.69e-10 -9.47   -5.27
vcov(m1) %>% round(2) # variance matrix
#>      (Intercept)      x
#> (Intercept)  0.34 -0.54
#> x          -0.54  1.12
vcov(m1) %>% diag() %>% sqrt() %>% round(3) # standard errors
#> (Intercept)      x
#> 0.584      1.058
```

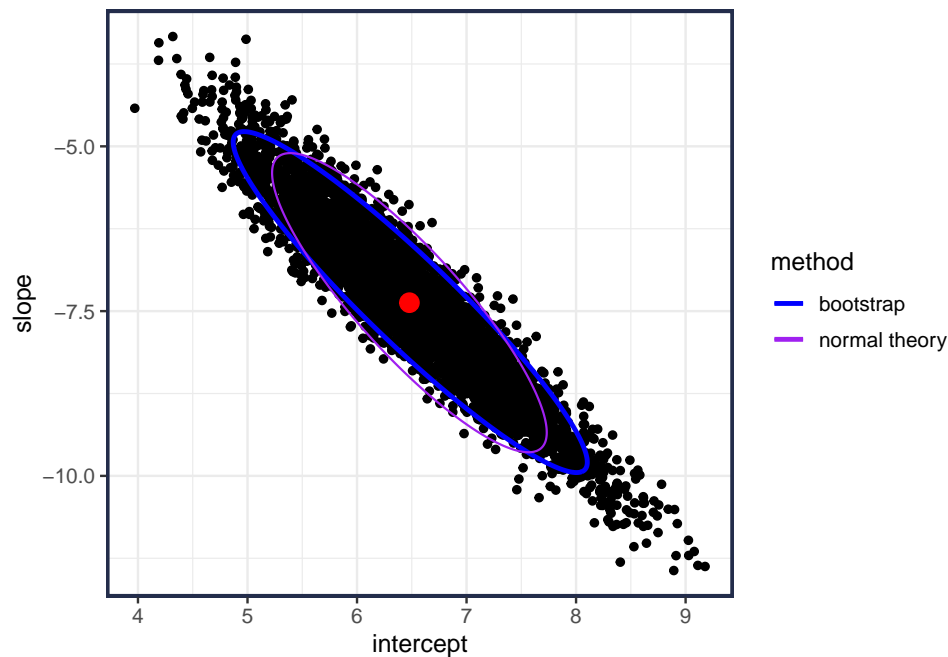
### 2.1 Bootstrap the $\beta$ 's

```

#-- Bootstrap Distribution
M = 5000                                # number of bootstrap samples
beta = list()                           # initialize list for test statistics
set.seed(201910)                         # set random seed
for(m in 1:M){
  # sample from empirical distribution
  ind = sample(n, replace=TRUE)          # sample indices with replacement
  data.boot = data_train[ind,]           # bootstrap sample
  # fit regression model
  m.boot = lm(y~x, data=data.boot)       # fit simple OLS
  # save test statistics
  beta[[m]] = broom::tidy(m.boot) %>% select(term, estimate)
}
# convert to tibble (and add column names)
beta = bind_rows(beta, .id = "iteration") %>%
  pivot_wider(names_from = term, values_from=estimate) %>%
  select(intercept = "(Intercept)", slope = "x", -iteration)

#- Plot
ggplot(beta, aes(intercept, slope)) +
  geom_point() +
  geom_point(data=tibble(intercept=coef(m1)[1], slope = coef(m1)[2]),
             color="red", size=4)

```



