Preprocessing

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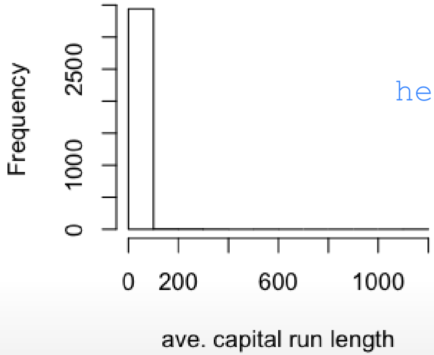
Why preprocess?

```
library(caret); library(kernlab); data(spam)
inTrain <- createDataPartition(y=spam$type,
                              p=0.75, list=FALSE)
training <- spam[inTrain,]
testing <- spam[-inTrain,]
hist(training$capitalAve,main="",xlab="ave. capital run length")
```

Preprocessing often more useful/important
when using "model based" algorithms.



here: very skewed
-> not all that useful
so preprocessing might
help

Why preprocess?

```
mean(training$capitalAve)
```

```
[1] 4.709
```

```
sd(training$capitalAve)
```

```
[1] 25.48
```

very high!

Standardizing

```
trainCapAve <- training$capitalAve
trainCapAveS <- (trainCapAve  - mean(trainCapAve))/sd(trainCapAve)
mean(trainCapAveS)
```

```
[1] 5.862e-18          mean is 0
```

```
sd(trainCapAveS)
```

```
[1] 1              sd is 1
```

Standardizing - test set

```
testCapAve <- testing$capitalAve
testCapAveS <- (testCapAve  - mean(trainCapAve))/sd(trainCapAve)
mean(testCapAveS)
```

hm! why not standardizing first, then splitting test and training set?

```
[1] 0.07579
```

```
sd(testCapAveS)
```

```
[1] 1.79
```

Standardizing - *preProcess* function

```
preObj <- preProcess(training[,-58],method=c("center","scale"))
trainCapAveS <- predict(preObj,training[,-58])$capitalAve
mean(trainCapAveS)
```

```
[1] 5.862e-18
```

```
sd(trainCapAveS)
```

```
[1] 1
```

Standardizing - *preProcess* function

```
testCapAveS <- predict(preObj,testing[,-58])$capitalAve
mean(testCapAveS)
```

that's theh preObj that we generated before with the preProcess function, using the training data.

```
[1] 0.07579
```

```
sd(testCapAveS)
```

```
[1] 1.79
```

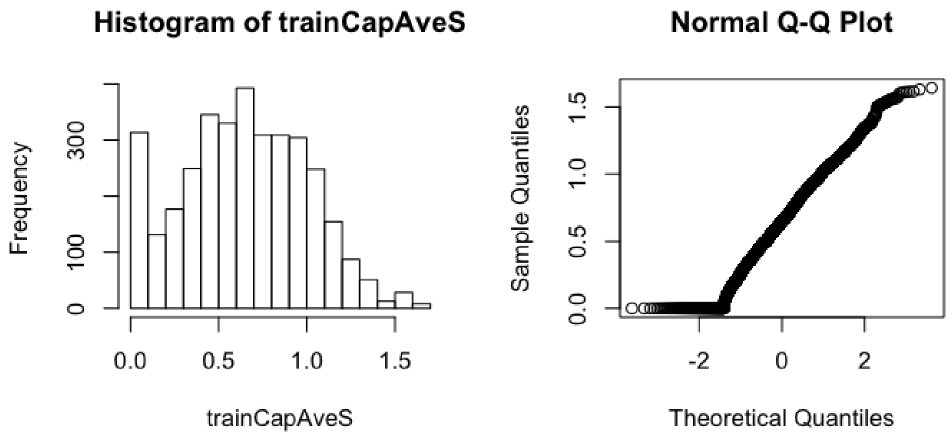
Standardizing - *preProcess* argument

```
set.seed(32343)
modelFit <- train(type ~.,data=training,
                  preProcess=c("center","scale"),method="glm")
modelFit
```

```
3451 samples
  57 predictors
   2 classes: 'nonspam', 'spam'

Pre-processing: centered, scaled
Resampling: Bootstrap (25 reps)

Summary of sample sizes: 3451, 3451, 3451, 3451, 3451, 3451, ...

Resampling results

  Accuracy  Kappa  Accuracy SD  Kappa SD
  0.9       0.8    0.007        0.01
```

Standardizing - Box-Cox transforms

```
preObj <- preProcess(training[,-58],method=c("BoxCox"))
trainCapAveS <- predict(preObj,training[,-58])$capitalAve
par(mfrow=c(1,2)); hist(trainCapAveS); qqnorm(trainCapAveS)
```



Viel besser als vorher (aber noch nicht perfekt: immer noch grosser Haufen bei 0).

Standardizing - Imputing data

```
set.seed(13343)

# Make some values NA  just for demonstrating/testing:
training$capAve <- training$capitalAve
selectNA <- rbinom(dim(training)[1],size=1,prob=0.05)==1
training$capAve[selectNA] <- NA

# Impute and standardize
preObj <- preProcess(training[,-58],method="knnImpute")  k nearest neighbor imputation:
capAve <- predict(preObj,training[,-58])$capAve          average k nearest neighbors and
                                                          use this to impute.

# Standardize true values
capAveTruth <- training$capitalAve
capAveTruth <- (capAveTruth-mean(capAveTruth))/sd(capAveTruth)
```

Standardizing - Imputing data

```
quantile(capAve - capAveTruth)
```

```
        0%        25%        50%        75%       100% 
-1.1324388 -0.0030842 -0.0015074 -0.0007467  0.2155789 
```

```
quantile((capAve - capAveTruth)[selectNA])
```

```
        0%        25%        50%        75%       100% 
-0.9243043 -0.0125489 -0.0001968  0.0194524  0.2155789 
```

```
quantile((capAve - capAveTruth)[!selectNA])
```

```
        0%        25%        50%        75%       100% 
-1.1324388 -0.0030033 -0.0015115 -0.0007938 -0.0001968 
```

Notes and further reading

- Training and test must be processed in the same way
- Test transformations will likely be imperfect
  - Especially if the test/training sets collected at different times
- Careful when transforming factor variables!
- preprocessing with caret