Allstate Purchase Prediction Challenge

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Class Project: General Assembly Data Science DC

Agenda

- What is the competition goal?
- Why is this difficult?
- What data do we have?
- What can we learn from the data?
- Can machine learning help?
- What worked?
- What did I learn?
- Most importantly: Did I profit? ($25K prize!)

What is the competition goal?

- Machine learning competition run by Kaggle
  - “Machine learning” = computers learning patterns from data
- Sponsored by Allstate (insurance company)
- Goal: Predict which car insurance options a customer will buy

Problem context

- There are 7 car insurance options, each with 2 to 4 possible values
- Values are identified by number (0, 1, 2, etc.)
- A “quote” consists of a single combination of those 7 options
- Customers review one or more quotes before making their purchase

Example

- One customer's quote history (in order):

	A	B	C	D	E	F	G
Quote 1	0	0	1	1	0	0	2
Quote 2	1	0	3	3	1	0	1
Quote 3	1	0	1	1	1	0	1
Quote 4	2	0	1	1	1	0	1
Quote 5	2	0	1	1	1	0	1
Quote 6	2	0	1	1	1	0	1
Quote 7	2	0	1	1	1	0	2

- What did they purchase?

Purchase	2	0	1	1	1	0	2

Another example

- This one should be easy:

	A	B	C	D	E	F	G
Quote 1	1	1	3	3	0	2	2
Quote 2	1	1	4	3	0	2	2
Quote 3	1	1	4	3	0	2	2
Quote 4	1	1	4	3	0	2	2
Quote 5	1	1	4	3	0	2	2
Quote 6	1	1	4	3	0	2	2

- What did they purchase?

Purchase	2	1	4	3	0	1	2

How does the competition work?

- “Training data”:
  - 97,009 customers
  - Complete quote history plus purchase
- “Test data”:
  - 55,716 customers
  - Partial quote history
  - Goal is to predict the purchase
  - Evaluation metric is prediction accuracy

Why is this difficult?

- 2,304 possible combinations of options
- Your prediction is only “correct” if you get all 7 options right!
  - No “partial credit”
  - No feedback given on which options were wrong
- Options are not identified as to their meaning

Start with a naïve approach

- For every customer, simply predict that they will purchase the last set of options they were quoted
  - Public leaderboard score: 0.53793
- Good news: Works pretty well, and much better than random guessing (0.00043)
- Bad news: Everyone figured out this strategy (46% of competitors have that identical score)

Data to the rescue!