```

#- bootstrap estimate
var(beta) %>% round(2)                  # variance matrix
#>           intercept slope
#> intercept    0.57 -0.85
#> slope        -0.85  1.45
apply(beta, 2, sd) %>% round(2)        # standard errors (sqrt of diagonal)
#> intercept    slope
#>    0.75      1.21

```

### 3 Non-linear Modeling via Basis Expansion

For a univariate  $x$ , a linear basis expansion is

$$\hat{f}(x) = \sum_j \hat{\theta}_j b_j(x)$$

where  $b_j(x)$  is the value of the  $j$ th basis function at  $x$  and  $\theta_j$  is the coefficient to be estimated.

- The  $b_j(x)$  are sometimes specified in advanced (i.e., not estimated). But other approaches use sample data to estimate (e.g., using quantiles for knot placement).
  - Just be sure to estimate everything from the training data so there is no data leakage!

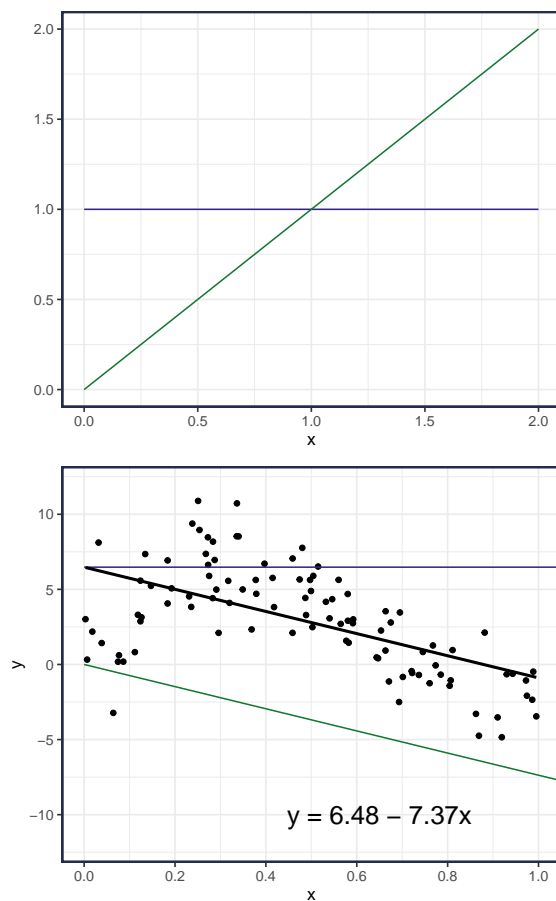
Examples:

#### • Linear Regression

$$\hat{f}(x) = \hat{\beta}_0 + \hat{\beta}_1 x$$

$$b_0(x) = 1$$

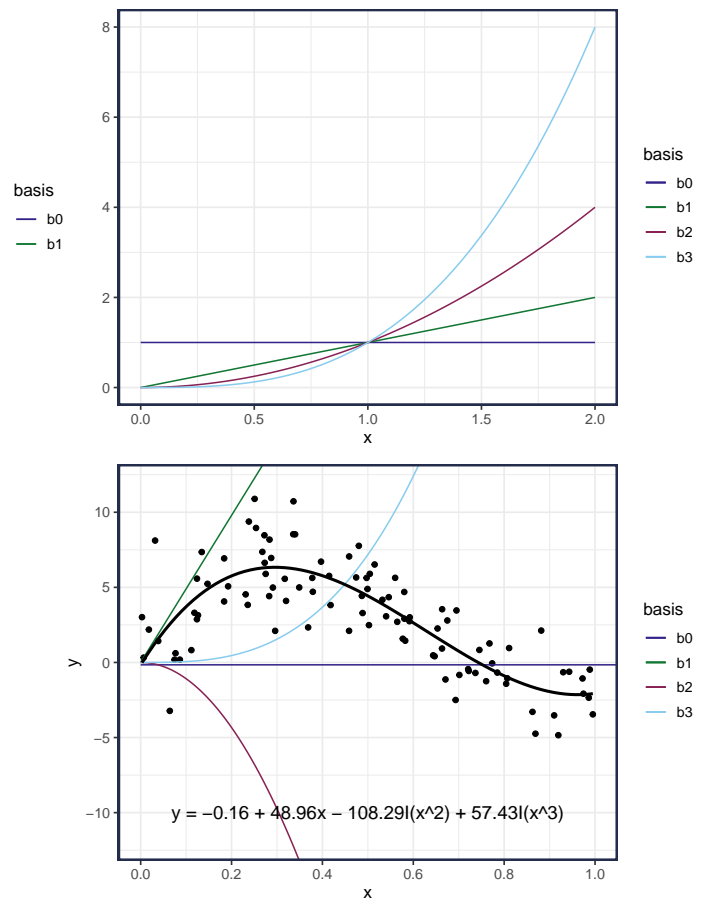
$$b_1(x) = x$$



#### • Polynomial Regression

$$\hat{f}(x) = \sum_{j=1}^d \hat{\beta}_j x^j$$

$$b_j(x) = x^j$$



- **Piecewise Constant Regression (Regressogram)**

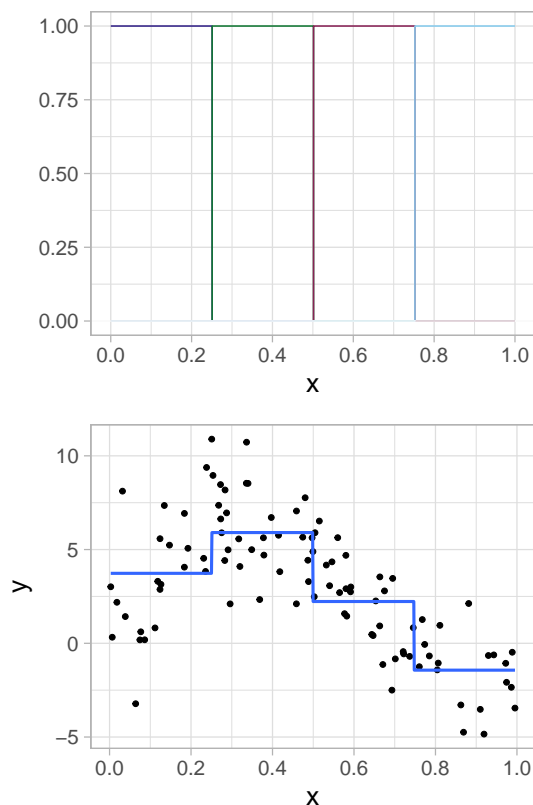
$$\hat{f}(x) = \sum_{j=1}^p \hat{\beta}_j \mathbb{1}(x \in R_j)$$

$$b_1(x) = \mathbb{1}(x \in R_1)$$

$$b_2(x) = \mathbb{1}(x \in R_2)$$

$$\vdots$$

$$b_p(x) = \mathbb{1}(x \in R_p)$$



- **Categorical encoding (dummy, one-hot)**

$$x \in \{c_1, c_2, \dots, c_p\}$$

$$\hat{f}(x) = \sum_{j=1}^p \hat{\beta}_j \mathbb{1}(x = c_j) \quad \text{one-hot}$$

$$= \hat{\beta}_0 + \sum_{j=2}^p \hat{\beta}_j \mathbb{1}(x = c_j) \quad \text{dummy}$$

$$b_1(x) = \mathbb{1}(x = c_1)$$

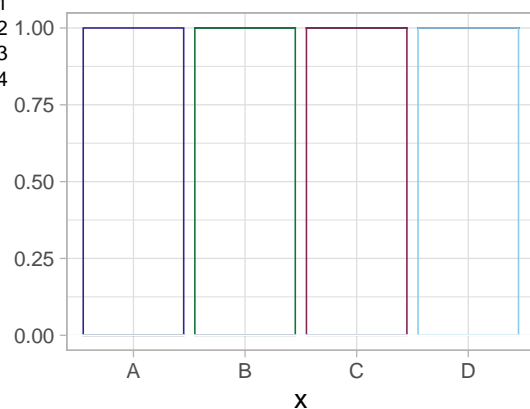
$$b_2(x) = \mathbb{1}(x = c_2)$$

$$\vdots$$

$$b_p(x) = \mathbb{1}(x = c_p)$$

basis

— b1  
— b2  
— b3  
— b4

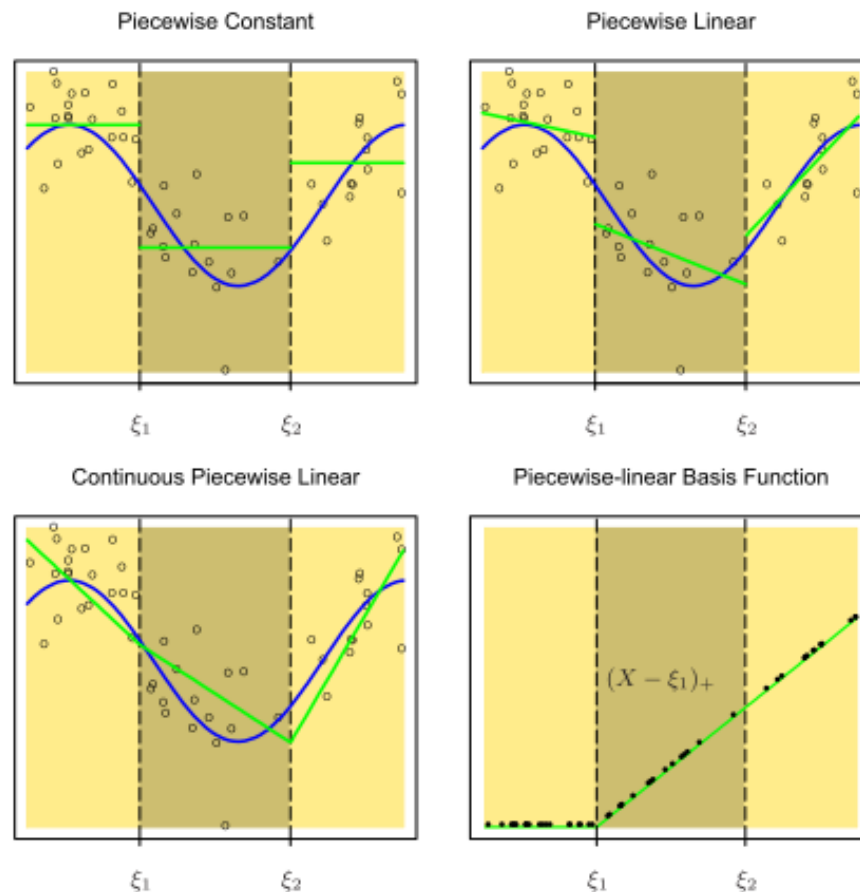


basis

□ A  
□ B  
□ C  
□ D



### 3.1 Piecewise Polynomials



**FIGURE 5.1.** The top left panel shows a piecewise constant function fit to some artificial data. The broken vertical lines indicate the positions of the two knots  $\xi_1$  and  $\xi_2$ . The blue curve represents the true function, from which the data were generated with Gaussian noise. The remaining two panels show piecewise linear functions fit to the same data—the top right unrestricted, and the lower left restricted to be continuous at the knots. The lower right panel shows a piecewise-linear basis function,  $h_3(X) = (X - \xi_1)_+$ , continuous at  $\xi_1$ . The black points indicate the sample evaluations  $h_3(x_i)$ ,  $i = 1, \dots, N$ .

### 3.2 B-Splines

- A degree = 0 B-spline is a *regressogram* basis. Will lead to a piecewise constant fit.
- A degree = 3 B-spline (called *cubic splines*) is similar in shape to a Gaussian pdf. But the B-spline has finite support and facilitates quick computation (due to the induced sparseness).

#### 3.2.1 Parameter Estimation

$$\hat{f}(x) = \sum_j \hat{\theta}_j b_j(x)$$

In matrix notation,

$$\hat{f}(X) = B\hat{\theta}$$

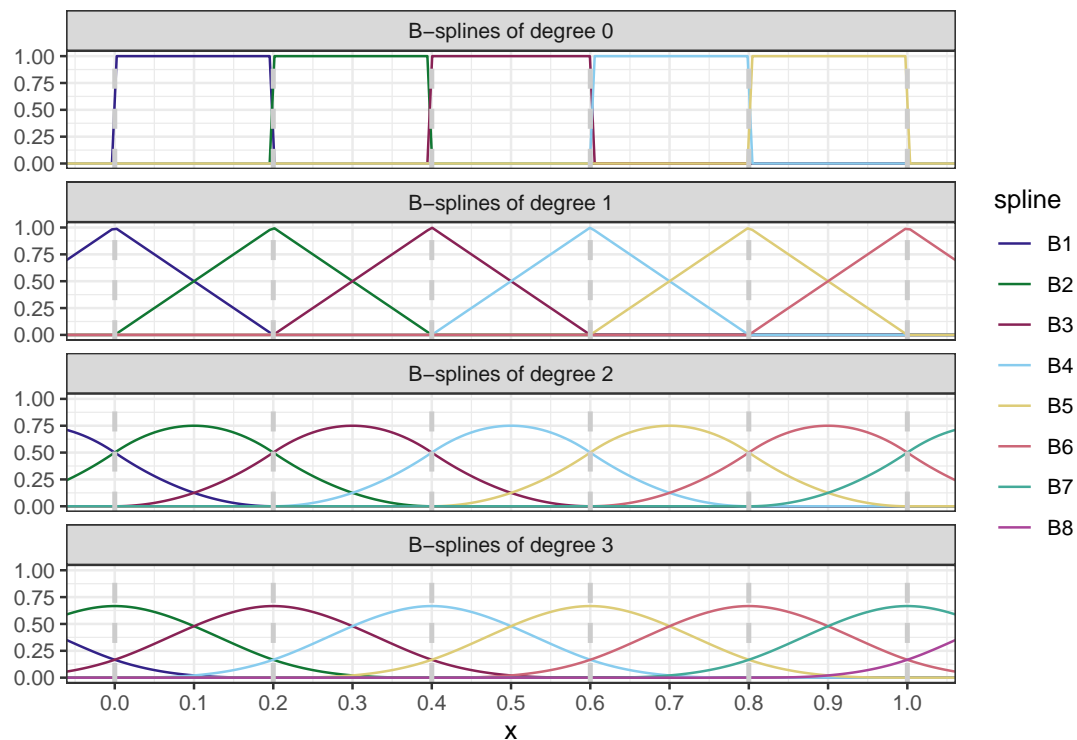


Figure 1: Like ESL Fig 5.20, B-splines (knots shown by vertical dashed lines)

where  $B$  is the *basis matrix* and  $X$  is the model matrix.

- For example, a polynomial matrix is

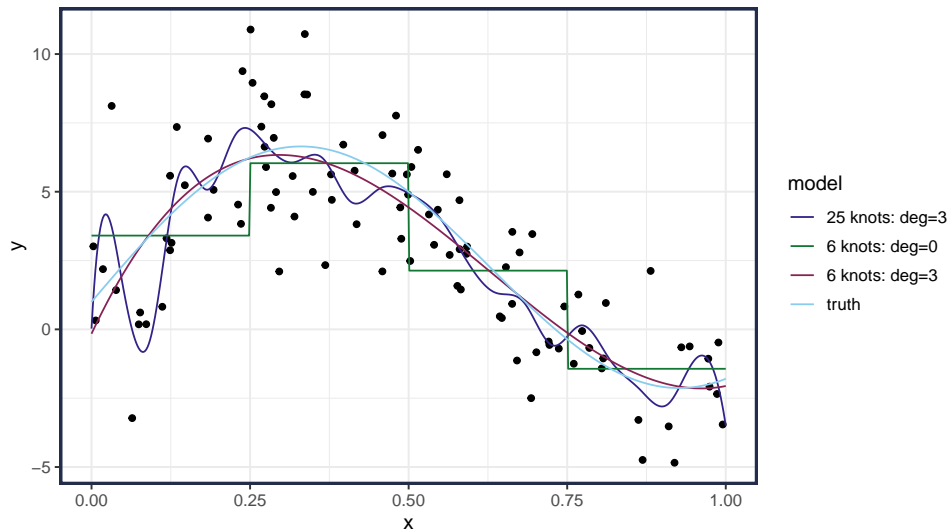
$$B = \begin{bmatrix} 1 & X_1 & X_1^2 & \dots & X_1^J \\ 1 & X_2 & X_2^2 & \dots & X_2^J \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_n & X_n^2 & \dots & X_n^J \end{bmatrix}$$

- More generally,

$$B = \begin{bmatrix} b_1(x_1) & b_2(x_1) & \dots & b_J(x_1) \\ b_1(x_2) & b_2(x_2) & \dots & b_J(x_2) \\ \vdots & \vdots & \vdots & \vdots \\ b_1(x_n) & b_2(x_n) & \dots & b_J(x_n) \end{bmatrix}$$

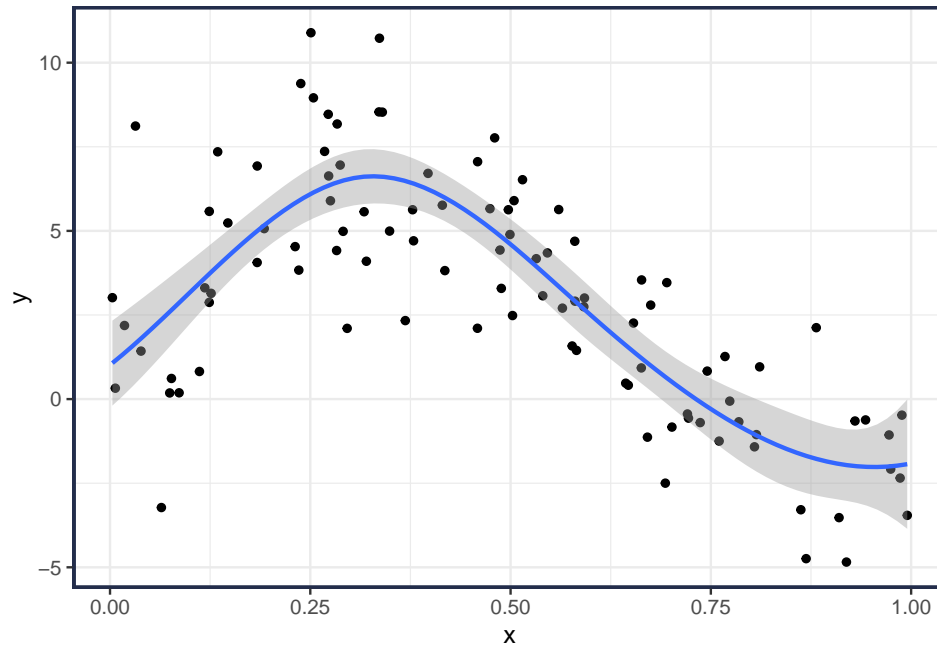
- Now, its in a form just like linear regression! Estimate with OLS

$$\hat{\theta} = (B^T B)^{-1} B^T Y$$

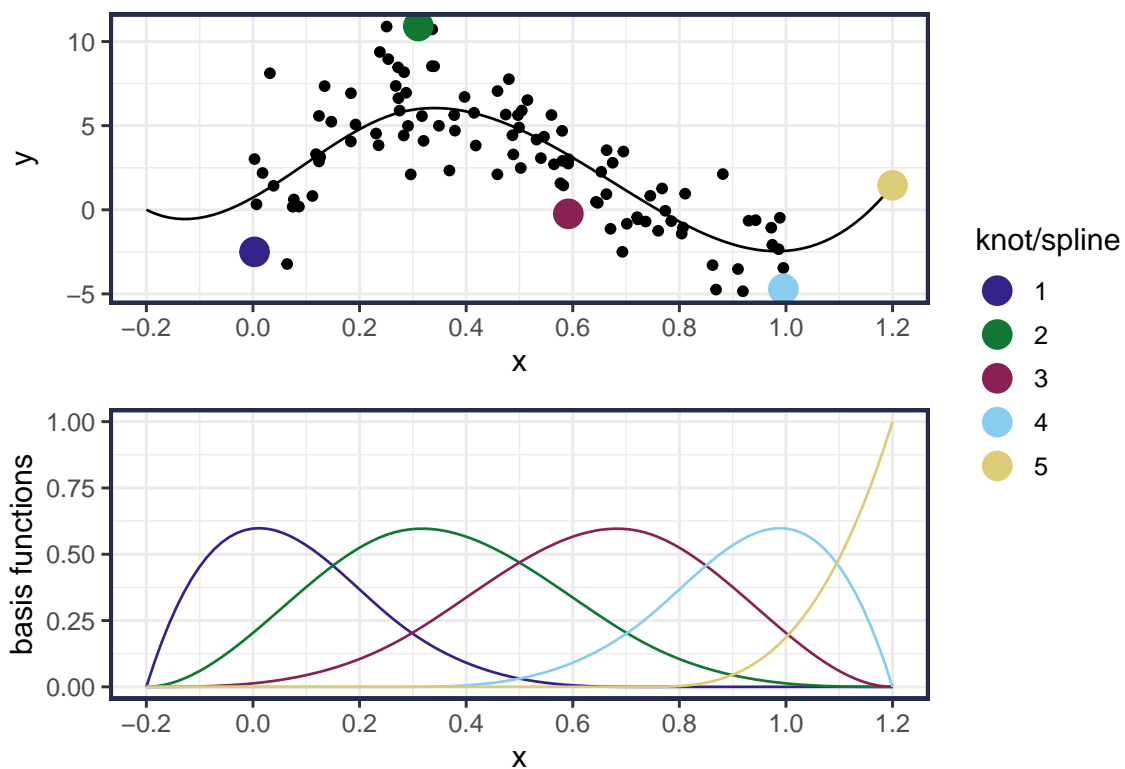


- It may be helpful to think of a basis expansion as similar to a dummy coding for categorical variables.
  - This expands the single variable  $x$  into  $df$  new variables.
- In R, the function `bs()` can be put directly in formula to make a B-spline.

