Practical Machine Learning in R

Input Processing

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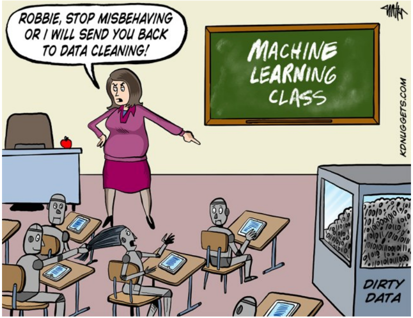
[1] with slides from Bernd Bischl and Michel Lang
[2] slides available at http://www.cs.uwyo.edu/~larsko/ml-fac

Why do we care?

- real-world data often messy
- missing values
- uninformative features
- outliers
- a lot of time is spent cleaning up data



Replacing Missing Values

- many learners cannot handle missing values at all ("missings" property)
- numeric features: impute with constant, mean, median, mode, min, max, random value of estimated normal/uniform/ECDF
- factor features: impute with constant, mode, random value of ECDF

```
data = data.frame(x = c(1, NA, 3, 4), y = c("a", "b", NA, "b"))
imputed = impute(data, cols = list(x = imputeMean(),
    y = imputeMode()))
imputed$data

##          x y
## 1 1.000000 a
## 2 2.666667 b
## 3 3.000000 b
## 4 4.000000 b
```

Replacing Missing Values

- can specify imputation depending on data type
- can add new columns to indicate what was imputed

```
imputed = impute(data,
    classes = list(numeric = imputeMean(), factor = imputeMode()),
     dummy.classes = c("numeric", "factor"))
imputed$data

##          x y x.dummy y.dummy
## 1 1.000000 a   FALSE   FALSE
## 2 2.666667 b    TRUE   FALSE
## 3 3.000000 b   FALSE    TRUE
## 4 4.000000 b   FALSE   FALSE
```

Wrapped Learners

- wrap learner in imputation method
- imputation happens transparently – wrapped learner can be used just like original learner
- test data is imputed like training data (e.g. with same mode value)

```
learner = makeImputeWrapper("classif.rpart",
    classes = list(numeric = imputeMedian()))
learner

## Learner classif.rpart.imputed from package rpart
## Type: classif
## Name: ; Short name:
## Class: ImputeWrapper
## Properties: twoclass,multiclass,missings,numerics,factors,ordered,pr
## Predict-Type: response
## Hyperparameters: xval=0
```

Constant Features

- most models technically break in presence of constant features
- constant features hold no information

```
data = data.frame(target = c("a", "a", "b"), x = 1:3, y = c(1, 1, 1))
task = makeClassifTask(data = data, target = "target")
# remove all features where fraction of values differing
# from mode value is <= 5%
getTaskData(removeConstantFeatures(task, perc = 0.05))

## Removing 1 columns: y

##   target x
## 1      a 1
## 2      a 2
## 3      b 3
```

Merging of Factor Levels

- For the target variable:

```
task = joinClassLevels(iris.task, new.levels =
    list(new = c("setosa", "virginica")))
table(getTaskTargets(task))

##
##        new versicolor
##        100         50
```

- For the features:

```
mergeSmallFactorLevels(task, min.perc = 0.01)
```

Unbalanced Classes

- one class much more/less frequent than others
- always predicting largest class gives good accuracy
- never predicting smallest class loses little accuracy
- solution: under- and oversample (for binary tasks)

Unbalanced Classes

```
task = makeClassifTask(id = "test",
    data = data.frame(a = sample(1:100, 100),
                      class = factor(c(rep("a", 98), "b", "b"))),
    target = "class")
task.under = undersample(task, rate = 0.5)
table(getTaskTargets(task.under))

##
##  a  b
## 49  2

task.over = oversample(task, rate = 100, cl = "b")
table(getTaskTargets(task.over))

##
##   a   b
##  98 200
```

Unbalanced Classes

- can under-/oversample in wrappers
- can wrap wrappers

```
learner = makeUndersampleWrapper("classif.rpart", usw.rate = 0.5)
learner = makeImputeWrapper(learner,
    classes = list(numeric = imputeMedian()))
learner

## Learner classif.rpart.undersampled.imputed from package mlr,rpart
## Type: classif
## Name: ; Short name:
## Class: ImputeWrapper
## Properties: numerics,factors,ordered,missings,weights,prob,twoclass,
## Predict-Type: response
## Hyperparameters: xval=0,usw.rate=0.5
```

Exercises

`http://www.cs.uwyo.edu/~larsko/ml-fac/05-input-exercises.Rmd`