Covariate creation

aka "features" or predictors.

Jeffrey Leek
Johns Hopkins Bloomberg School of Public Health

Two levels of covariate creation

Level 1: From raw data to covariate

HI

WE'VE DISCOVERED YOU ARE THE HEIR TO AN INCREDIBLE FORTUNE. PLEASE SUBMIT YOUR NAME, ADDRESS AND BANK ACCOUNT SO WE CAN SEND YOU $$$$$$$$.

JOE JOHNSON

capitalAve	you	numDollar	...
1	2	8	...

Level 2: Transforming tidy covariates

```
library(kernlab);data(spam)
spam$capitalAveSq <- spam$capitalAve^2
```

Level 1, Raw data -> covariates

- Depends heavily on application
- The balancing act is summarization vs. information loss
- Examples:
  - Text files: frequency of words, frequency of phrases (Google ngrams), frequency of capital letters.
  - Images: Edges, corners, blobs, ridges (computer vision feature detection))
  - Webpages: Number and type of images, position of elements, colors, videos (A/B Testing)
  - People: Height, weight, hair color, sex, country of origin.
- The more knowledge of the system you have the better the job you will do.
- When in doubt, err on the side of more features
- Can be automated, but use caution!

Level 2, Tidy covariates -> new covariates

- More necessary for some methods (regression, svms) than for others (classification trees).
- Should be done *only on the training set*
- The best approach is through exploratory analysis (plotting/tables)
- New covariates should be added to data frames

Load example data

```
library(ISLR); library(caret); data(Wage);
inTrain <- createDataPartition(y=Wage$wage,
                               p=0.7, list=FALSE)
training <- Wage[inTrain,]; testing <- Wage[-inTrain,]
```

Common covariates to add, dummy variables

Basic idea - convert factor variables to indicator variables

```
table(training$jobclass)
```

```
 1. Industrial 2. Information
          1090           1012
```

categorial variable w/ 2 levels

```
dummies <- dummyVars(wage ~ jobclass,data=training)
head(predict(dummies,newdata=training))
```

create dummy (0,1) variables for each level

```
       jobclass.1. Industrial jobclass.2. Information
231655                       1                       0
86582                        0                       1
11141                        0                       1
```

Removing zero covariates

```
nsv <- nearZeroVar(training,saveMetrics=TRUE)
nsv
```

	freqRatio	percentUnique	zeroVar	nzv
year	1.029	0.33302	FALSE	FALSE
age	1.122	2.80685	FALSE	FALSE
sex	0.000	0.04757	TRUE	TRUE
maritl	3.159	0.23787	FALSE	FALSE
race	8.529	0.19029	FALSE	FALSE
education	1.492	0.23787	FALSE	FALSE
region	0.000	0.04757	TRUE	TRUE
jobclass	1.077	0.09515	FALSE	FALSE
health	2.452	0.09515	FALSE	FALSE
health_ins	2.269	0.09515	FALSE	FALSE
logwage	1.198	17.26927	FALSE	FALSE
wage	1.185	18.07802	FALSE	FALSE

Variables with very little variability don't make good predictors, so they can be removed.

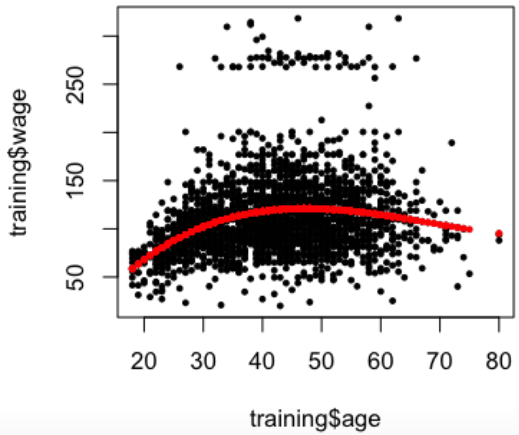
Spline basis

```
library(splines)
bsBasis <- bs(training$age,df=3)  create a polynom with degree 3
bsBasis                           -> includes 3 new variables:
```

```
          age     age^2    age^3
              1         2         3
   [1,] 0.00000 0.0000000 0.000e+00
   [2,] 0.23685 0.0253768 9.063e-04
   [3,] 0.44309 0.2436978 4.468e-02
   [4,] 0.43081 0.2910904 6.556e-02
   [5,] 0.42617 0.1482327 1.719e-02
   [6,] 0.41709 0.1331149 1.416e-02
   [7,] 0.31823 0.0540390 3.059e-03
   [8,] 0.36253 0.3866940 1.375e-01
   [9,] 0.44436 0.2275981 3.886e-02
  [10,] 0.20449 0.0179375 5.245e-04
  [11,] 0.07768 0.3601465 5.566e-01
  [12,] 0.13145 0.0066841 1.133e-04
  [13,] 0.39290 0.1042387 9.218e-03
  [14,] 0.26654 0.0339238 1.439e-03
  [15,] 0.20449 0.0179375 5.245e-04
```

Fitting curves with splines

```
lm1 <- lm(wage ~ bsBasis,data=training)
plot(training$age,training$wage,pch=19,cex=0.5)
points(training$age,predict(lm1,newdata=training),col="red",pch=19,cex=0.5)
```



Splines on the test set

```
predict(bsBasis,age=testing$age)
```

now use /the same/ bsBasis data to make predictions in the test set!

```
            1         2         3
  [1,] 0.00000 0.0000000 0.000e+00
  [2,] 0.23685 0.0253768 9.063e-04
  [3,] 0.44309 0.2436978 4.468e-02
  [4,] 0.43081 0.2910904 6.556e-02
  [5,] 0.42617 0.1482327 1.719e-02
  [6,] 0.41709 0.1331149 1.416e-02
  [7,] 0.31823 0.0540390 3.059e-03
  [8,] 0.36253 0.3866940 1.375e-01
  [9,] 0.44436 0.2275981 3.886e-02
 [10,] 0.20449 0.0179375 5.245e-04
 [11,] 0.07768 0.3601465 5.566e-01
 [12,] 0.13145 0.0066841 1.133e-04
 [13,] 0.39290 0.1042387 9.218e-03
 [14,] 0.26654 0.0339238 1.439e-03
 [15,] 0.20449 0.0179375 5.245e-04
 [16,] 0.29109 0.4308138 2.125e-01
 [17,] 0.23685 0.0253768 9.063e-04
```

Notes and further reading

- Level 1 feature creation (raw data to covariates)
  - Science is key. Google "feature extraction for [data type]" where [data type] is e.g.
  - Err on overcreation of features Ask: Which features are different in the 2 categories that I want to distinguish?
  - In some applications (images, voices) automated feature creation is possible/necessary
  - http://www.cs.nyu.edu/~yann/talks/lecun-ranzato-icml2013.pdf deep learning; tutorial
- Level 2 feature creation (covariates to new covariates)
  - The function *preProcess* in *caret* will handle some preprocessing.
  - Create new covariates if you think they will improve fit
  - Use exploratory analysis on the training set for creating them
  - Be careful about overfitting!
- preprocessing with caret
- If you want to fit spline models, use the *gam* method in the *caret* package which allows smoothing of multiple variables.
- More on feature creation/data tidying in the Obtaining Data course from the Data Science course