```
#- fit a 5 df B-spline
# Note: don't need to include an intercept in the lm()
# Note: the boundary.knots are set just a bit outside the range of the data
#       so prediction is possible outside the range (see below for usage).
#       You probably won't need to set this in practice.
kts_bdry = c(-.2, 1.2)
model_bs = lm(y~bs(x, df=5, deg=3, Boundary.knots = kts_bdry)-1,
              data=data_train)
tidy(model_bs)
#> # A tibble: 5 x 5
#>   term                                estim~1 std.e~2 stati~3 p.value
#>   <chr>                                <dbl>    <dbl>    <dbl>    <dbl>
#> 1 bs(x, df = 5, deg = 3, Boundary.knots = kts_~ -2.50      1.51    -1.65  1.02e- 1
#> 2 bs(x, df = 5, deg = 3, Boundary.knots = kts_~ 10.9       1.27     8.61  1.53e-13
#> 3 bs(x, df = 5, deg = 3, Boundary.knots = kts_~ -0.241     1.53    -0.157 8.76e- 1
#> 4 bs(x, df = 5, deg = 3, Boundary.knots = kts_~ -4.71      3.07    -1.53  1.28e- 1
#> 5 bs(x, df = 5, deg = 3, Boundary.knots = kts_~  1.45      6.90     0.211 8.34e- 1
#> # ... with abbreviated variable names 1: estimate, 2: std.error, 3: statistic
ggplot(data_train, aes(x,y)) + geom_point() +
  geom_smooth(method='lm', formula='y~bs(x, df=5, deg=3, Boundary.knots = kts_bdry)-1')
```



- Setting `df=5` will create a B-spline design matrix with 5 columns
  - So there are 5 basis functions



### 3.3 Bootstrap Confidence Interval for $f(x)$

Bootstrap can be used to understand the uncertainty in the fitted values