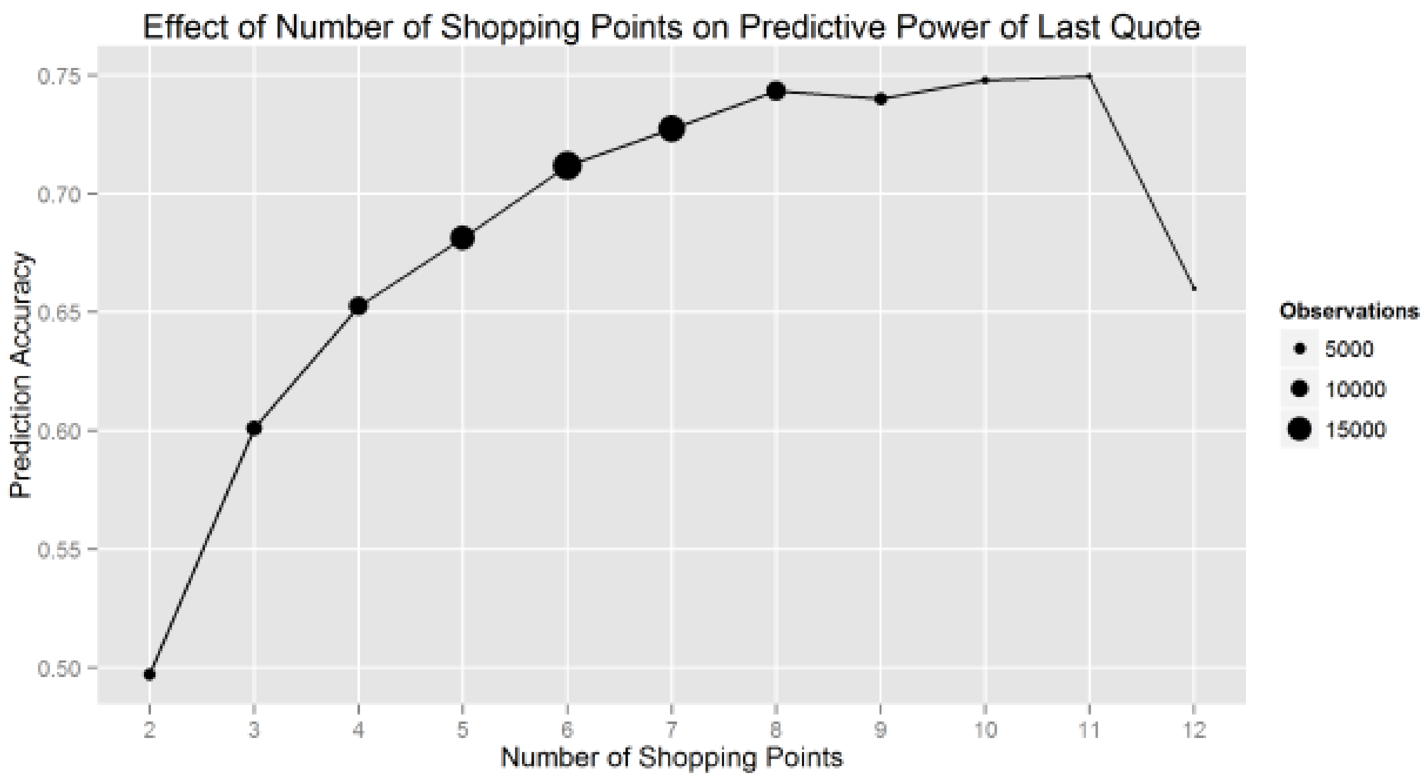
- Customer data
  - State, location ID, group size, homeowner?, married?, risk factor, oldest person covered, youngest person covered, years covered by previous issuer, previous C option
- Car data
  - Age, value
- Additional quote data
  - Day, time, cost

What can we learn from the data?

- There are 2,304 **possible** option combinations, but perhaps only a small subset are ever actually purchased?
- Nope:
  - 1,878 unique combinations appear in training or test data
  - 1,522 unique combinations are purchased in training data

