# Game Show Modeling with Utility Theory and Machine Learning

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## Sample Round


## Questions of Interest

1. Given the lack of a publicly available framework, how can we accurately model the banker's offers?
2. What do we notice about past players' gameplay?
3. How can we replicate empirical gameplay data and describe it in terms of utility theory?
4. What methods are best to generate an optimal player strategy?

## Background Information

- A **utility theory** contains a binary **preference relation** on a set of $X$ elements that represent choices or actions.
- $x \preccurlyeq y \iff$ "$x$ is not preferred to $y$"
- Utility functions characterize the behavior of $\preccurlyeq$ via assigning values to outcomes that respect the preference relation.
- **Expected Utility Theory** is a method that identifies optimal decisions when presented with a risky choice. It is based off of expected value of the choice and individuals' utility functions.

## Sample Data

| Player | Education | Stop | Their Case | Winnings |
|---|---|---|---|---|
| Bezos | High | 9 | $750 | $202,281.22 |

| Round | Expected Value | Banker Offer |
|---|---|---|
| 1 | $168,368.30 | $25,521.51 |
| 2 | $169,089.40 | $31,617.91 |
| 3 | $212,348.20 | $70,336.80 |
| 4 | $290,718.80 | $187,661.90 |
| 5 | $337,625.00 | $279,990.97 |
| 6 | $205,150.00 | $146,986.90 |
| 7 | $156,437.50 | $91,962.48 |
| 8 | $175,250.00 | $100,024.67 |
| 9 | $250,375.00 | $202,281.22 |

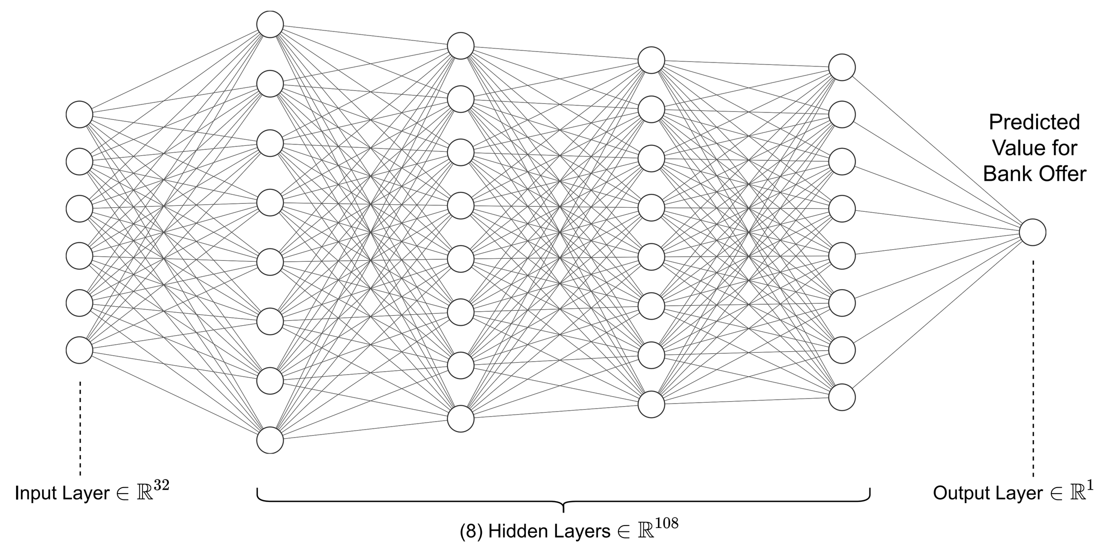
## Banker Models

**Initial Banker Models**

| Model | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Log Linear Regression | 13977.03 | 22824.64 | 0.92 |
| Random Forest | 15372.02 | 23571.23 | 0.91 |
| kNN (k=8) | 16181.01 | 22654.55 | 0.92 |
| Deep Neural Net | 11368.58 | 16849.30 | 0.95 |

### Neural Net Measures of Fit

- MAE: ranges from $11,000-$13,000
- MSE: ranges from $16,000-$19,000
- $R^2$: ranging between 0.940-0.957




## Player Models

### Logistic Regression

This model predicted the player's decision with 92.7% accuracy and a 50% cutoff. It was used to generate decisions for the 1000 simulated players.