```
-- Bootstrap CI (Percentile Method)
M = 100 # number of bootstrap samples
```

```

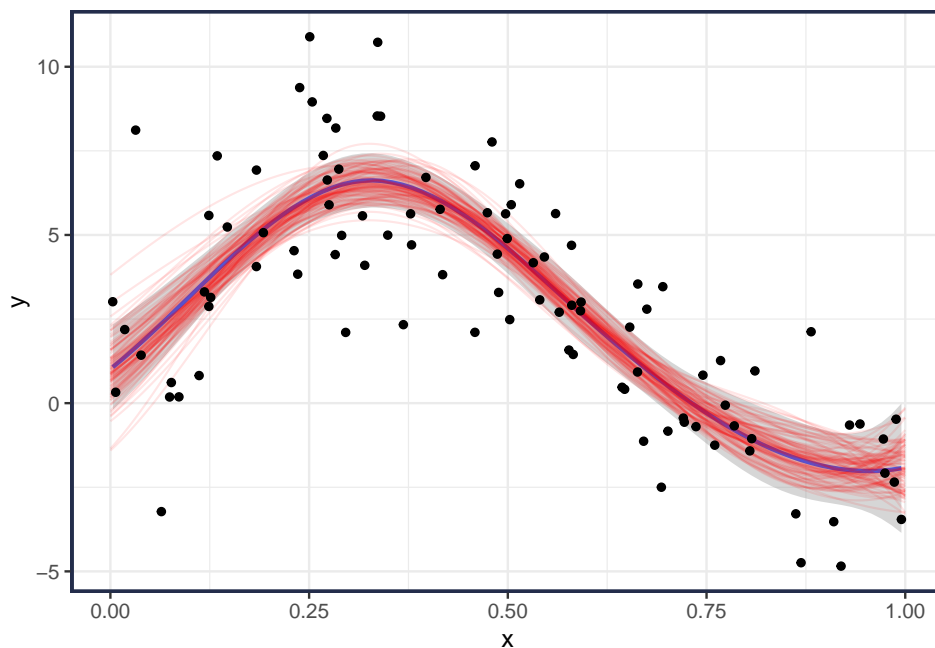
data_eval = tibble(x=seq(0, 1, length=300)) # evaluation points
YHAT = matrix(NA, nrow(data_eval), M)      # initialize matrix for fitted values

#-- Spline Settings
for(m in 1:M){
  #- sample from empirical distribution
  ind = sample(n, replace=TRUE)             # sample indices with replacement
  #- fit bspline model
  m_boot = lm(y~bs(x, df=5, Boundary.knots=kts_bdry)-1,
              data=data_train[ind,])        # fit bootstrap data
  #- predict from bootstrap model
  YHAT[,m] = predict(m_boot, data_eval)
}

#-- Convert to tibble and plot
data_fit = as_tibble(YHAT) %>% # convert matrix to tibble
  bind_cols(data_eval) %>%    # add the eval points
  pivot_longer(-x, names_to="simulation", values_to="y") # convert to long format

ggplot(data_train, aes(x,y)) +
  geom_smooth(method='lm',
             formula=as.formula('y~bs(x, df=5, deg=3, Boundary.knots = kts_bdry)-1')) +
  geom_line(data=data_fit, color="red", alpha=.10, aes(group=simulation)) +
  geom_point()

```



```

#-- Calculate Confidence intervals
## for a 90% CI, find the upper and lower 5% values at every x location
## Homework Exercise

```

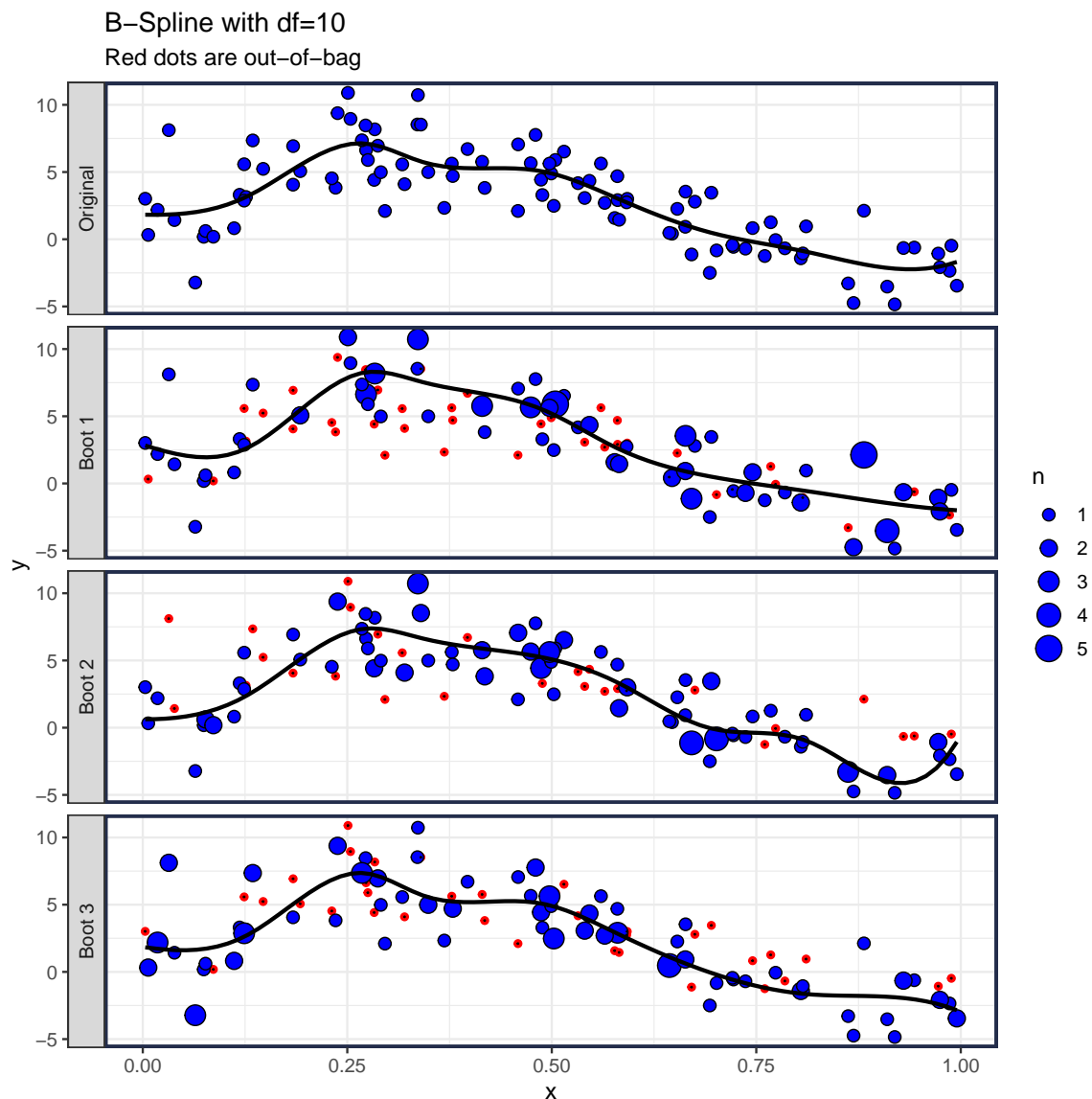
## 4 More Bagging

### 4.1 Out-of-Bag Samples

#### Your Turn #1 : Observations not in bootstrap sample

What is the expected number of observations that will *not* be in a bootstrap sample? Suppose  $n$  observations.

Let's look at a few bootstrap fits:



- Notice that each bootstrap sample does not include about 37% of the original observations.
- These are called *out-of-bag* samples and can be used to assess model fit
  - The out-of-bag observations were not used to estimate the model parameters, so will be sensitive to over/under fitting
- Below, we evaluate the oob error over the spline complexity ( $df$  = number of estimated coefficients)

