# Business Analytics - ETC3250 2017 - Lab 4

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## Regression

#### Exercise 1

Understand all the steps in the proof of the bias-variance decomposition (see https://github.com/bsouhaib/BA2017/blob/master/slides/2/2-biasvardecomp.pdf)

### Assignment - Question 1

Let  $y = f(x) + \varepsilon$  where  $\varepsilon$  is iid noise with zero mean and variance  $\sigma^2$ . Using the bias-variance decomposition, show that  $E[(y - \hat{f}(x_0))^2]$  is minimum when  $\hat{f}(x_0) = E[y|x = x_0]$ . What is this minimum value?

#### Exercise 2

Do some exploratory data analysis on the Wage data set.

- Tabulate education and marital status
- Tabulate education and race
- Tabulate marital status race
- Plot marital status as a function of age
- Try other combinations

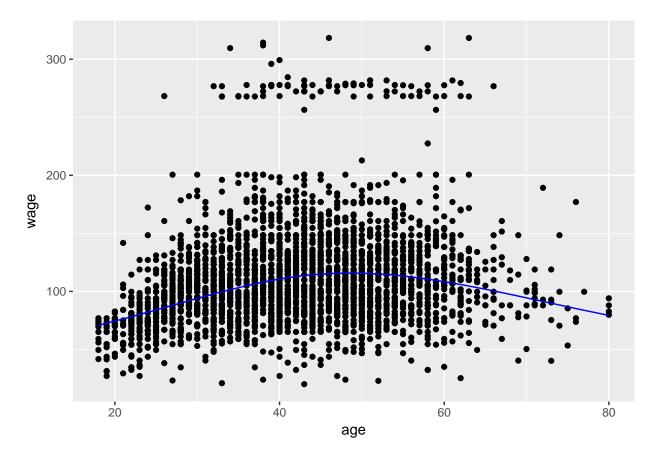
### Exercise 3

The following code fits a spline curve to the relationship between wage and age.

```
library(ISLR)
library(splines)
library(ggplot2)
p <- qplot(age, wage, data=Wage)

fit <- lm(log(wage) ~ ns(age, df=2), data=Wage)
Wage$fc <- exp(fitted(fit))

p + geom_line(aes(age, fc), data=Wage, col='blue')</pre>
```



- Experiment with different values of df (degrees of freedom)
- Select one that you think is about right.

Now we will test which value of df minimizes the MSE on some test data.

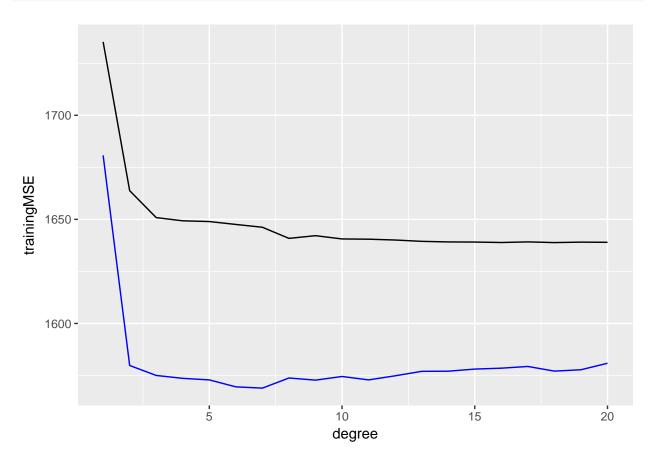
First, we randomly split the Wage data set into training and test sets, with 2000 observations in the training data and 1000 observations in the test data.

```
idx <- sample(1:nrow(Wage), size=2000)
train <- Wage[idx,]
test <- Wage[-idx,]</pre>
```

### Exercise 4

Next try different values of df:

```
# MSE on training and test sets
trainingMSE <- testMSE <- numeric(20)
for(i in 1:20)
{
   fit <- lm(log(wage) ~ ns(age, df=i), data=train)
   trainingMSE[i] <- mean((train$wage - exp(fitted(fit)))^2)
   testMSE[i] <- mean((test$wage - exp(predict(fit,newdata=test)))^2)
}</pre>
```



- Which value of df gives the minimum training MSE?
- Which value of df gives the minimum test MSE?
- Plot a vertical line at your "guessed" value of df. How close is it to the optimal?
- Do you get the same results if you repeat the exercise on different splits of training and test data?

# A model for wages

Repeat this analysis, but use the full linear model including the other variables in the data set. That is, fit models like this (but choose the optimal df):

```
fit <- lm(log(wage) ~ year + ns(age, df=5) + education + race + jobclass + health + maritl, data=Wage)
```

How much better is the test MSE once you include the other predictor variables?

Finally, we will check the residuals, assuming your best model is stored as fit.

```
library(gridExtra)
res <- residuals(fit)
resplots <- list()</pre>
```

```
resplots[[1]] <- qplot(res)
resplots[[2]] <- qplot(age,res, data=Wage)
resplots[[3]] <- qplot(factor(year),res, data=Wage, geom="boxplot")
resplots[[4]] <- qplot(education,res, data=Wage, geom="boxplot")
resplots[[5]] <- qplot(race,res, data=Wage, geom="boxplot")
resplots[[6]] <- qplot(jobclass,res, data=Wage, geom="boxplot")
resplots[[7]] <- qplot(health,res, data=Wage, geom="boxplot")
resplots[[8]] <- qplot(maritl,res, data=Wage, geom="boxplot")
marrangeGrob(resplots, ncol=2, nrow=4, top="Residual plots")</pre>
```

### Residual plots 40 60 80 Ö age res 2003 2004 2005 2006 2007 2008 2009 1. < HS GradHS Gradbme Gollaghesge AGwadced Deg factor(year) education 1. Industrial 2. Information 1. White 2. Black 3. Asian 4. Other jobclass race 2. >=Very Good 1. Never Marzieldlarriedl. Widoweld DivorcedSeparated 1. <=Good health maritl

Do you see anything unusual in the residual plots?

```
res <- residuals(fit)
outliers <- subset(Wage, abs(res) > 1.5)
```

What makes the outlier unusual?

### Assignment - Question 2

Write code that includes:

- 1. fitting your final model above;
- 2. summary statistics for the residuals;
- 3. a plot of the residuals against the fitted values.

### Classification

### Assignment - Question 3

Do the exercise 7 in Section 2.4 of ISLR.

### Assignment - Question 4

We want to predict whether a given car gets high or low gas mileage based on a set of features describing the car. We will use the *Auto* dataset in library ISLR.

- 1. Create a binary variable, mpg01, that contains a 1 if mpg contains a value above its median, and a 0 if mpg contains a value below its median. Add the variable mpg01 to the data.frame Auto
- 2. Explore the data graphically in order to investigate the association between mpg01 and the other features. Which of the other features seem most likely to be useful in predicting mpg01? Scatterplots and boxplots may be useful tools to answer this question. Describe your findings.
- 3. Split the data into a training set and a test set.
- 4. Perform KNN on the training data, with several values of K, in order to predict mpg01. Use only the variables that seemed most associated with mpg01. Plot the training and testing errors a function of 1/k. Compare which value of K seems to perform the best when using training or testing errors?

### TURN IN

- Your .Rmd file (which should knit without errors and without assuming any packages have been pre-loaded)
- Your Word (or pdf) file that results from knitting the Rmd.
- DUE: 20 August, 11:55pm (late submissions not allowed), loaded into moodle