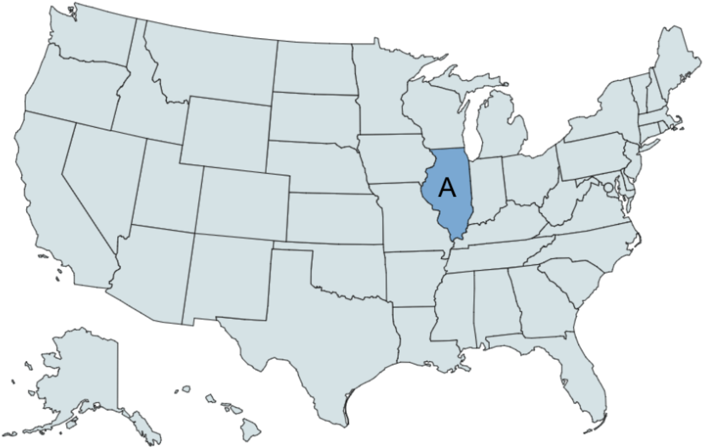
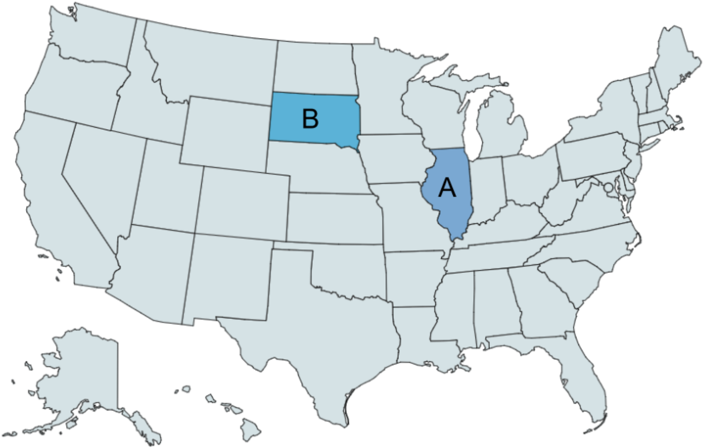
Data Mining Cup 2016

