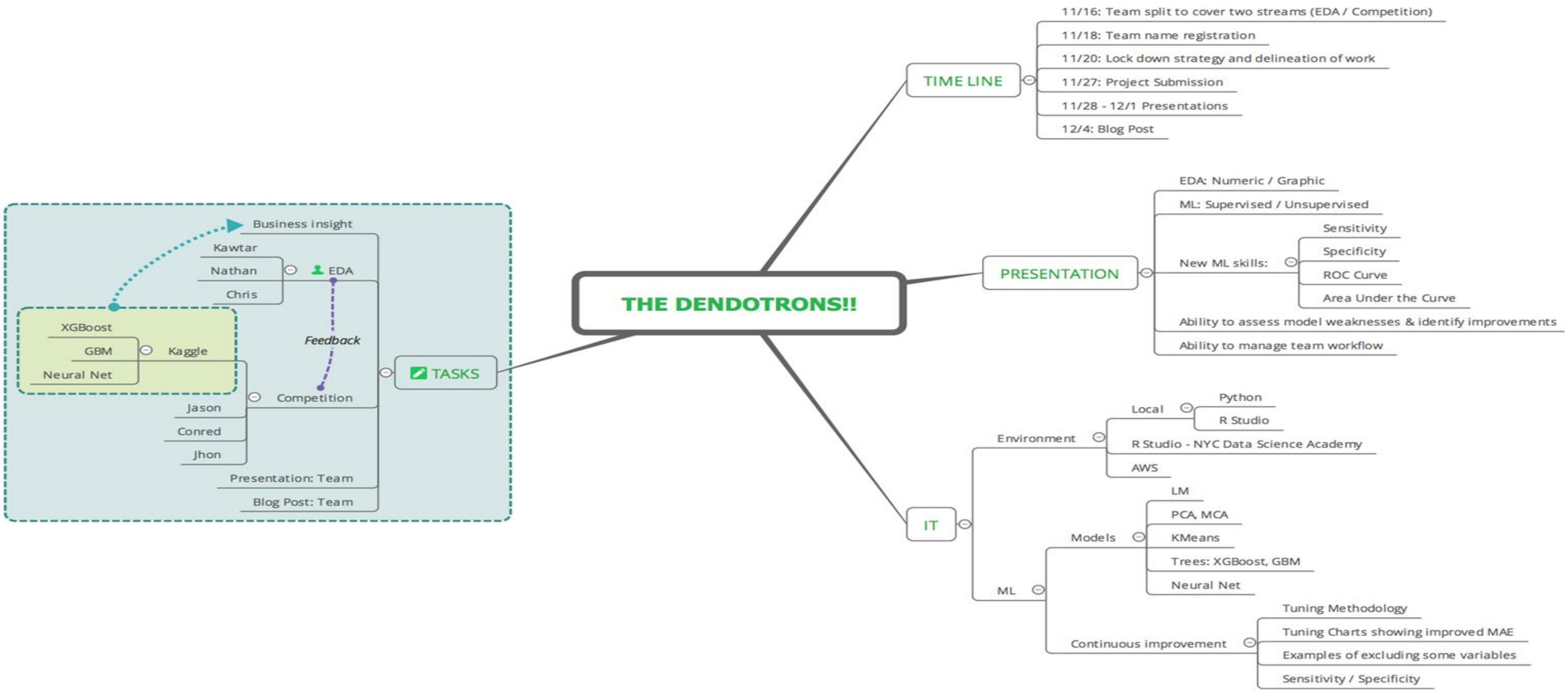
The Dendotrons
Kaggle: Allstate

Kawtar Belmkaddem
Jhonasttan Regalado
Jason Sippie
Nathan Stevens
Chris Valle
Conred Wang

