Combining predictors

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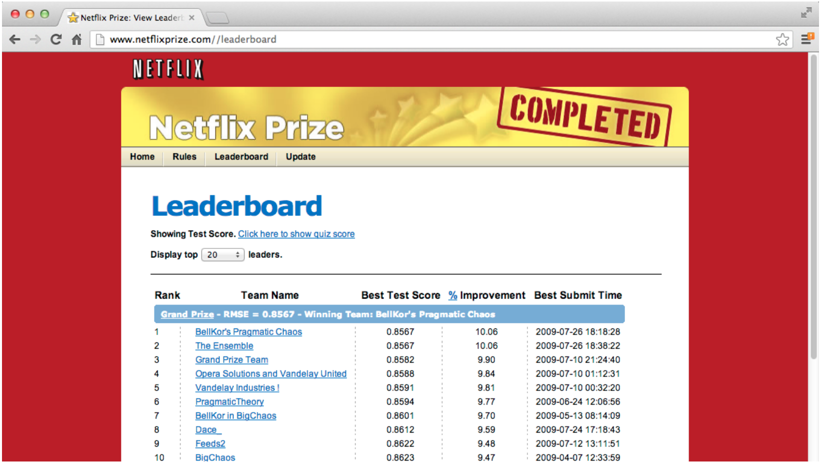
Key ideas

- You can combine classifiers by averaging/voting
- Combining classifiers improves accuracy
- Combining classifiers reduces interpretability
- Boosting, bagging, and random forests are variants on this theme

Netflix prize

BellKor = Combination of 107 predictors



Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace_	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59

http://www.netflixprize.com//leaderboard

Heritage health prize - Progress Prize 1

2. *Predictive Modelling*

   Predictive models were built utilising the data sets created in Step 1. Numerous mathematical techniques were used to generate a set of candidate solutions.

3. *Ensembling*

   The individual solutions produced in Step 2 were combined to create a single solution that was more accurate than any of its components.

Marke

Makers

1 Introduction

My milestone 1 solution to the Heritage Health Prize with a RMSLE score of 0.457239 on the leaderboard consists of a linear blend of 21 result. These are mostly generated by relatively simple models which are all trained using stochastic gradient descent. First in section 2 I provide a description of the way the data is organized and the features that were used. Then in section 3 the training method and the post-processing steps are described. In section 4 each individual model is briefly described, all the relevant meta-parameter settings can be found in appendix Parameter settings. Finally the weights in the final blend are given in section 5.

Mestrom

Basic intuition - majority vote

Suppose we have 5 completely independent classifiers

If accuracy is 70% for each: *
$10 \times (0.7)^3(0.3)^2 + 5 \times (0.7)^4(0.3)^2 + (0.7)^5$ * 83.7% majority vote accuracy

With 101 independent classifiers * 99.9% majority vote accuracy

Approaches for combining classifiers

1. Bagging, boosting, random forests

- Usually combine similar classifiers

2. Combining different classifiers

- Model stacking
- Model ensembling

Example with Wage data

Create training, test and validation sets

```
library(ISLR); data(Wage); library(ggplot2); library(caret
```

```
## Loading required package: lattice
```

```
Wage <- subset(Wage,select=-c(logwage))

# Create a building data set and validation set
inBuild <- createDataPartition(y=Wage$wage,
                               p=0.7, list=FALSE)
validation <- Wage[-inBuild,]; buildData <- Wage[inBuild,]

inTrain <- createDataPartition(y=buildData$wage,
                               p=0.7, list=FALSE)
training <- buildData[inTrain,]; testing <- buildData[-inT
```

Wage data sets

Create training, test and validation sets

```r
dim(training)
```

```
## [1] 1474   11
```

```r
dim(testing)
```

```
## [1] 628  11
```

```r
dim(validation)
```

```
## [1] 898  11
```