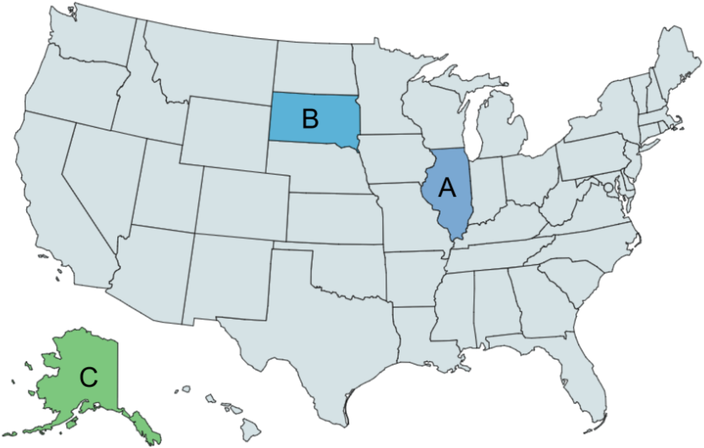
Iowa State University Team 2

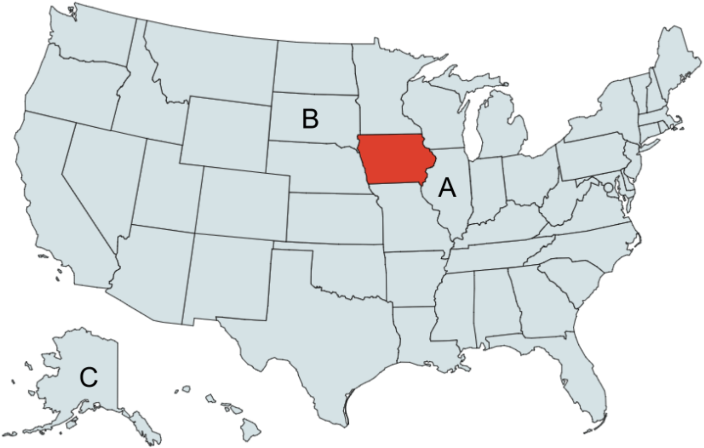
June 27, 2016

Geography Quiz


A


B
A


B
A
C


B
A
C

What we used

R and Python modules - size weighted by # of occurences in code

Feature Engineering

Numerical features

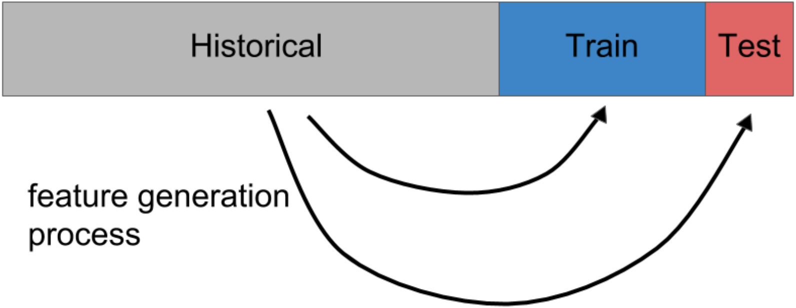
- Clustering customers by their behavior such as:
  - The frequency of their visits and time in between visits
  - The quantities that they buy in
  - The variability of the goods they buy in terms of sizes, colors, product groups, etc.
- Standardizing size, price, and other variables within product groups
- When all else failed we simply took differences, products, and quotients of existing features to account for interactions

Categorical features

- Need to map categorical variables to numerical variables in a meaningful way
- One-hot encoding (indicator variables) is one option, but this greatly increases the number of features
  - If one categorical variable has 800 levels, then 800 new columns will have to be made
  - If you want to include an interaction with another categorical variable that has 50 levels, then $800 \times 50 = 40000$ new variables will have to be made
- Even though tree-based methods are designed to ignore useless features, in practice they can be cumbersome

Alternative to one-hot encoding

- Map categorical features to meaningful numeric features using the response variable (returnQuantity)
- To prevent leaking information from returnQuantity into training set and test set, we build these features based on a historical set which is disjoint from any data we train on



Example with sizeCode

- For each row with sizeCode = S, the new variable is created like so:

$$\mathrm{S} \mapsto \log \frac{(\#\text{ rows with sizeCode} = \mathrm{S}\text{ and } \mathrm{Y} \geq 1) + \epsilon_1}{(\#\text{ rows with sizeCode} = \mathrm{S}\text{ and } \mathrm{Y} = 0) + \epsilon_0}$$

- ϵ_1 and ϵ_0 are chosen in a Bayesian way to reflect prior information and to add numerical stability

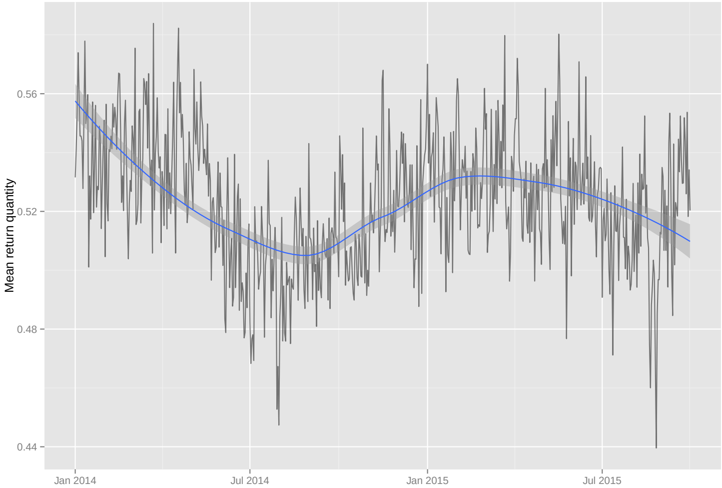
sizeCode
S
L
...