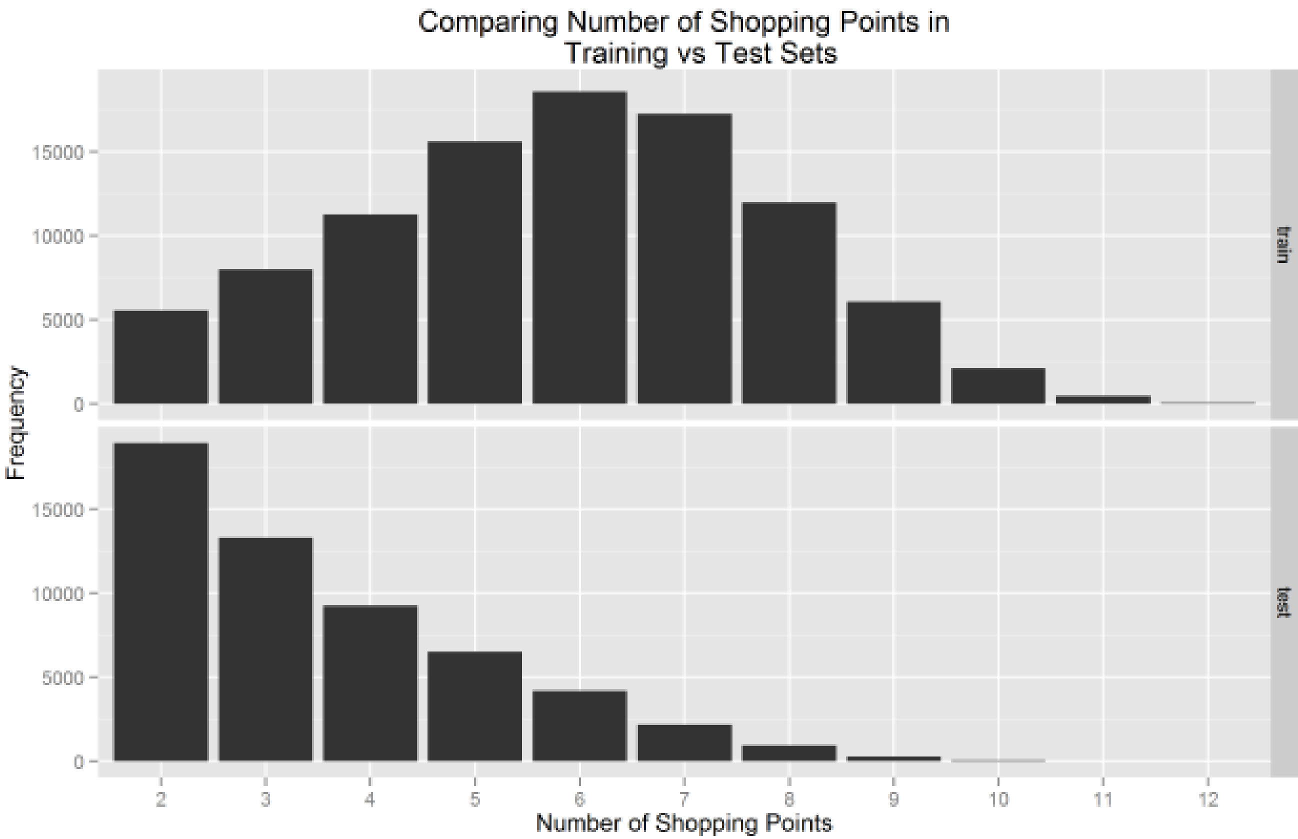
What can we learn from the data?

- The more quotes you have for a customer, the better the naïve strategy will work.