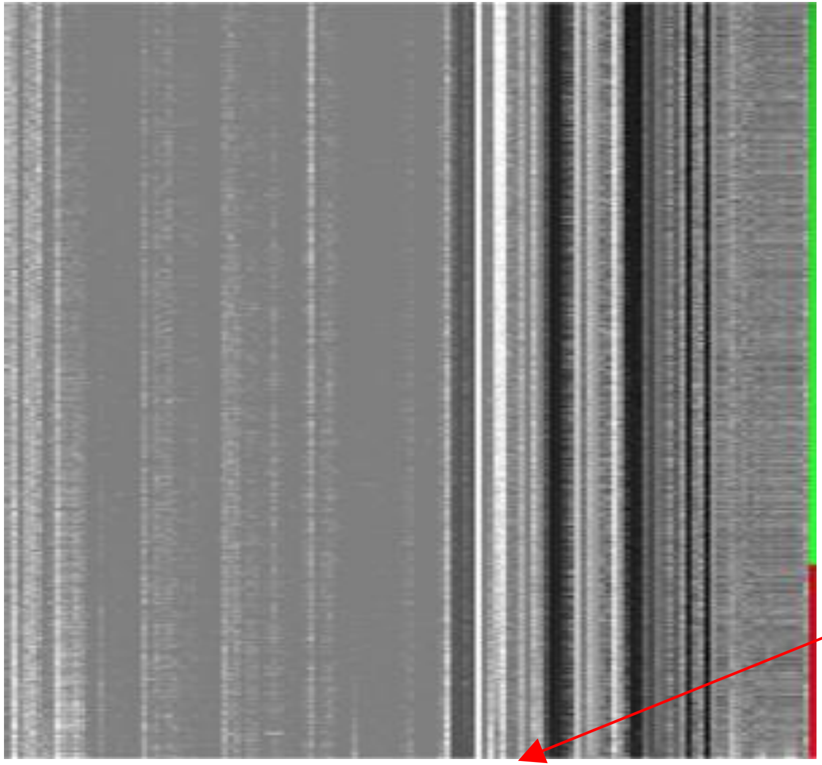
Outline

- Team Dynamics
- EDA
- Unsupervised ML
- Supervised ML
- Takeaways

Team Development / Management

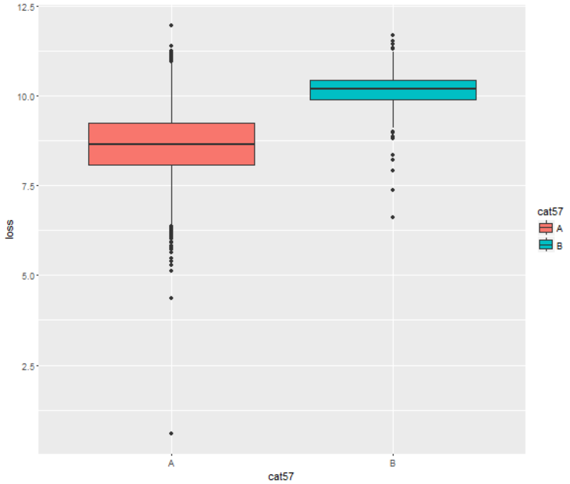


EDA



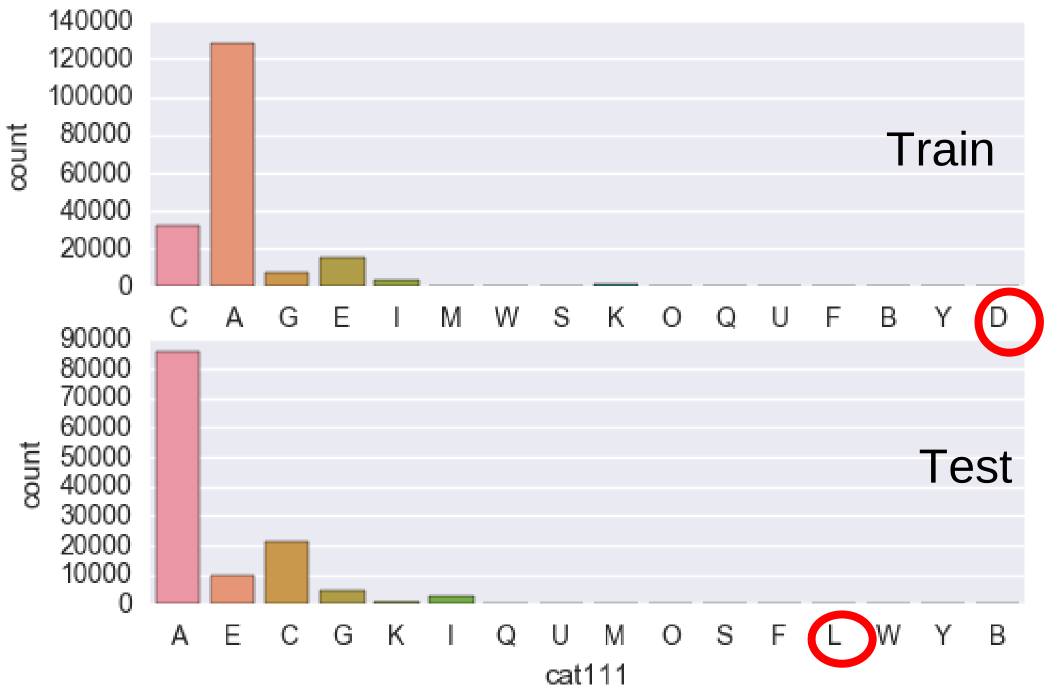
Gray scale image visualising the dataset with features ordered by the log loss. You can see patterns in which the values of particular features change as loss increases.

CAT57 versus Log Loss



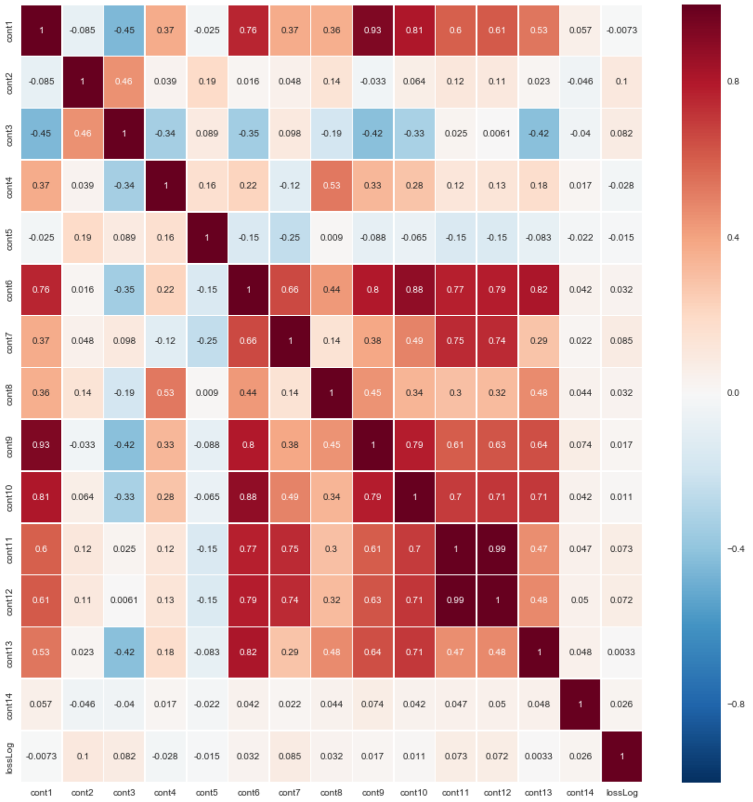
EDA - Comparison between test and train datasets