```

# Settings
M = 50                                # number of bootstrap samples
DF = seq(4, 15, by=1)                 # edfs for spline
n = nrow(data_train)

# set-up
results = list()                      # initialize results list
set.seed(2019)                        # set seed so reproducible

# loop over M bootstraps
for(m in 1:M){

  # sample from empirical distribution
  ind = sample(n, replace=TRUE)        # sample indices with replacement
  oob.ind = setdiff(1:n, ind)          # out-of-bag samples

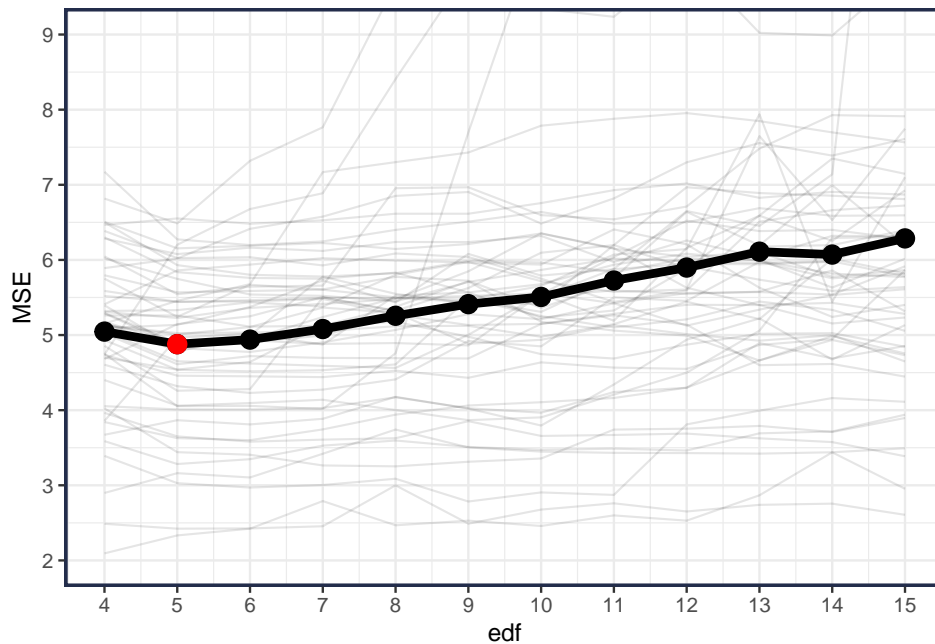
  # fit bspline models to all df in DF
  for(df in DF){
    if(length(oob.ind) < 1) next        # protection in case of no OOB
    # fit with bootstrap data
    m_boot = lm(y~bs(x, df=df, Boundary.knots=kts_bdry)-1,
                 data=data_train[ind,])
    # predict on oob data
    yhat.oob = predict(m_boot, data_train[oob.ind, ])
    # evaluate
    sse = sum( (data_train$y[oob.ind] - yhat.oob)^2 )
    n.oob = length(oob.ind)
    # save results
    results = c(results, list(tibble(m, df, sse, n.oob)))
  }
}
results = bind_rows(results)           # convert from list to tibble

avg = results %>% group_by(df) %>% summarize(mse = sum(sse)/sum(n.oob))
plot1 = results %>%
  ggplot(aes(x=df, y=sse/n.oob)) +
  geom_line(aes(group=m), alpha=.10) +
  coord_cartesian(ylim=c(2, 9)) +
  scale_x_continuous(breaks=1:20) + scale_y_continuous(breaks=1:20) +
  labs(x = "edf", y="MSE")

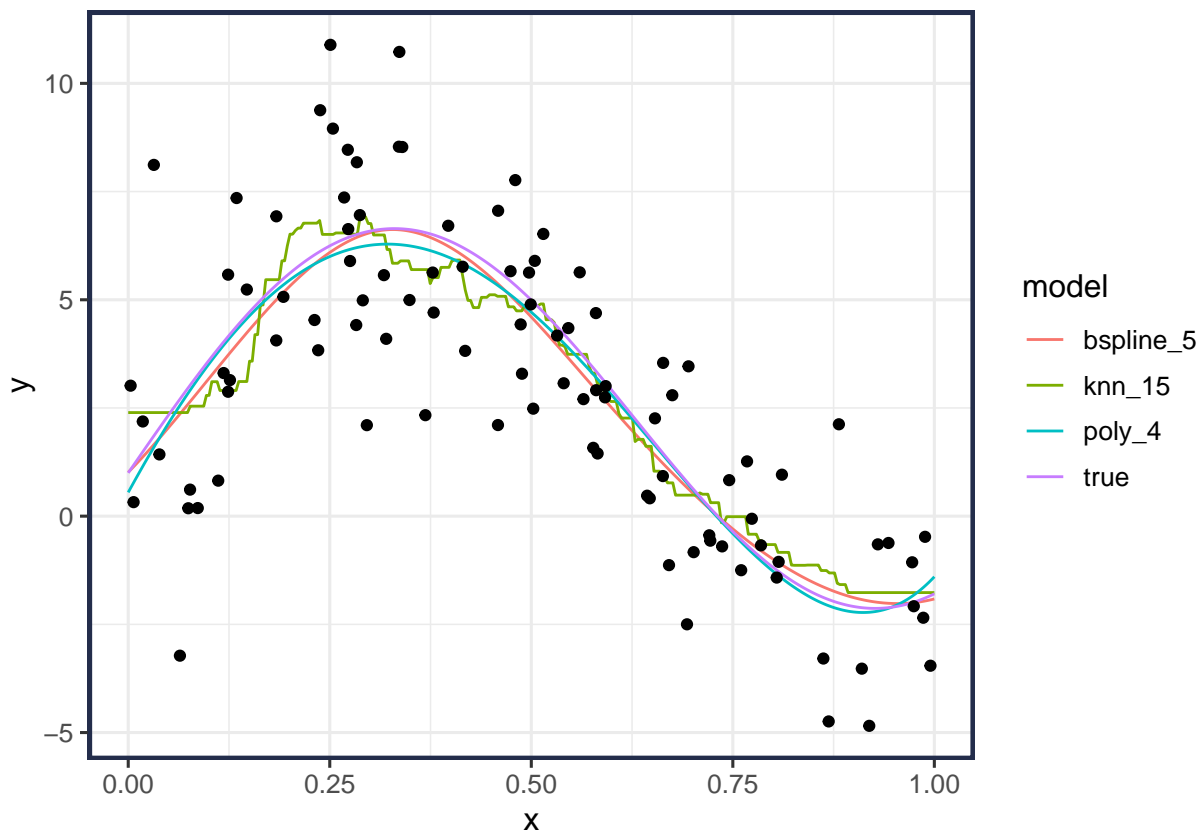
plot1 +
  geom_point(data=avg, aes(df,mse), size=4) + geom_line(data=avg, aes(df,mse), size=2) +
  geom_point(data=avg %>% slice_min(mse), aes(df, mse), color="red", size=4)

```





- The minimum out-of-bag error occurs at  $\text{edf}=5$ . This matches the optimal complexity in a polynomial fit from the previous lecture notes.



## 4.2 Number of Bootstrap Simulations

[Hesterberg](#) recommends using  $M \geq 15,000$  for real applications to remove most of the Monte Carlo

variability.

- For the examples in class I used much less to demonstrate the principles.

## 5 More Resources

- Bootstrap
  - ISL 5.2
  - ESL 7.11
- Splines
  - ISL 7.2-7.5
  - ESL 5.1-5.4
- [What Teachers Should Know About the Bootstrap: Resampling in the Undergraduate Statistics Curriculum](#), by Tim C. Hesterberg
- The `boot` package and `boot()` function provides some more advanced options for bootstrapping
- R's [tidymodels package](#)
  - [Bootstrap resampling and tidy regression models](#)
  - [rsample](#) for resampling
  - [yardstick](#) for evaluation metrics
  - [broom](#) for extracting properties (e.g., estimated parameters) of fitted models in a tidy form

### 5.1 Variations of the Bootstrap

- We have discussed only one type of bootstrap, *nonparametric/empirical/ordinary* where the observations are resampled
- Another option is to simulate from the *fitted model*. This is called the *parametric* bootstrap.
  - For example, in the regression setting, estimate  $\hat{\theta}$  and  $\hat{\sigma}$
  - Then given the original  $X$ 's simulate new  $y_i^* \mid x_i \sim f(x_i; \hat{\theta}) + \epsilon(\hat{\sigma})$

## 6 R Code

### 6.1 Simulate Data