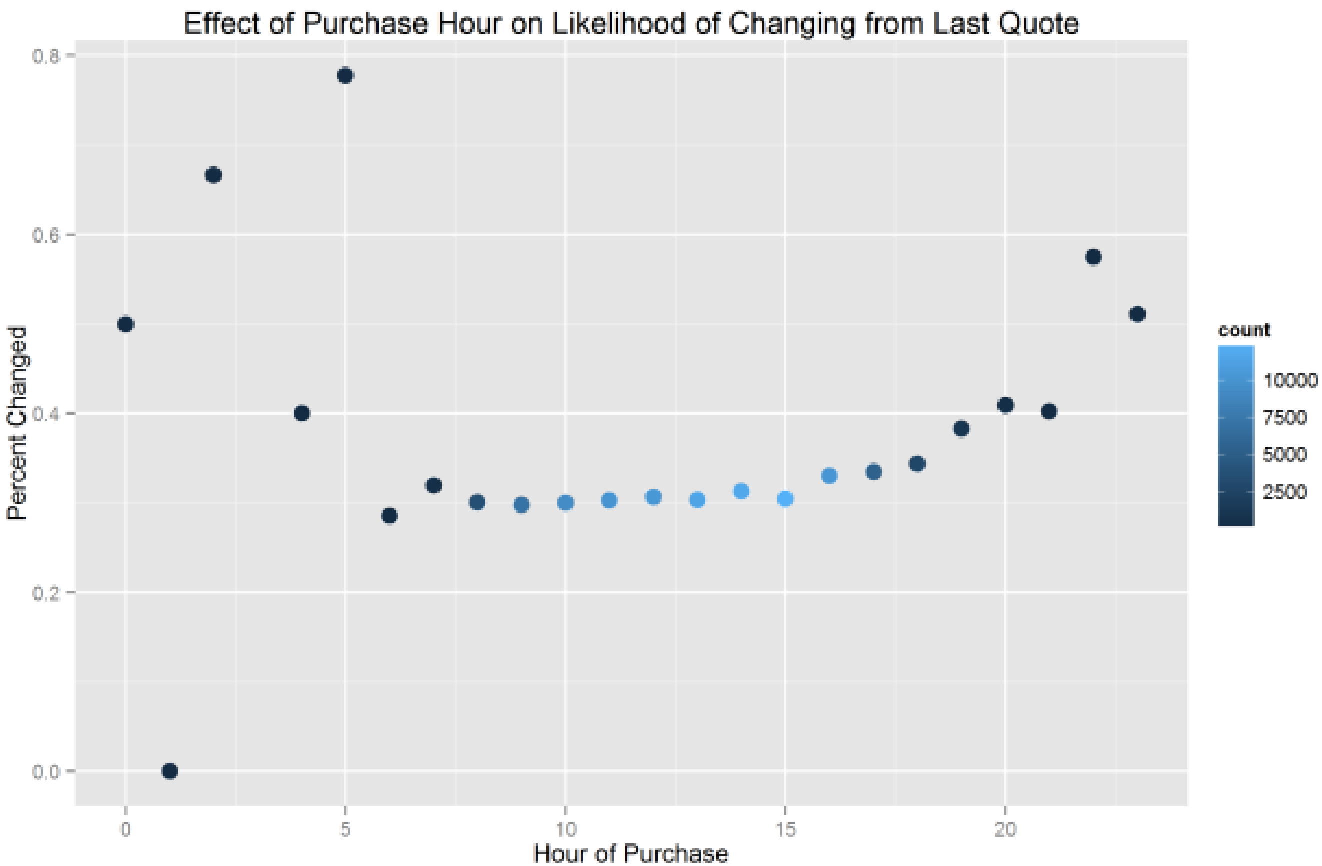
What can we learn from the data?

- Test set has been significantly truncated



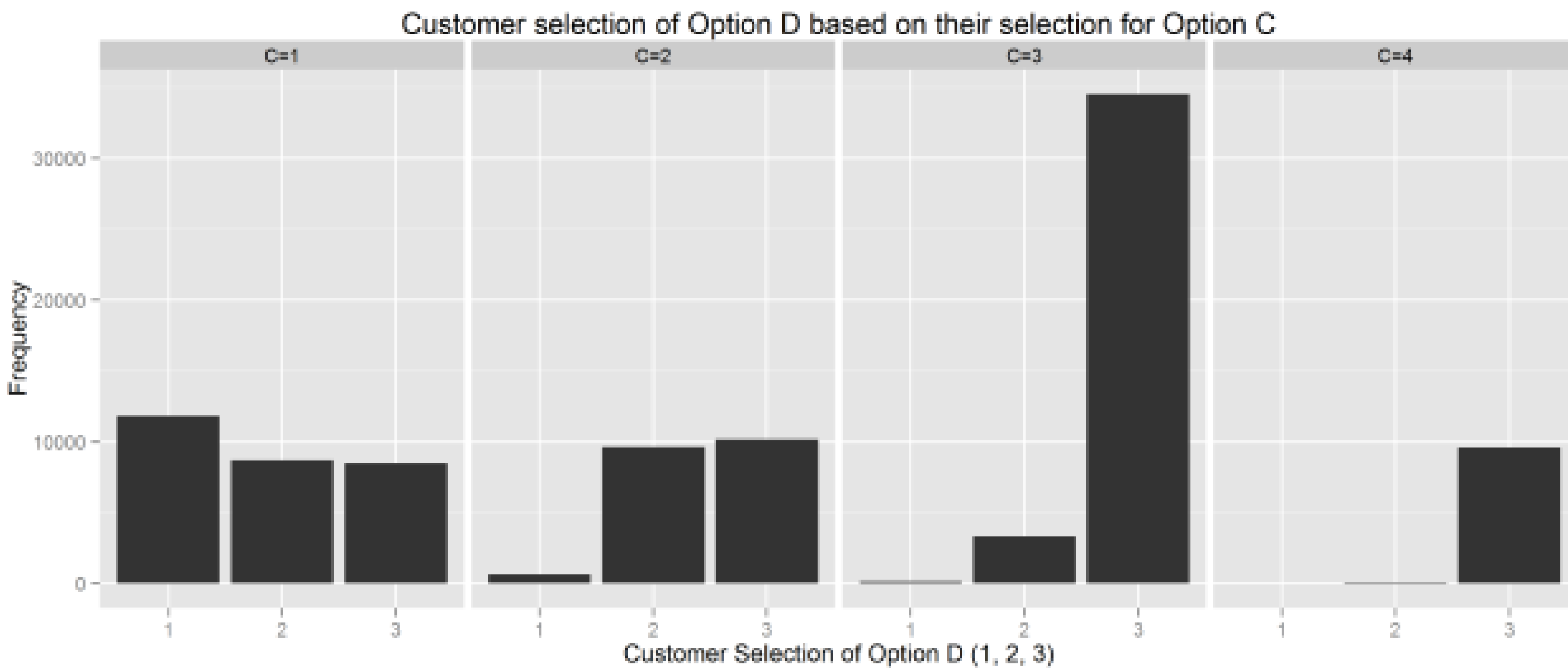
What can we learn from the data?