Some categorical variables are not present in the test set in total 45 variables



EDA - Correlation between continuous features

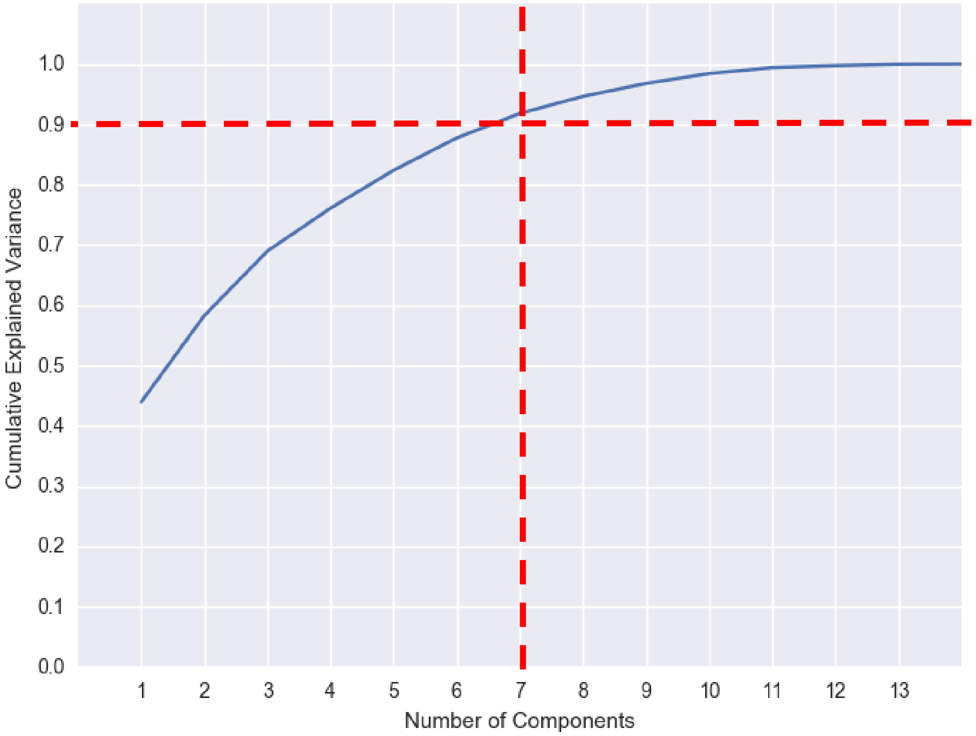
Continuous variables

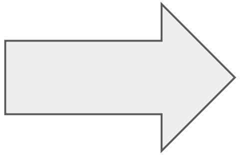


Variables	Correlation
Cont 11 & Cont 12	0.994384
Cont 1 & Cont 9	0.929912
Cont 6 & Cont 10	0.883351
Cont 6 & Cont 13	0.815091
Cont 1 & Cont10	0.808551
Cont 9 & Cont 6	0.797544
Cont 9 & Cont 10	0.785697
Cont 6 & Cont12	0.785144

PCA- Dimensionality reduction

Dimensionality reduction for continuous variables using PCA : We have 14 continuous features





We can can reduce the number of continuous data to the half

EDA - Correlation between 2-variables categorical features

72, 2-variables categorical data (A,B)

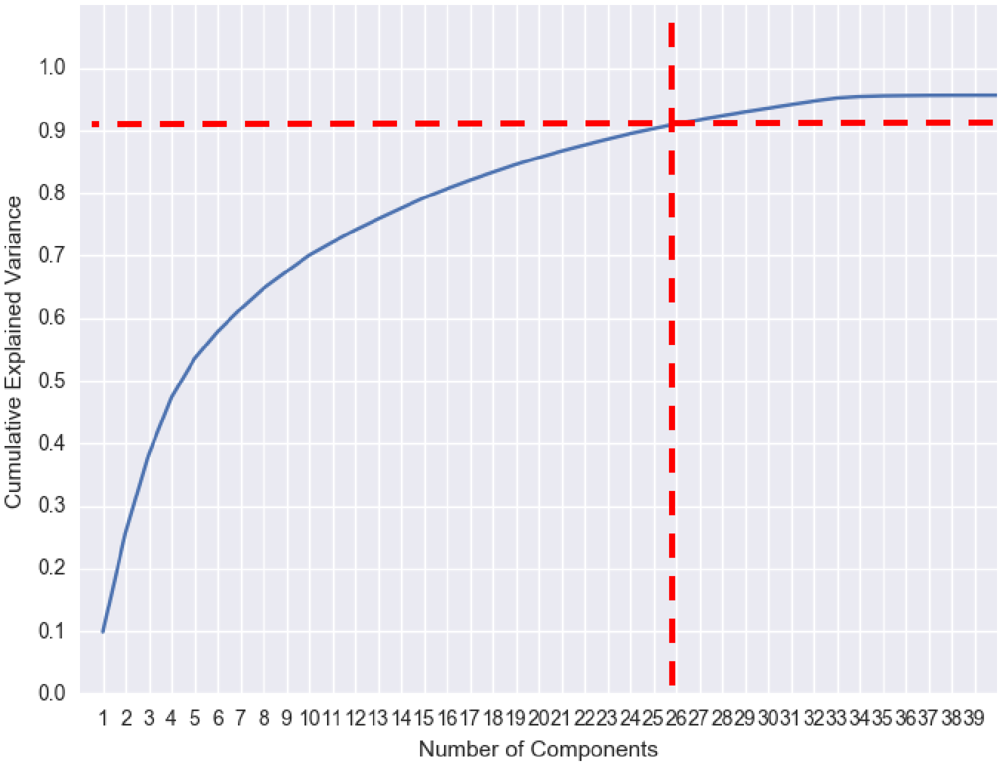
Label encoding

Numerical values

Correlation

Variables	Correlation
Cat 2 & Cat 9	0.932420
Cat 50 & Cat 6	0.925731
Cat 8 & Cat 66	0.862231
Cont 57 & Cont 7	0.809418
Cont 3 & Cont 16	0.783480