### Utility Model

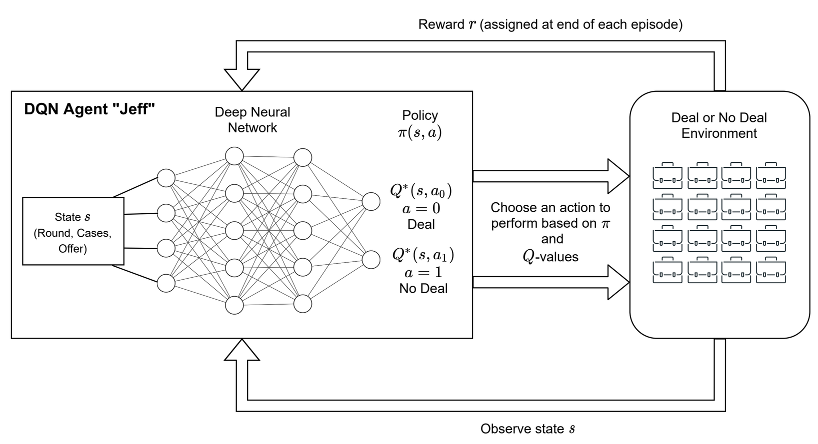
Utility for a deal, inspired by Khoszegi and Rabin's path dependent model, is the bank offer plus the scaled difference between the expected value of the round and the expected value that had been predicted for that round:

$$u(\text{offer}) + 0.1 \cdot (EV - PEV)$$

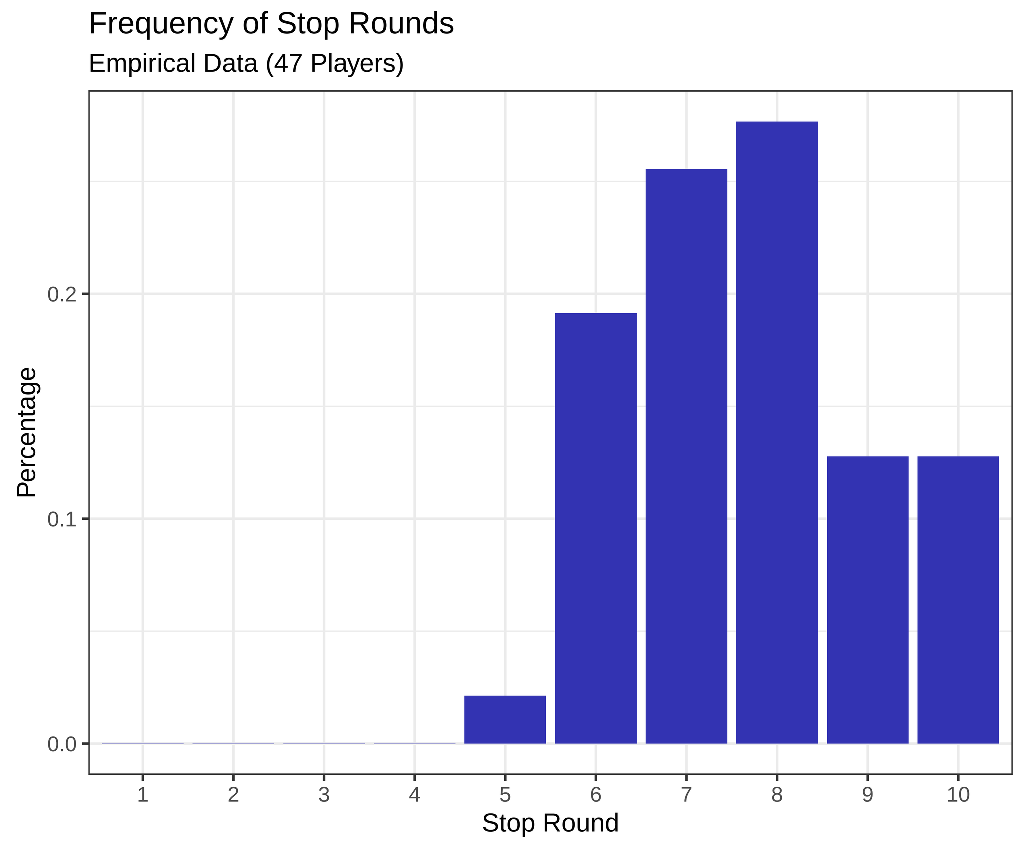
Utility for a no deal is the the average expected utility over all possible states of the next round, plus a scaled average predicted banker offer.
This resulted in an accuracy of up to 92.12% on the empirical data and 86.74% on the simulation data.