- Behavior can vary based upon time of day



What can we learn from the data?

- Option selections affect other options



Predict based on option interactions

- Use the naïve approach to make the "baseline" predictions
- Create a list of "rules" about pairs of options, and use these rules to "fix" the baseline predictions
  - Example: If C=3 or C=4, choose D=3
- Result: Worse than naïve approach!

Why didn't this approach work?

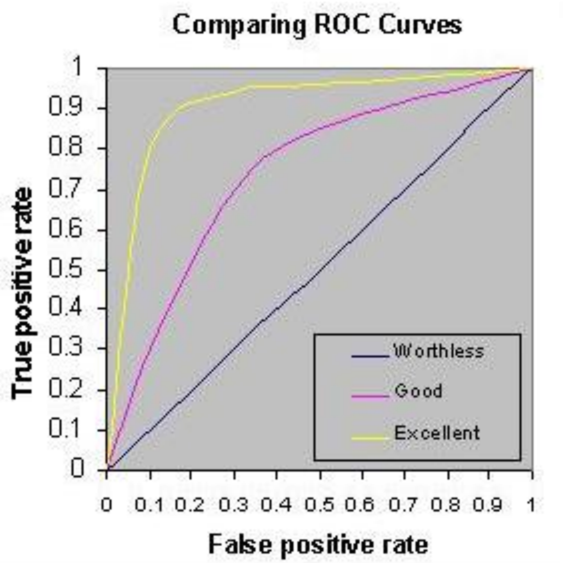
- These "rules" are based on strong **patterns** in the data, but patterns are not always correct
- You don't know how many of the 7 options need to be changed from the baseline
- Key insight: There is a **huge risk** when changing any baseline prediction:
  - There is a 53.793% chance you will "break" a prediction that is already correct.
  - Balance that against the 0.043% chance that you will change an incorrect prediction to be correct!