```
n = 100                                # number of observations
sim_x <- function(n) runif(n)           # U[0,1]
f <- function(x) 1 + 2*x + 5*sin(5*x)   # true mean function
sd = 2                                  # stdev for error

set.seed(825)                           # set seed for reproducibility
x = sim_x(n)                             # get x values
y = f(x) + rnorm(n, sd=sd)              # get y values
data_train = tibble(x,y)                # create a data frame/tibble
```

### 6.2 Fit Linear Model; get coefficients

```
m1 = lm(y~x, data=data_train) # fit simple OLS
broom::tidy(m1, conf.int=TRUE) # OLS estimated coefficients
#> # A tibble: 2 x 7
#>   term          estimate std.error statistic  p.value conf.low conf.high
#>   <chr>          <dbl>     <dbl>     <dbl>    <dbl>   <dbl>   <dbl>
#> 1 (Intercept)      6.48      0.584      11.1 5.39e-19     5.32     7.64
#> 2 x                -7.37      1.06      -6.97 3.69e-10    -9.47    -5.27
vcov(m1) # normal theory based uncertainty
#>           (Intercept)          x
#> (Intercept)    0.3414 -0.5359
#> x              -0.5359  1.1183
```

Note that the linear model is poorly fitting, so don't expect good results for coefficients.

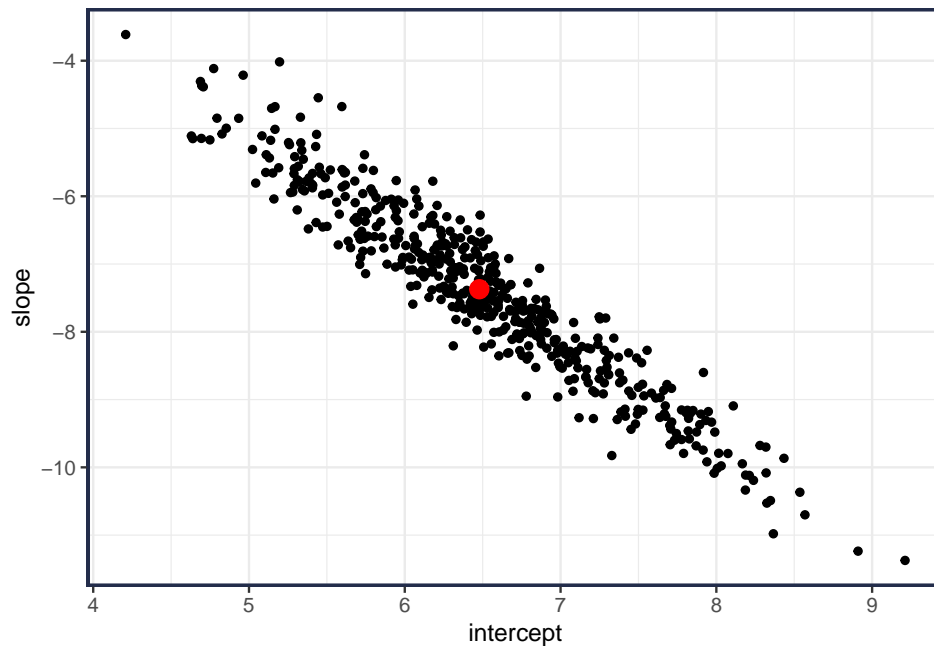
### 6.3 Bootstrap distribution

```
M = 500                                # number of bootstrap samples
set.seed(2019)                          # set random seed

beta = vector("list", M)                # initialize list for test statistics
for(m in 1:M) {
  # sample from empirical distribution
  ind = sample(n, replace=TRUE)          # sample indices with replacement
  data.boot = data_train[ind,]           # bootstrap sample
  # fit regression model
  m.boot = lm(y~x, data=data.boot)       # fit simple OLS
  # save test statistics
  beta[[m]] = broom::tidy(m.boot) %>% select(term, estimate)
}

# convert to tibble (and add column names)
beta = bind_rows(beta, .id = "iteration") %>%
  pivot_wider(names_from = term, values_from=estimate) %>%
  select(intercept = "(Intercept)", slope = "x", -iteration)