Build two different models

```
mod1 <- train(wage ~.,method="glm",data=training)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1
## ifelse(type == : prediction from a rank-deficient fit ma

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## Warning in predict.lm(object, newdata, se.fit, scale = 1
```
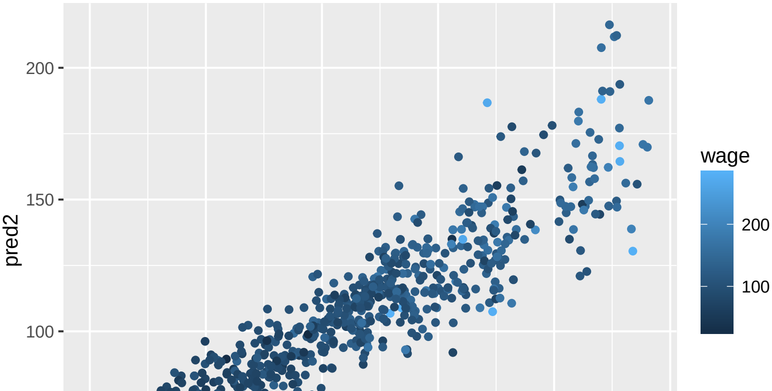

Predict on the testing set

```
pred1 <- predict(mod1,testing); pred2 <- predict(mod2,testi
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1
## ifelse(type == : prediction from a rank-deficient fit ma
```

```
qplot(pred1,pred2,colour=wage,data=testing)
```



Fit a model that combines predictors

```
predDF <- data.frame(pred1,pred2,wage=testing$wage)
combModFit <- train(wage ~.,method="gam",data=predDF)
```

```
## Loading required package: mgcv

## Loading required package: nlme

## This is mgcv 1.8-12. For overview type 'help("mgcv-packa
```

```
combPred <- predict(combModFit,predDF)
```

Testing errors

```r
sqrt(sum((pred1-testing$wage)^2))
```

```
## [1] 779.6741
```

```r
sqrt(sum((pred2-testing$wage)^2))
```

```
## [1] 814.6758
```

```r
sqrt(sum((combPred-testing$wage)^2))
```

```
## [1] 765.4154
```

Predict on validation data set

```
pred1V <- predict(mod1,validation); pred2V <- predict(mod2,
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1
## ifelse(type == : prediction from a rank-deficient fit ma
```

```
predVDF <- data.frame(pred1=pred1V,pred2=pred2V)
combPredV <- predict(combModFit,predVDF)
```

Evaluate on validation

```
sqrt(sum((pred1V-validation$wage)^2))
```

```
## [1] 1036.07
```

```
sqrt(sum((pred2V-validation$wage)^2))
```

```
## [1] 1069.625
```

```
sqrt(sum((combPredV-validation$wage)^2))
```

```
## [1] 1034.298
```

Notes and further resources

- Even simple blending can be useful
- Typical model for binary/multiclass data
- Build an odd number of models
- Predict with each model
- Predict the class by majority vote
- This can get dramatically more complicated
- Simple blending in caret: caretEnsemble (use at your own risk!)
- Wikipedia ensemble learning

Recall - scalability matters

Innovation
by Mike Masnick
Fri, Apr 13th 2012
12:07am

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Why Netflix Never Implemented The Algorithm That Won The Netflix $1 Million Challenge

from the *times-change* dept

You probably recall all the excitement that went around when a group **finally won** the big Netflix $1 million prize in 2009, improving Netflix's recommendation algorithm by 10%. But what you might *not* know, is that **Netflix never implemented that solution itself.** Netflix recently put up a blog post **discussing some of the details of its recommendation system**, which (as an aside) explains why the winning entry never was used. First, they note that they *did* make use of an earlier bit of code that came out of the contest:

`http://www.techdirt.com/blog/innovation/articles/20120409/03412518422/`

`http://techblog.netflix.com/2012/04/netflix-recommendations-beyond-5-stars.html`