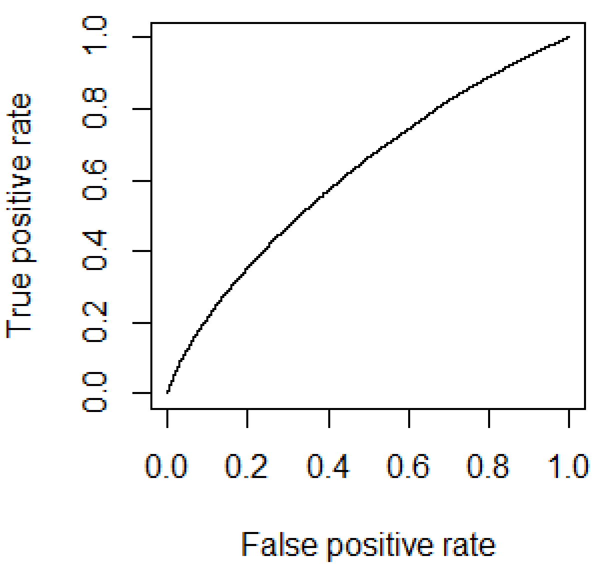
New strategy: Model stacking

- It is **very** important to only change a baseline prediction if you’re sure it’s wrong.
- Use a “stacked model” approach:
  - First, predict which customers are likely to change options after their final quote.
  - Then, fix the baseline predictions **only for those customers.**

Step 1: Predict who will change

- Model with logistic regression, random forests
- Evaluate using ROC curve
  - Reference ROC curve (left) vs. my curve (right)



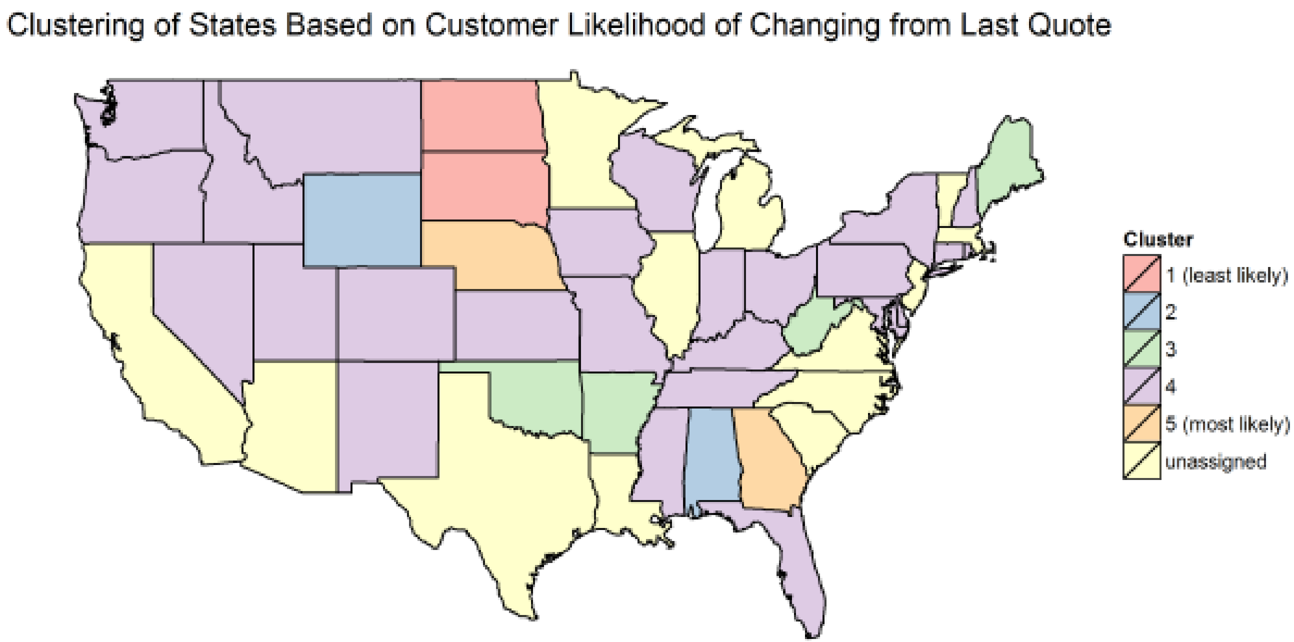


Feature engineering to the rescue!