# Plot
ggplot(beta, aes(intercept, slope)) + geom_point() +
  geom_point(data=tibble(intercept=coef(m1)[1],
                        slope = coef(m1)[2], color="red", size=4))
```



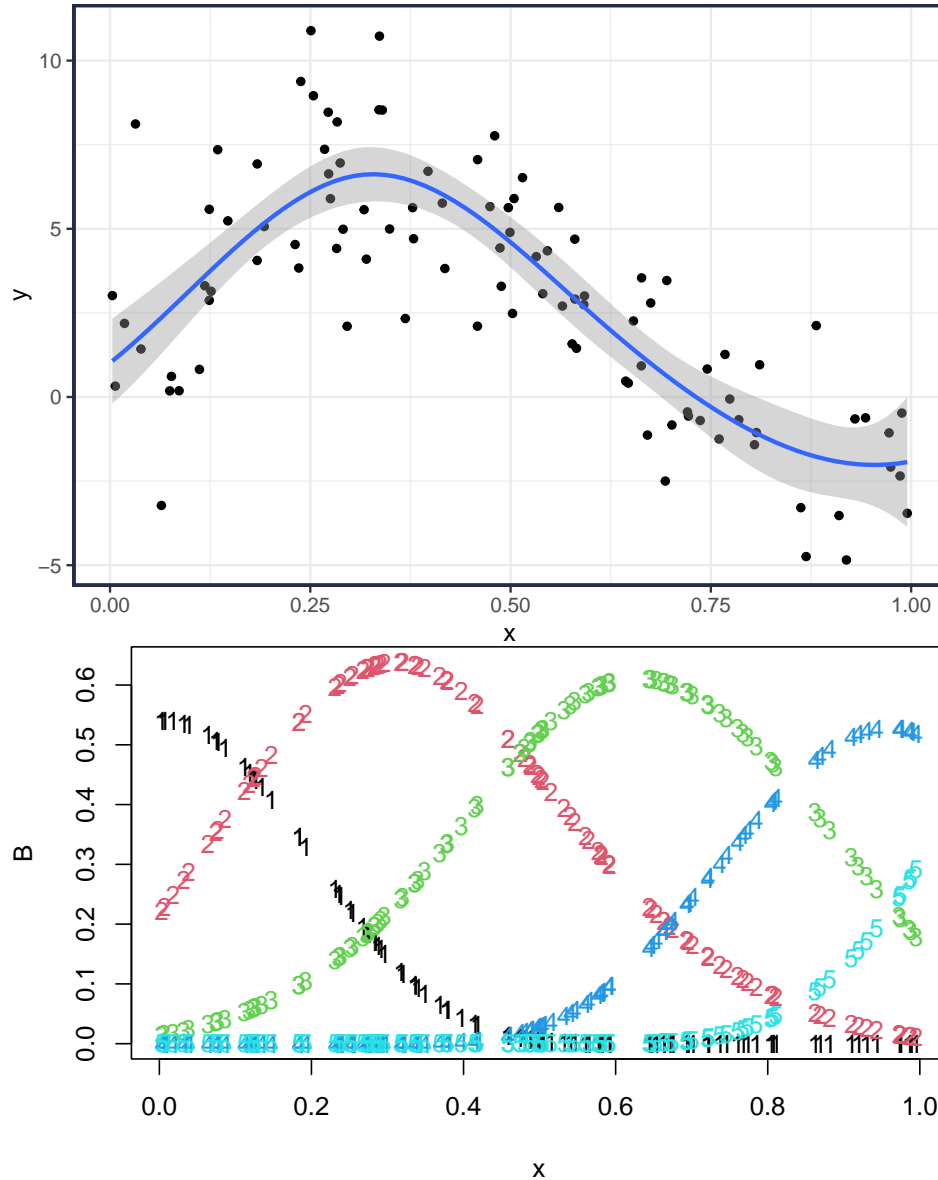
```
#- bootstrap estimate
var(beta)           # variance matrix
#>      intercept  slope
#> intercept    0.6989 -1.068
#> slope        -1.0676  1.792
apply(beta, 2, sd)   # standard errors (sqrt of diagonal)
#> intercept      slope
#>      0.836      1.338
```

## 6.4 B-spline model

```
#- fit a 5 df B-spline
# Note: don't need to include an intercept in the lm()
# Note: the boundary.knots are set just a bit outside the range of the data
#       so prediction is possible outside the range (see below for usage).
#       You probably won't need to set this in practice, unless you need
#       predictions for outside the range of your training data.
kts.bdry = c(-.2, 1.2)
model_bs = lm(y~bs(x, df=5, deg=3, Boundary.knots = kts.bdry)-1,
              data=data_train)
tidy(model_bs)
#> # A tibble: 5 x 5
#>   term                                estim~1 std.e~2 stati~3 p.value
#>   <chr>                                <dbl>    <dbl>    <dbl>    <dbl>
#> 1 bs(x, df = 5, deg = 3, Boundary.knots = kts.~ -2.50      1.51    -1.65  1.02e- 1
#> 2 bs(x, df = 5, deg = 3, Boundary.knots = kts.~ 10.9        1.27     8.61  1.53e-13
#> 3 bs(x, df = 5, deg = 3, Boundary.knots = kts.~ -0.241      1.53    -0.157 8.76e- 1
#> 4 bs(x, df = 5, deg = 3, Boundary.knots = kts.~ -4.71        3.07    -1.53  1.28e- 1
#> 5 bs(x, df = 5, deg = 3, Boundary.knots = kts.~  1.45        6.90     0.211 8.34e- 1
#> # ... with abbreviated variable names 1: estimate, 2: std.error, 3: statistic
ggplot(data_train, aes(x,y)) + geom_point() +
  geom_smooth(method='lm', formula='y~bs(x, df=5, deg=3, Boundary.knots = kts.bdry)-1')

#-- Evaluate the B-spline Basis
B = bs(x, df=5, deg=3, Boundary.knots = kts.bdry)
```

```
matplot(x, B, type='p')
```



## 6.5 Bootstrap Uncertainty in B-spline Fit

```
M = 100 # number of bootstrap samples
data_eval = tibble(x=seq(0, 1, length=300)) # evaluation points
YHAT = matrix(NA, nrow(data_eval), M) # initialize matrix for fitted values

#-- loop
set.seed(2019)
for(m in 1:M){
  #- sample from empirical distribution
  ind = sample(n, replace=TRUE) # sample indices with replacement
  #- fit bspline model
  m_boot = lm(y~bs(x, df=5, Boundary.knots=kts.bdry)-1,
              data=data_train[ind,]) # fit bootstrap data
```

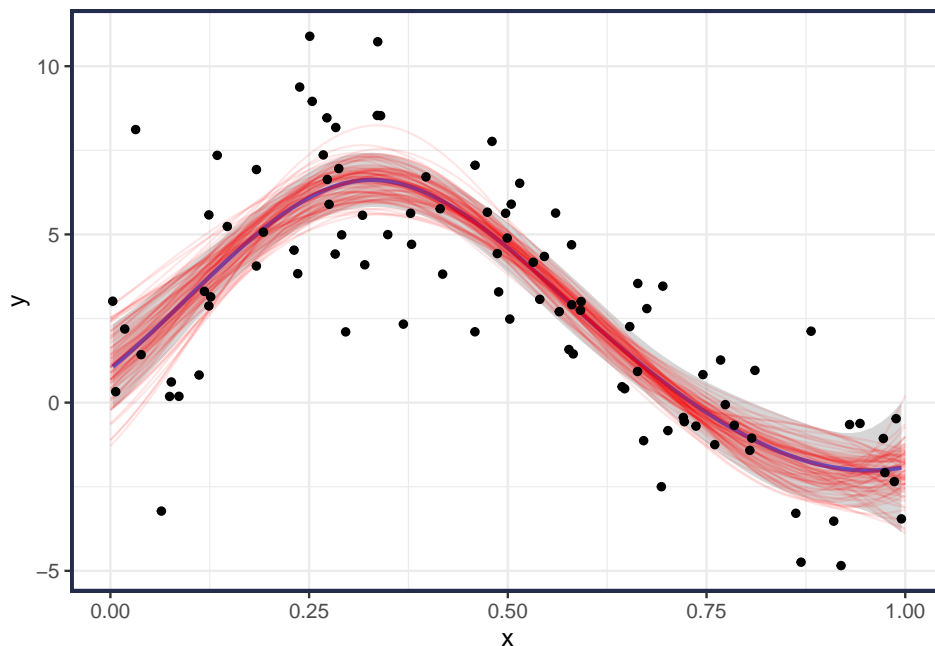
```

#- predict from bootstrap model
YHAT[,m] = predict(m_boot, data_eval)
}

#-- Convert to tibble and plot
data_fit = as_tibble(YHAT) %>% # convert matrix to tibble
  bind_cols(data_eval) %>% # add the eval points
  pivot_longer(-x, names_to="simulation", values_to="y") # convert to long format

ggplot(data_train, aes(x,y)) +
  geom_smooth(method='lm',
             formula='y~bs(x, df=5, deg=3, Boundary.knots = kts.bdry)-1') +
  geom_line(data=data_fit, color="red", alpha=.10, aes(group=simulation)) +
  geom_point()

```



## 6.6 Out-of-bag performance evaluation

```

M = 500 # number of bootstrap samples
DF = seq(4, 12, by=1) # edfs for spline
results = list() # initialize results list
set.seed(2019) # set seed so reproducible

#-- Spline Settings
for(m in 1:M){
  #- sample from empirical distribution
  ind = sample(n, replace=TRUE) # sample indices with replacement
  oob.ind = setdiff(1:n, ind) # out-of-bag samples
  #- fit bspline models
  for(df in DF){
    if(length(oob.ind) < 1) next
    #- fit with bootstrap data
    m_boot = lm(y~bs(x, df=df, Boundary.knots=kts.bdry)-1,
               data=data_train[ind,])
    #- predict on oob data
    yhat.oob = predict(m_boot, data_train[oob.ind, ])
  }
}