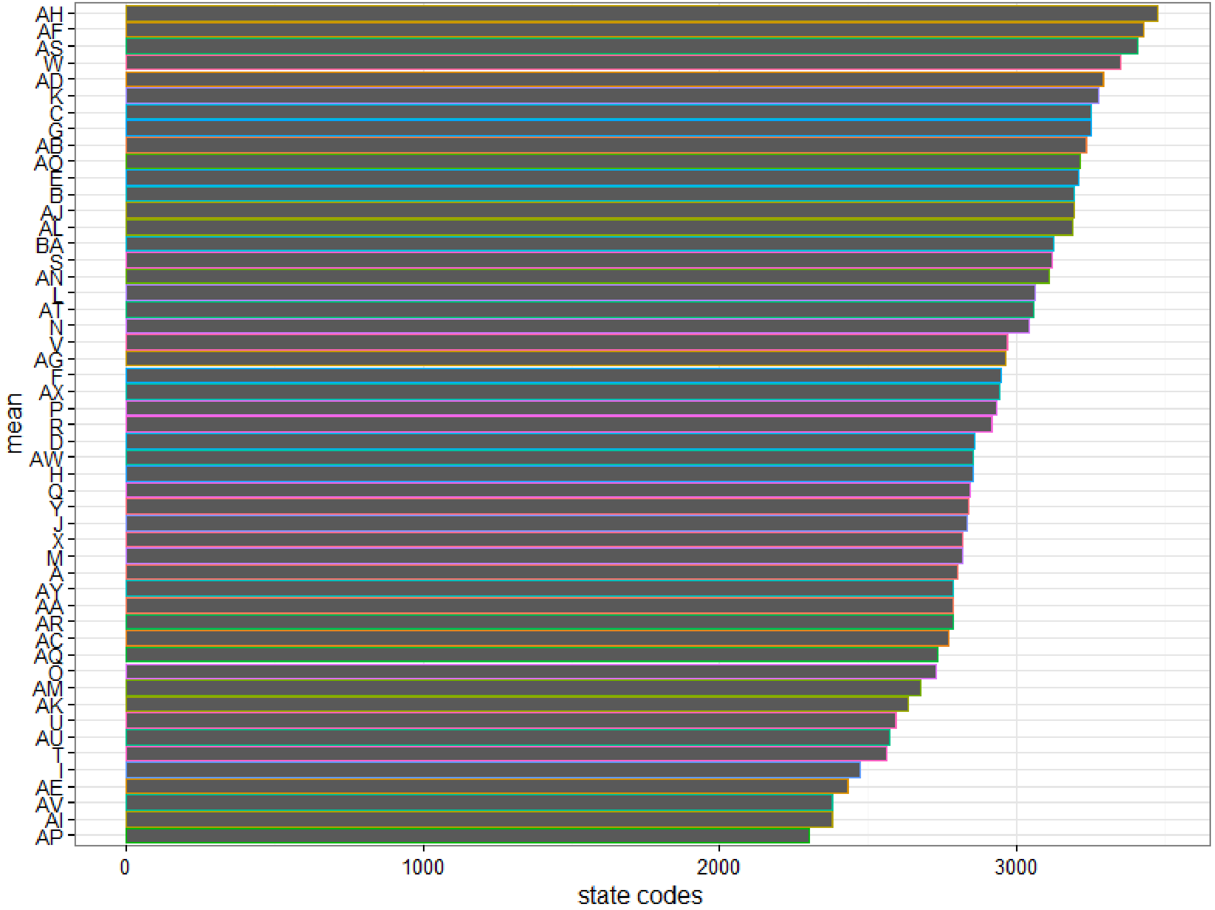
SVD - Correlation between 2-variables categorical features



SVD: Singular Value Decomposition

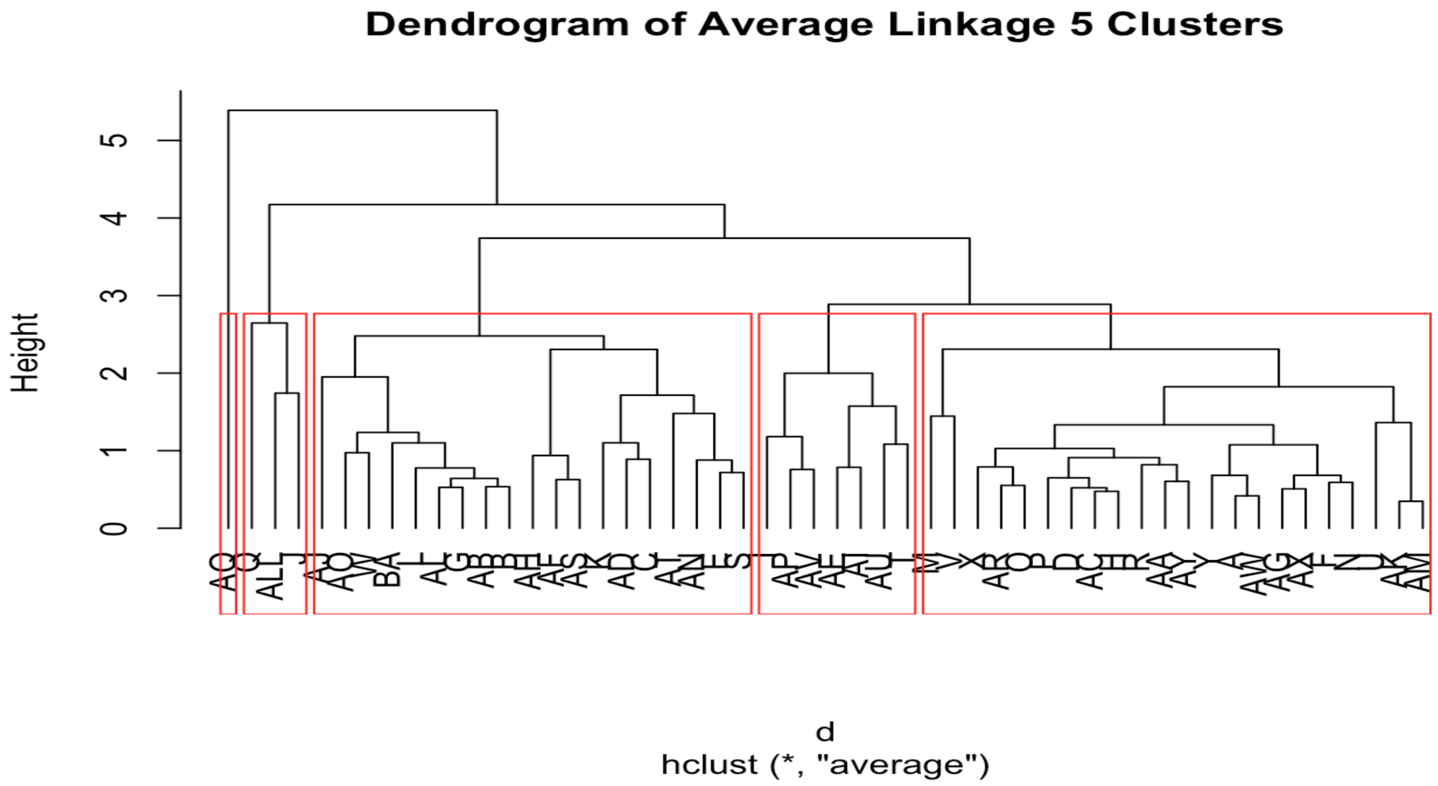
We can reduce the number of 2-variable categorical data to 26 variables