- Create new features by transforming or combining existing features
- Perhaps less noisy than the raw features (and less likely to overfit the training data?)
- Examples:
  - "family" (yes/no): married, group size > 2, youngest covered individual < 25 years old
  - "timeofday" (day/evening/night): 6am-3pm, 4pm-6pm, 7pm-5am

Feature engineering

- Examples:
  - "stategroup": cluster states based upon observed likelihood of changing from last quote

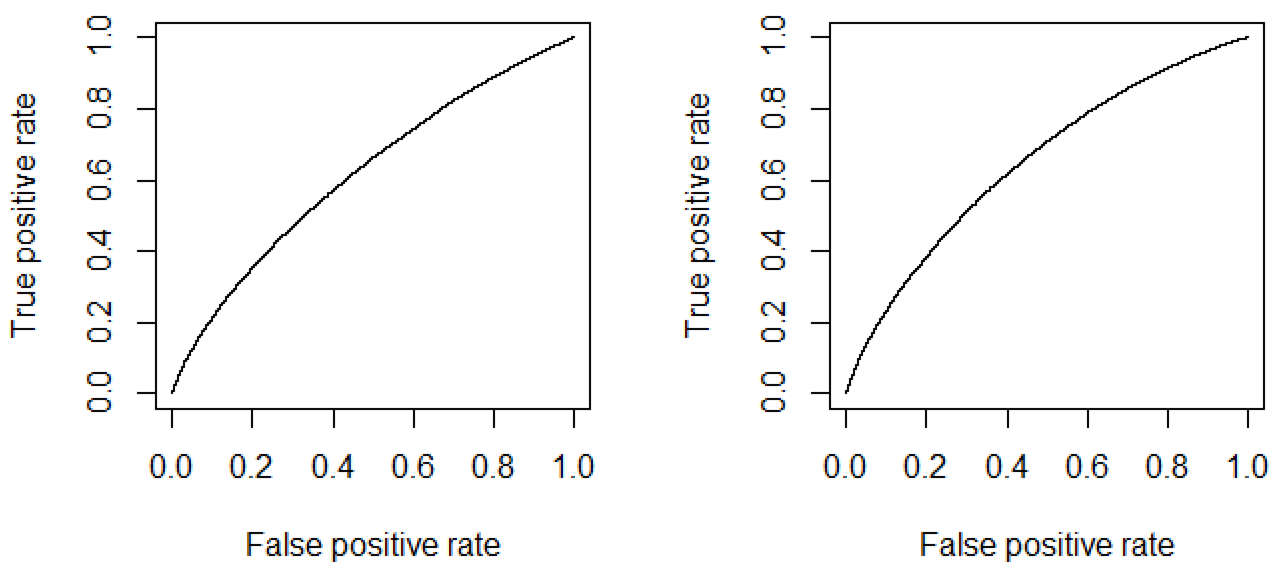


Feature engineering

- Examples:
  - “stability”: calculation of how much a customer changed their plan options during the quoting process (low stability = more likely to change?)
  - “planfreq”: calculated frequency with which a given plan appears in the data (low planfreq = more likely to change?)

Step 1 (redux): Predict who will change

- Redo model, except with new features!
- Evaluate using ROC curve
  - My old curve (left) vs. my new curve (right)



New strategy: Precision not accuracy

- Key insight: When predicting which customers will change, it's much more important to optimize for **precision** than **accuracy**
  - Thus: minimize false positives by setting a high probability threshold
- Example:
  - In test set, about 25,000 customers will change options after their final quote
  - Don't try to find all 25,000; instead find 100 customers you are sure will change (and fix their baseline predictions)

Optimizing for precision

- Created a cross-validation framework to predict the test set precision of my model
- Tuned the probability threshold for predicting change to 0.85 (rather than 0.50)
  - Obtained 91% cross-validated precision on training set
  - Also validated (somewhat) on test set

Step 2: Predict new plans

- Option 1: Build a single model to predict the entire combination of 7 options at once
- Option 2: Build 7 models to predict each option one at a time, and then combine the results
  - Chose this option, and used random forests and single-hidden-layer neural networks

Poor prediction results

- In order for the 7-model approach to produce a correct combination of options at least 50% of the time, each model needs to be at least **90% accurate** (since $0.90^7 = 0.50$)
- Instead, models performed with **60-80% accuracy** and thus rarely predicted a completely correct combination of options

Backup plan: Human learning!