$\Rightarrow$

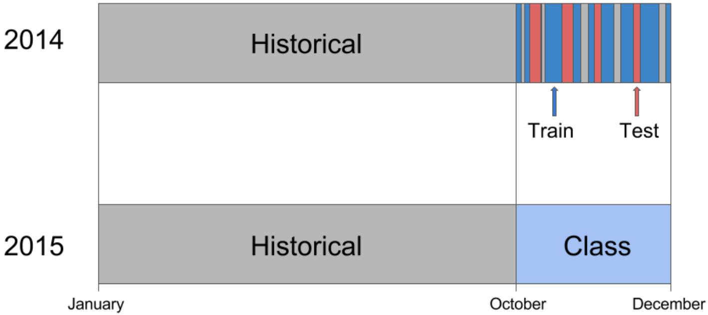
sizeCode2
3.416
1.209
...

Feature Matrices

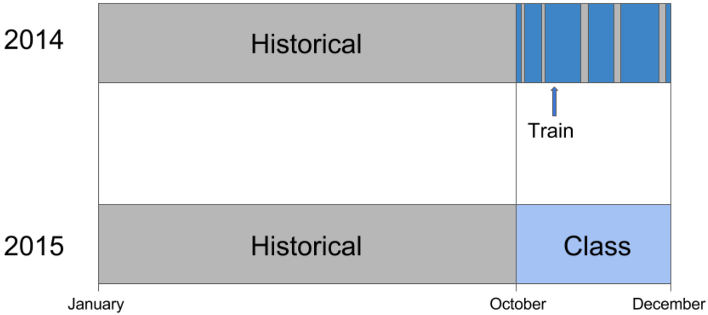
Dealing with seasonality



Version 5(d)


2014
Historical
Train
Test
2015
Historical
Class
January
October
December

Version 5(d) Final



Version 6


2014
Historical
Train
Test
2015
Historical
Class
January
October
December

Version 6 Final

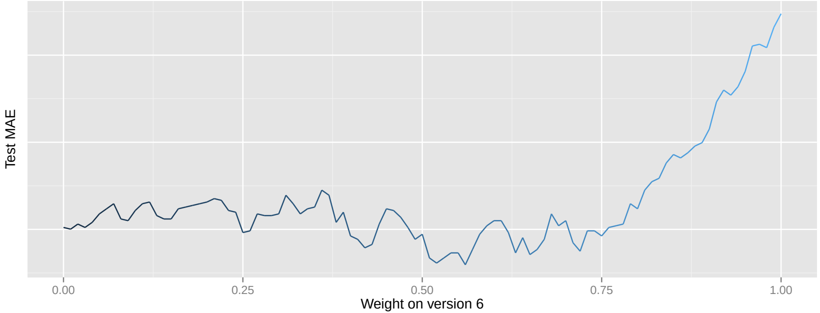
Final Model

Xgboost outperformed all

- We found that training a tree-based xgboost model with a binary classification objective produced the best mean absolute error (MAE)
- We primarily focused on tuning 3 parameters:
  - **eta:** the learning rate for boosting
  - **max_depth:** the maximum depth of each tree
  - **colsample_bytree:** the number of features to randomly choose for determining each split
- Xgboost performed so well that combining anything and everthing else with xgboost could not improve the MAE

Ensembling

- Ultimately the best ensemble of models was a combination of two xgboost models:
  - 45% xgboost trained on feature matrix version 5(d)
  - 55% xgboost trained on feature matrix version 6



- While combining these models only improved MAE slightly, there was another motivation for doing it this way. . .
- Neither feature matrix was perfect:
  - A model trained on version 5(d) would be training on data one year in the past, not the most recent data, which could add bias
  - For version 6, the final training set had to be completely different from the initial training set, which was one year in the past
  - Since the parameters for our model were mostly tuned using the initial training set, this could hurt the final model if the optimal parameters changed from year-to-year
- Combining results from both feature matrices provided a way of hedging our bet in case one of the feature matrices was biased

Thank you for listening!

Iowa State University of Science and Technology