State Mean Loss



- Assuming cat112 == US states
- Average loss per state
- Calibrate premium setting for states with very high loss rate

Hierarchical Clustering into Five Groups



Hierarchical Clustering Cont...

```
## clusters.average
##  1  2  3  4  5
##  3 22 19  7  1
```

```
##    cluster    Min   Q1 Median Mean   Q3    Max
## 1        1  23.69 1200 1981.0 2844 3523 121000
## 2        2 123.05 1183 2025.5 2827 3537  24450
## 3        3 189.20 1376 2339.0 3216 4178  30440
## 4        4 201.60  998 1671.0 2428 3015  19620
## 5        5 786.30 1327 2187.0 2735 3123   7998
```

- We can consider performing feature engineering
- We can consider removing AQ - only has 30 observations

Machine Learning for Prediction

Tactics to Reduce Iteration Time:

Regularization
- Near-zero variance function
- Use p values from regression
- Reduced # levels (e.g., cat116)

Sampling
- Random sampling
- Sampling cat80D versus B

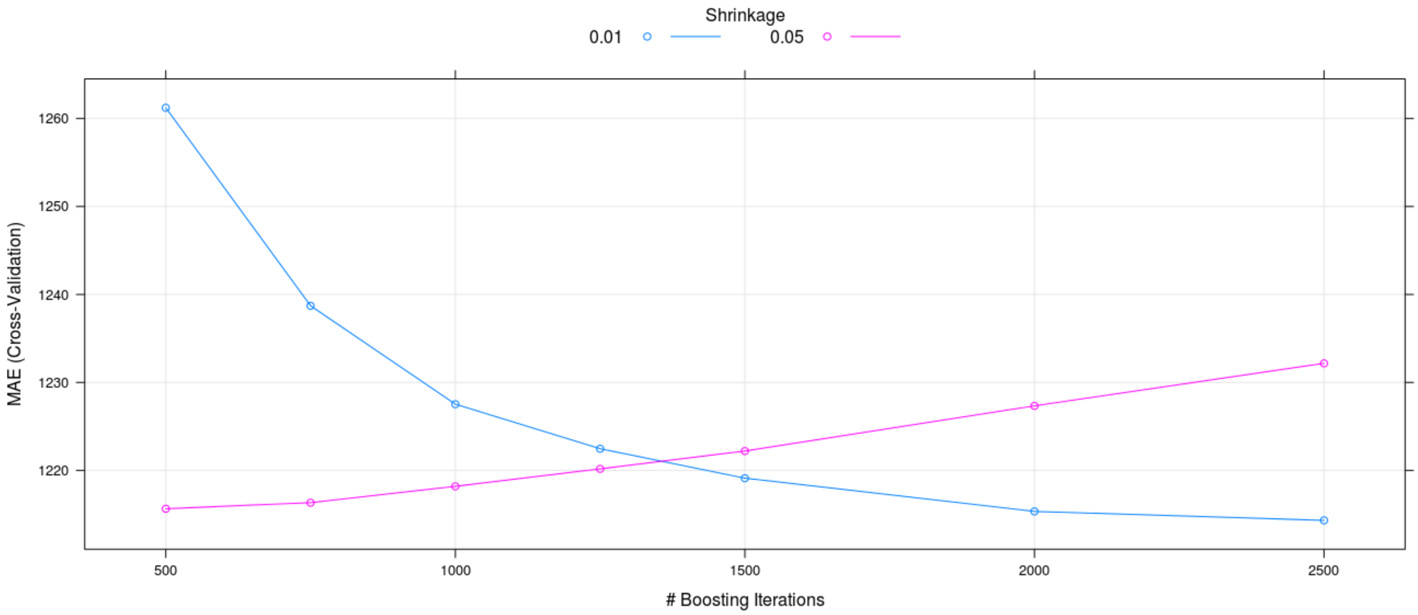
Other
- Used AWS, but parallel processing not always a turn-key solution
- Reduce # folds in validation

Models Examined:

Regression
- Linear regression -- R^2 of 50%. Good for initial analysis
- Boosted trees -- XGBoost had best performance
- Neural network -- close second to XGBoost
- XGBBoost + NN => marginal improvement MAE 1126