- Chose 9 customers in test set that had a very high probability of change
- Revise option combinations **by hand** using my list of “rules” about unlikely combinations
  - Example: If C=3 or C=4, choose D=3
- Completely non-scalable, but perhaps generates more nuanced predictions?
- Result: No improvement over the baseline

New strategy: Locate unlikely plans

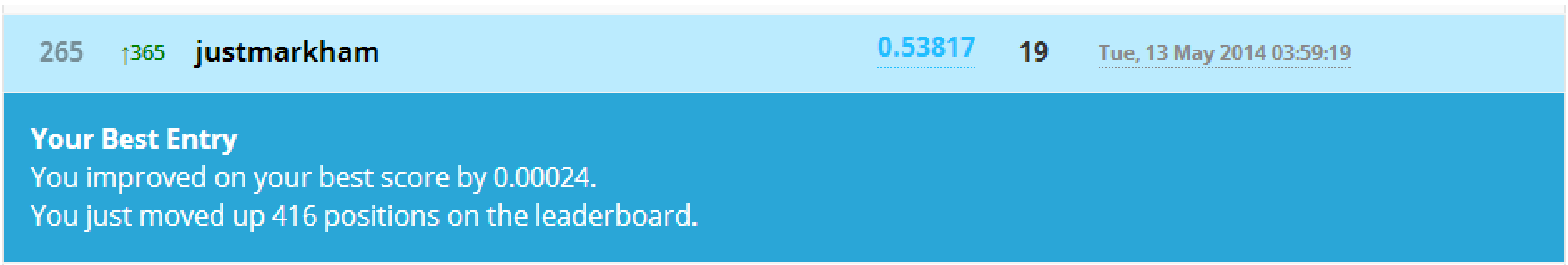
- Based on a tip from the Kaggle forums:
  - Locate plans (combinations of all 7 options) that were "rarely" purchased
  - If those plans were predicted by the baseline approach, replace them with "more likely" alternatives
- These are probably combinations of options that "don't make sense" to most people
- Note: This approach ignores all customer data!

Locating and replacing unlikely plans

- Determine which plans are “unlikely”
  - Calculate **view count** and **purchase likelihood** for every plan and set threshold values
- Determine the best replacement plan for each unlikely plan
  - Tally which plans were actually purchased by those who viewed them
  - Calculate **replacement plan commonality** and set threshold value

It worked!

- Improved upon baseline approach



- Tuned threshold values by submitting many different combinations to Kaggle
- My best submission beat baseline by 0.06%
  – Top competitor beat baseline by only 0.78%

What does this approach look like?

- Change the plans on the left to the plans on the right:

A	B	C	D	E	F	G
0	0	3	1	0	0	4
0	0	1	1	0	0	4
1	1	3	1	1	2	2
2	1	2	2	1	0	1
1	0	1	1	0	0	4
0	0	2	2	0	0	4
0	0	3	1	0	0	2
2	0	4	3	0	0	4
1	1	3	1	1	2	1
0	0	3	1	0	0	3

A	B	C	D	E	F	G
0	0	1	1	0	0	3
0	0	1	1	0	0	2
1	1	3	3	1	2	1
2	1	2	2	1	0	2
1	0	1	1	0	0	2
0	0	2	2	0	0	2
0	0	3	3	0	0	2
2	0	4	3	0	0	2
1	1	3	3	1	2	1
1	1	3	3	1	1	3

Improving this approach

- Stack this approach with one of my models
  - Did not succeed in improving test set accuracy
- Other ideas (didn’t have time to try them):
  - Don’t always replace an unlikely plan
  - Don’t always choose the same replacement plan for an unlikely plan
- Top competitors are likely using an ensemble of models that incorporates this approach

Lessons Learned

- Early in the competition, try many different approaches
- Smarter strategies trump more modeling and more data
- Real-world data is hard to work with
- Algorithms and processes that allow for rapid iteration are priceless
- Learn from others around you

Thank You!

GitHub repository with paper and code:

https://github.com/justmarkham/kaggle-allstate