DSCI6003: Ultimatum Game

A machine learning approach to maximizing your earnings

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Overview

1) What is the ultimatum game?

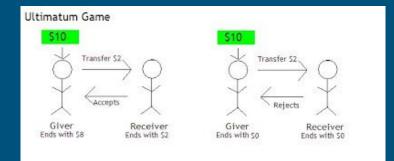
2) What does the data look like?

3) How to maximize how much money we make?

Traditional Ultimatum Game







Empirical Results

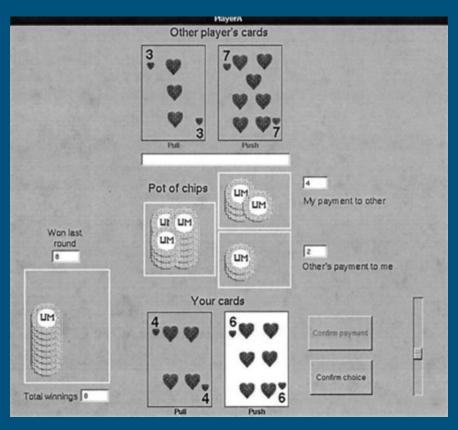
- Cooperation is very low (15-50%) even though nash equilibrium suggests responder should accept any offer.
- What is the accuracy for predicting our payoff playing this game?



Overview of game structure

- 1. Two rounds of experiments.
 - 1) First 15 rounds
 - Push: Give the other player money from the pot of money(\$6 or \$7)
 - Pull: Take money from the pot (\$3 or \$4)
 - 2) Rounds past 15 allowed each player to make a side payment for the other to push
 - Typically offer between \$1-\$3 for other player to push
- 2. Three rounds of analysis
 - 1) Rounds without a side payment (rounds 1-15)
 - 2) Rounds with a side payment (rounds past 15)
 - 3) All rounds
- 3. Players played multiple rounds

The experiment



The Data

- In total 1,920 rows. Each row was a full game experiment.
 - 720 without a side payment
 - 1200 with a side payment
- Features used (only use features available to you in the game).

- Rd 1-15

	rd	myside	opptside	mypush	mypull	opptpush	opptpull	mychoice	mychoicecard	mypayoff	opptpayoff	totalpayoff
0	1	0	0	6	4	7	3	0	4	11	0	11
1	1	0	0	7	3	6	4	1	7	0	11	11

- Past rd 15

		rd	myside	opptside	mypush	mypull	opptpush	opptpull	mychoice	mychoicecard	mypayoff	opptpayoff	totalpayoff
1	915	40	4	3	6	4	7	3	0	4	7	4	11
1	916	40	3	5	6	4	7	3	1	6	9	4	13

- Goal: Predict mypayoff

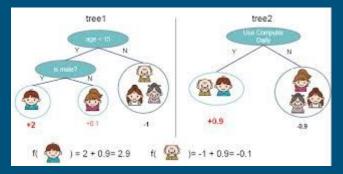
Algorithms Used

1) Random Forest



- Random Forest
- KNNregression
- Gradient Boosting
- Extreme Gradient Boosting
- GLM/Elastic Net

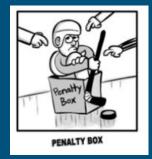
2) Boosting



Ensembles

- Linear ensemble of all models
- GB ensemble of all models and all original features