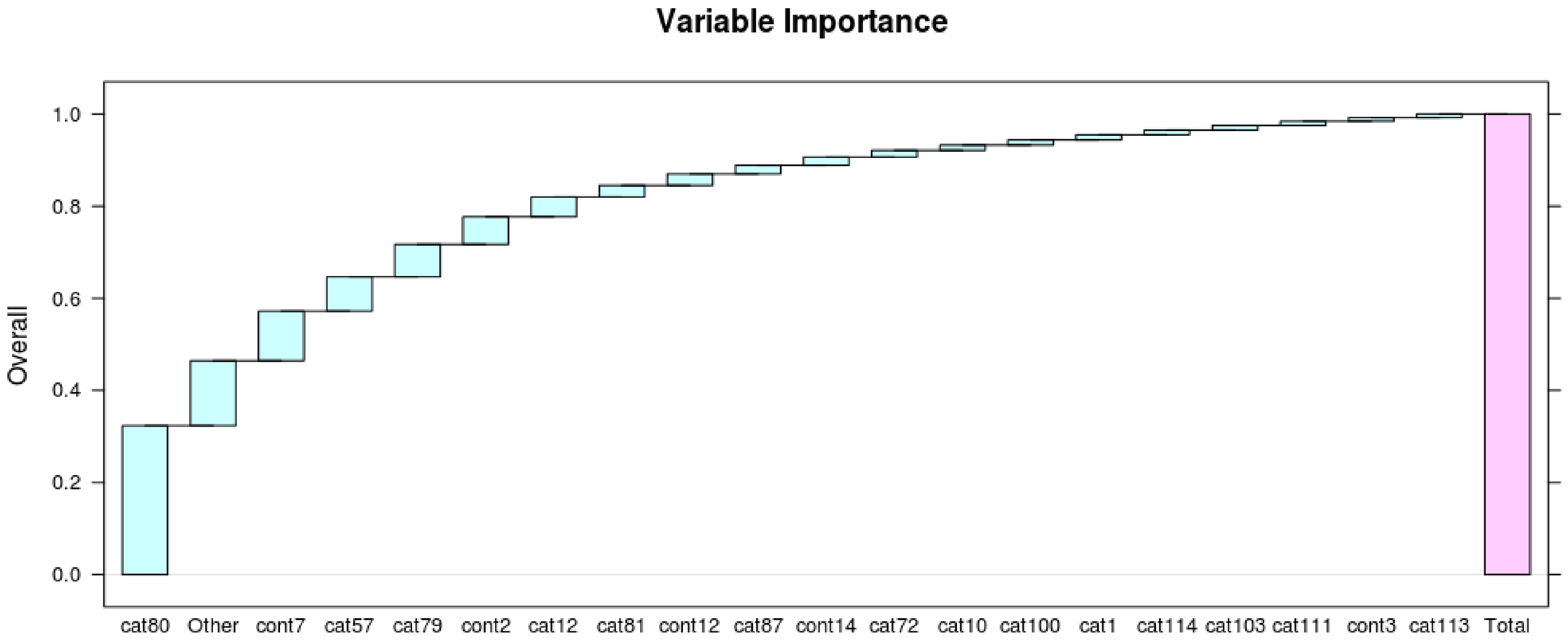
Classification
- Logistic regression
- SVM

Machine Learning for Prediction -- XGB Model Tuning



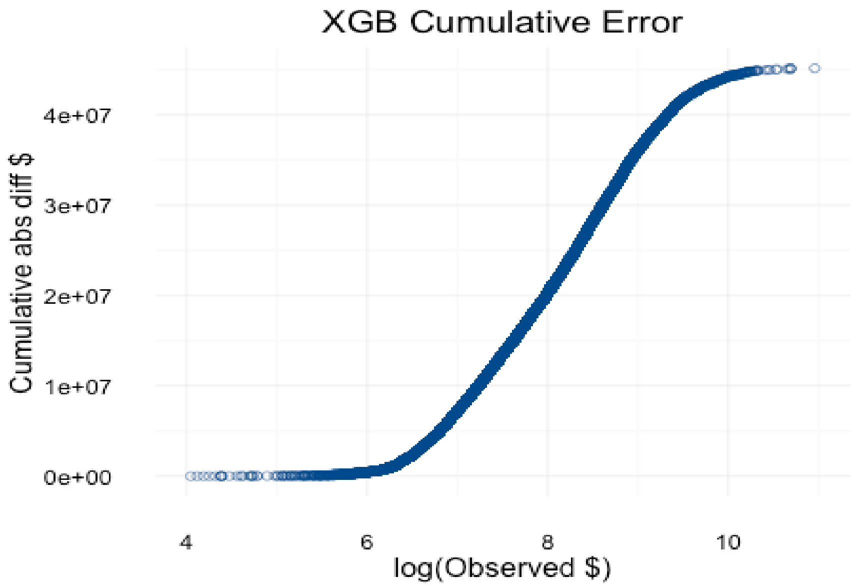
- Final result: 850 iterations, learning rate 0.05, 5 trees
- Prediction unstable with reduced cross-validation folds
- Regularization penalized MAE $300

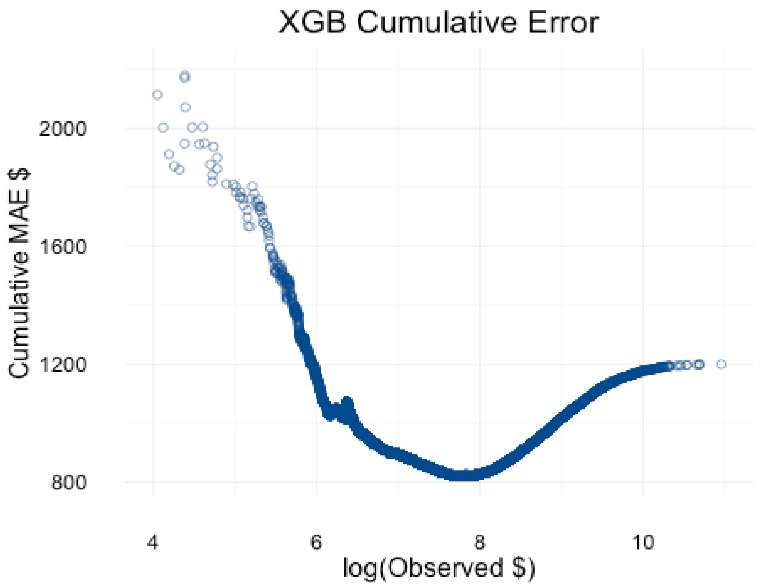
Machine Learning for Prediction -- Model Assessment