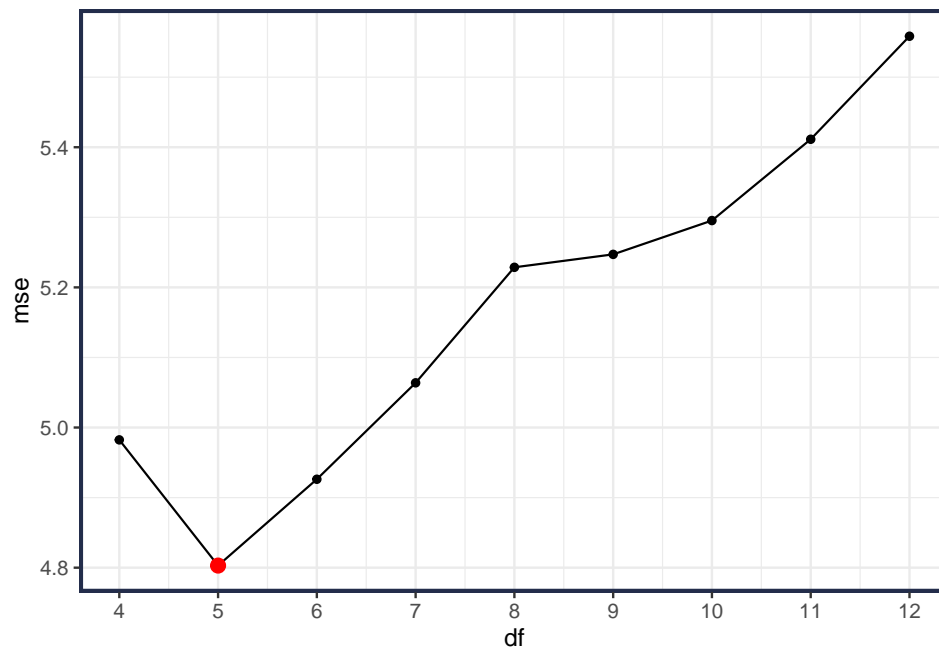
```

```

  #- get errors
  sse = sum( (data_train$y[oob.ind] - yhat.oob)^2 )
  n.oob = length(oob.ind)
  #- save results
  results = c(results, list(tibble(m, df, sse, n.oob)))
}
}
results = bind_rows(results) # convert from list to tibble

results %>%
  group_by(df) %>% summarize(mse = sum(sse)/sum(n.oob)) %>%
  ggplot(aes(df, mse)) + geom_point() + geom_line() +
  geom_point(data=., %>% slice_min(mse), color="red", size=3) +
  scale_x_continuous(breaks=1:20)

```



## 6.7 Using *tidymodels* (*rsample* package)

### 6.7.1 Use *rsample* package for bootstrapping

The *rsample* package provides methods for creating a low memory set of bootstrap samples.

```

library(rsample)
set.seed(2019)
boots = rsample::bootstraps(data_train, times = 500)

```

The *boots* object is a tibble with two columns. The *splits* column contains the bootstrap (in-bag) and out-of-bag samples. The *id* gives the iteration. The bootstrap samples can be extracted from the *splits* column with *training()* and *oob* with *testing()*.

```

boots
#> # A tibble: 500 x 2
#>   splits          id
#>   <list>        <chr>
#> 1 <split [100/38]> Bootstrap001
#> 2 <split [100/41]> Bootstrap002
#> 3 <split [100/42]> Bootstrap003

```

```
#> 4 <split [100/37]> Bootstrap004
#> 5 <split [100/34]> Bootstrap005
#> 6 <split [100/37]> Bootstrap006
#> # ... with 494 more rows
#> # i Use `print(n = ...)` to see more rows
```

## 6.7.2 bootstrap distribution of linear model coefficients

```
#: function to fit lm and extract coefficients
lm_get_coefs <- function(data){
  m = lm(y~x, data=data) # fit simple OLS
  broom::tidy(m) %>% select(term, estimate) %>% # extract coefficients
    pivot_wider(names_from = term, values_from = estimate) %>% # wide
    rename(intercept = "(Intercept)", slope = "x") # rename to intercept,slope
}

#: use map() to implement loop
purrr::map_df(
  .x = boots$splits,
  .f = ~lm_get_coefs(training(.x)),
  .id = "iteration"
)
#> # A tibble: 500 x 3
#>   iteration intercept slope
#>   <chr>          <dbl> <dbl>
#> 1 1             6.47 -7.10
#> 2 2             7.21 -8.87
#> 3 3             8.03 -9.98
#> 4 4             6.18 -7.12
#> 5 5             6.65 -7.93
#> 6 6             7.41 -9.14
#> # ... with 494 more rows
#> # i Use `print(n = ...)` to see more rows
```

## 6.7.3 Bootstrap Uncertainty in B-spline Fit

We will use the `bs()` function from the `splines` package for the model. I'll make a function `sp_predict()` that will fit a set of B-spline models (of varying complexity) to the training data, make predictions on the evaluation data.

```
library(splines) # for the bs() function

#: function to fit bspline and predict
sp_predict <- function(data_fit, data_eval, df = 5){
  fmla = "y ~ bs(x, df=df, Boundary.knots=kts.bdry) - 1"
  m = lm(as.formula(fmla), data=data_fit)
  tibble(x = data_eval$x, yhat = predict(m, data_eval))
}
```

Now we can get predictions from all bootstrap fits:

```
data_eval = tibble(x=seq(0, 1, length=300)) # evaluation points

map_df(
  .x = boots$splits[1:50],
  .f = ~sp_predict(training(.x), data_eval),
  .id = "iter"
```



```

)
#> # A tibble: 15,000 x 3
#>   iter      x  yhat
#>   <chr>   <dbl> <dbl>
#> 1 1      0      2.50
#> 2 1    0.00334  2.55
#> 3 1    0.00669  2.60
#> 4 1    0.0100   2.65
#> 5 1    0.0134   2.70
#> 6 1    0.0167   2.75
#> # ... with 14,994 more rows
#> # i Use `print(n = ...)` to see more rows

```

### 6.7.4 Out-of-bag performance evaluation

This function fits a b-spline using `data_fit`, make predictions on `data_eval`, and evaluates (using MSE). Uses a set of effective degrees of freedom `df`.

```

library(splines) # for the bs() function

# sp_eval(): fit set of B-spline models and evaluate on test data
#-----
# data_fit, data_eval: training and test data (requires column names x,y)
# df: set of spline degrees (tuning parameters)
# kts.bdry: boundary knots for the splines (to help extrapolate)
# output: tibble with df and associated mean squared error (MSE) on test data
sp_eval <- function(data_fit, data_eval, df = seq(3, 15, by=1), kts_bdry = c(-.2, 1.2)) {

  MSE = numeric(length(df)) # initialize

  for(i in 1:length(df)) {
    # set tuning parameter value
    df_i = df[i]
    # fit with training data (no intercept)
    fmla = "y~bs(x, df = df_i, degree = 3, Boundary.knots = kts_bdry) - 1"
    fit = lm(as.formula(fmla), data = data_fit)
    # predict on test data
    yhat = predict(fit, data_eval)
    # get errors / loss
    MSE[i] = mean( (data_eval$y - yhat)^2 )
  }
  tibble(df, n_eval = nrow(data_eval), mse = MSE) # output
}

results = map_df(
  .x = boots$splits,
  .f = ~sp_eval(training(.x), testing(.x)),
  .id = "iter"
)
# Note that I used the default valuse of df and kts_bdry specified in sp_eval().

results %>%
  group_by(df) %>%
  summarize(
    mean_mse_1 = sum(n_eval*mse) / sum(n_eval),
    mean_mse = mean(mse),
    se = sd(mse)/sqrt(n())
  ) %>%

```

```
arrange(mean_mse)
#> # A tibble: 13 x 4
#>       df mean_mse_1 mean_mse      se
#>   <dbl>     <dbl>     <dbl>  <dbl>
#> 1     5         4.80         4.80 0.0465
#> 2     6         4.93         4.93 0.0488
#> 3     4         4.98         4.98 0.0468
#> 4     7         5.06         5.06 0.0506
#> 5     8         5.23         5.22 0.0559
#> 6     9         5.25         5.24 0.0585
#> # ... with 7 more rows
#> # i Use `print(n = ...)` to see more rows
```