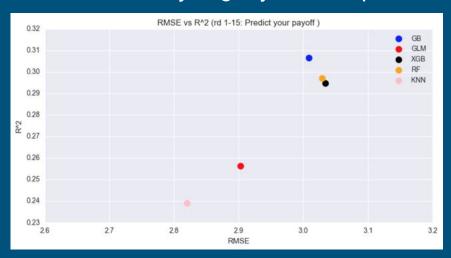
3) GLM/Elastic net

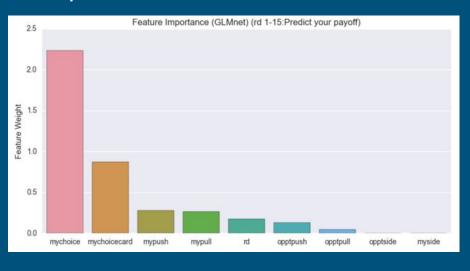


http://xgboost.readthedocs.io/en/latest/model.html

Rounds 1-15

- Results vary slightly based upon train test split

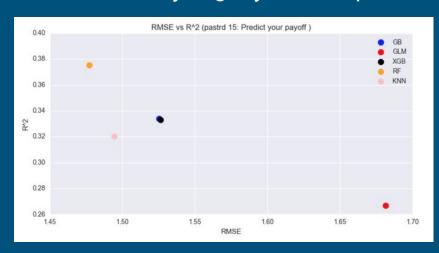


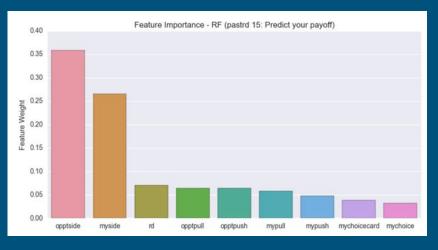


^{*} Best parameters found from randomized gridsearch. Feature importance from glmnet.

Rounds past 15

- Results vary slightly based upon train test split

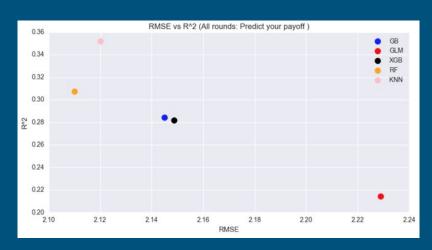


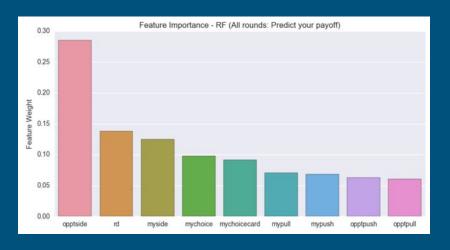


^{*} Best parameters found from randomized gridsearch. Feature importance from RF.

All rounds

- Results vary slightly based upon train test split





^{*} Best parameters found from randomized gridsearch. Feature importance from RF.

Ensemble

- Dataframe (linear):

2350	GLM_scaled_train	GB_train	RF_train	XGB_train	KNN_train	actual_training
0	5.342700	6.299544	6.238544	6.178087	5.53125	7
1	5.357743	6.536596	6.300855	6.752759	6.84375	7

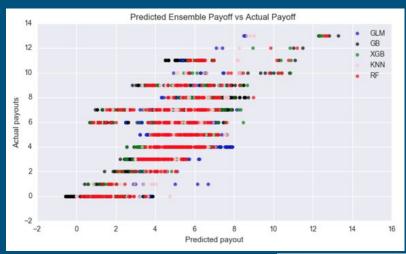
- Dataframe (meta):

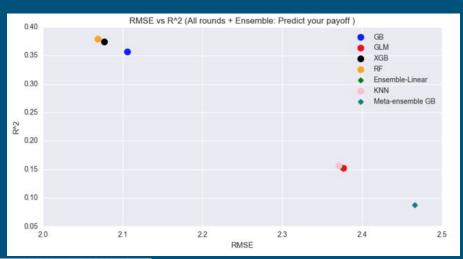
	rd	myside	opptside	mypush	mypull	opptpush	opptpull	mychoice	mychoicecard	GLM_scaled_test
count	384.000000	384.000000	384.000000	384.000000	384.000000	384.000000	384.000000	384.000000	384.000000	384.000000
mean	-0.092270	-0.141051	-0.078104	0.000000	0.000000	0.000000	0.000000	0.008464	0.027195	4.740063

- Weights per model (linear):
- Weights (meta):

```
##Column order = GLM_scaled , GB, RF, XGB , KNN
stacked_model.coef_
array([-0.12448028, 0.93010836, 0.28100216, -0.07034054, -0.05362199])
```

Ensemble results





Linear Ensemble RMSE: 2.3735259857168507 Linear Ensemble R2: 15.46% Meta-Ensemble GB RMSE: 2.4664525647799427 Meta-Ensemble GB R2: 8.71% RF RMSE: 2.069208444284043 RF R2: 37.89%

*Neither ensemble method could beat the final RF model.

Questions