Cat80 largest single predictor

Machine Learning for Prediction -- XGB Model Tuning

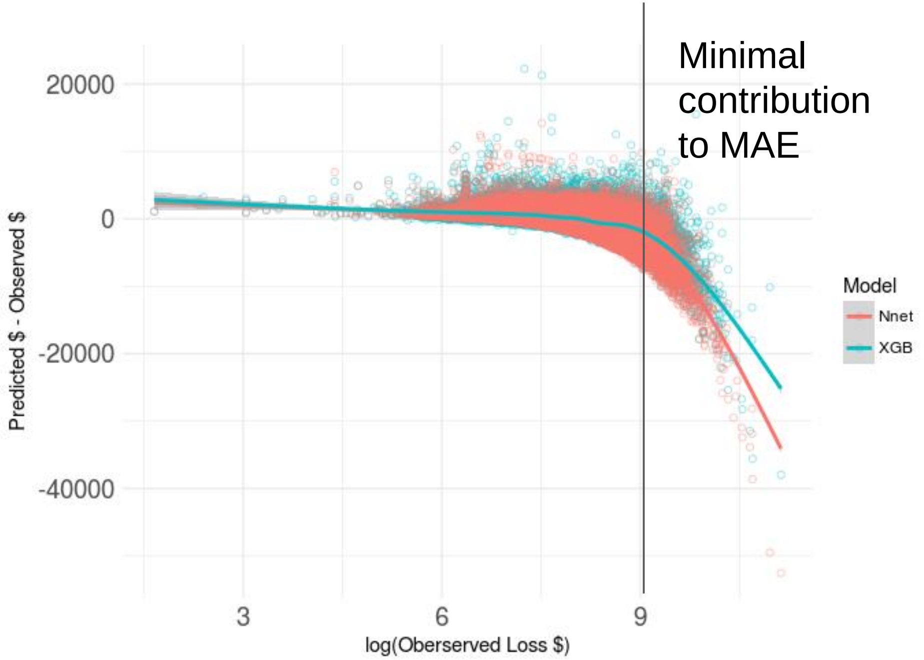




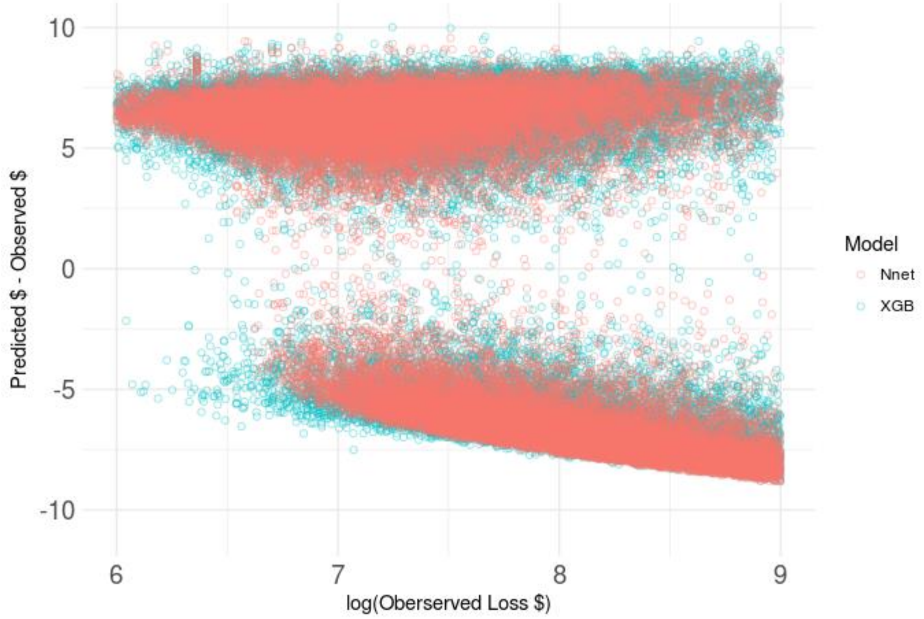
Most of error for claims between exp($6) and exp($9) ~($400-$8000), therefore no need to get distracted by tails

Model gets more accurate until exp($8) ~$3000, then performance degrades

Machine Learning for Prediction -- Model Assessment

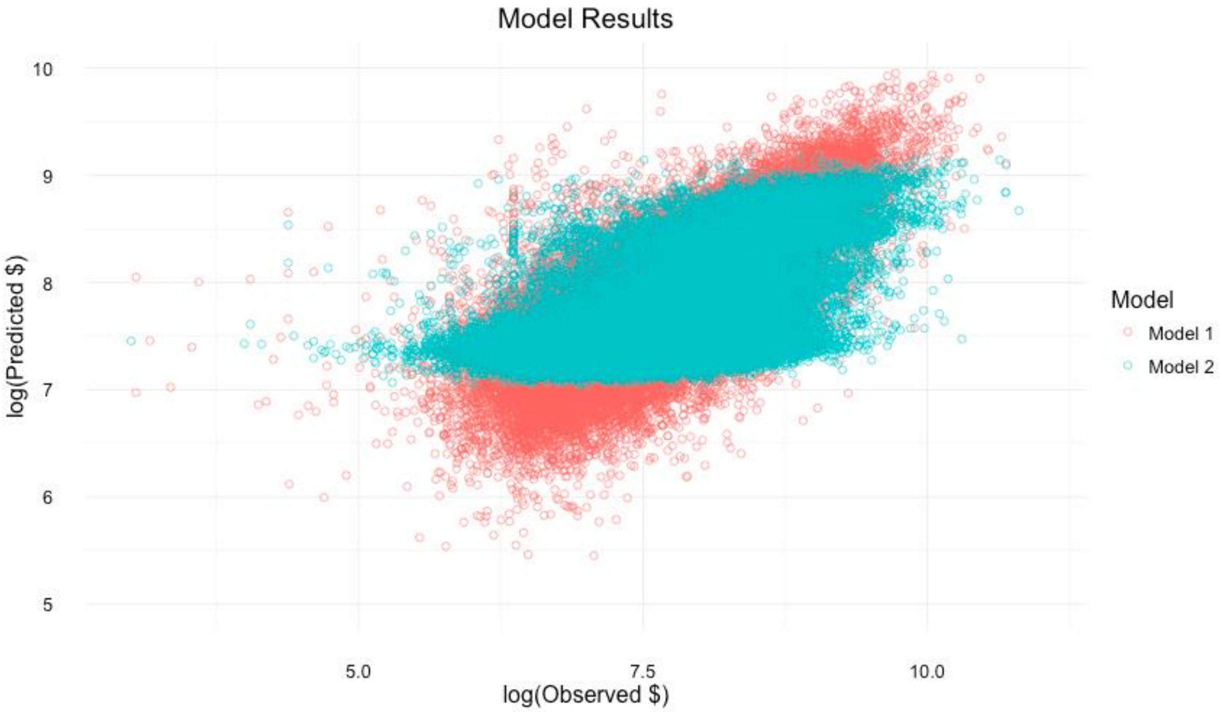


Minimal contribution to MAE



Underestimates increase with loss

Linear Regression w/ 6 Features vs XGBoost with all Features



What’s Salvageable?

When you’ve been devastated by a serious car accident, your focus is on the things that matter the most: family, friends, and other loved ones. Pushing paper with your insurance agent is the last place you want your time or mental energy spent.

Conclusion: claim size **can not be accurately predicted** based on provided features

Root Problem

- Doing paperwork for claim **protects insurer** against fraud
- May be able to **reduce paperwork** burden for claims if they don’t look “fishy”
- Can features support a classification question?

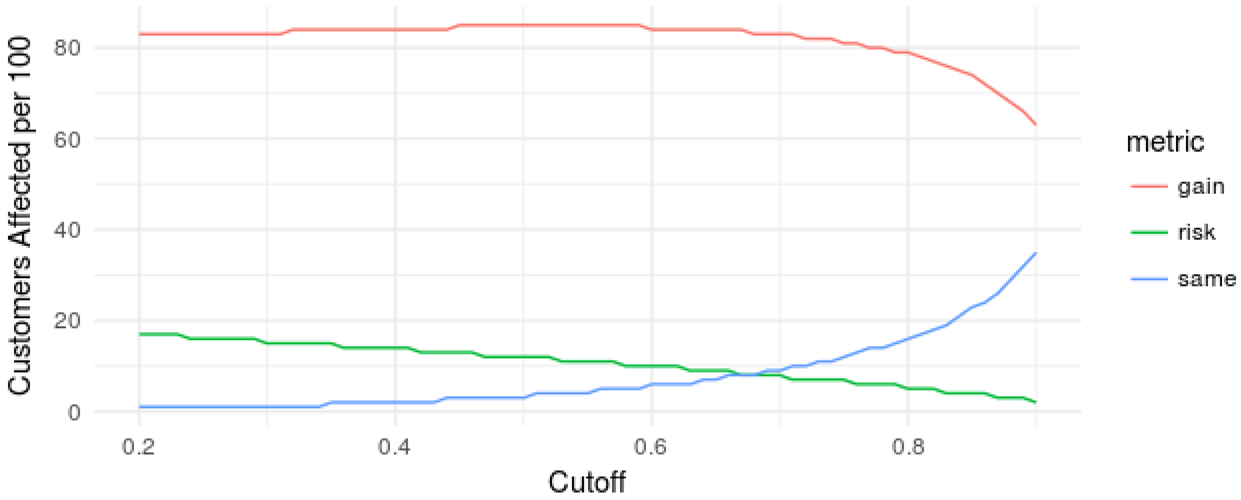
New classifier: “smallClaim”

- 80% of customers account for 50% of claims by value -- all below $4500
- “Fishy” claims: feature set associated with small claim value, but requested value is large
    - (the opposite is not important for protection against fraud)

Fishing for Fishy Claims

Models used: GB, SVM, logistic regression. All had high accuracy but ~50% sensitivity.

We needed something that can be optimized to minimize false positives (logistic)



Next Steps: quantify dollar risk of misclassification and dollar benefit to customer of reduced paperwork

Classification Model: Low Profile with High Valued Accounts

Confusion Matrix and Statistics		
	High	**Low**
High	1684	537
Low	1641	13097
Accuracy	0.8716	
95% CI	(0.8664, 0.8766)	
No Information Rate	0.8039	
Sensitivity	0.5065	
Specificity	0.9606	

Training a classification model (using GBM) with a profile having a loss value <= $4500 provides 87% accuracy.

Sensitivity (false positive) rate of 50% results in half the low profile accounts being falsely identified as high profile, hence increasing the paperwork process.

Specificity (false negatives) rate of 96% indicates a low error rate of 4%; thus a low probability of missing a low profile account with a high value claim request.

Conclusion

Kaggle Competition

- To what degree are we improving performance versus overfitting the test data?
- Continue to fine tune models to improve scoring (mean absolute estimate) in Kaggle

Business Insight

- Tune classifier model by incorporating missing categorical values into the training / test set
- Reducing CV folds is a mixed blessing: useful initially, but becomes easy to overfit