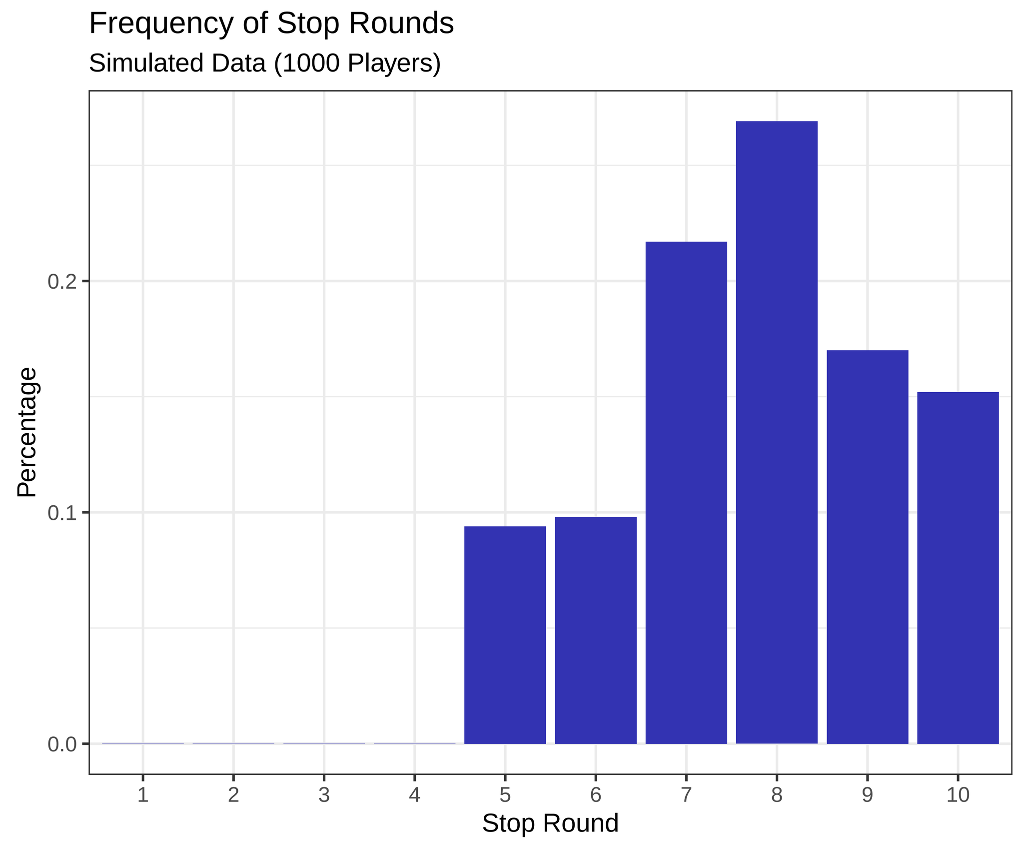
### Reinforcement Learning

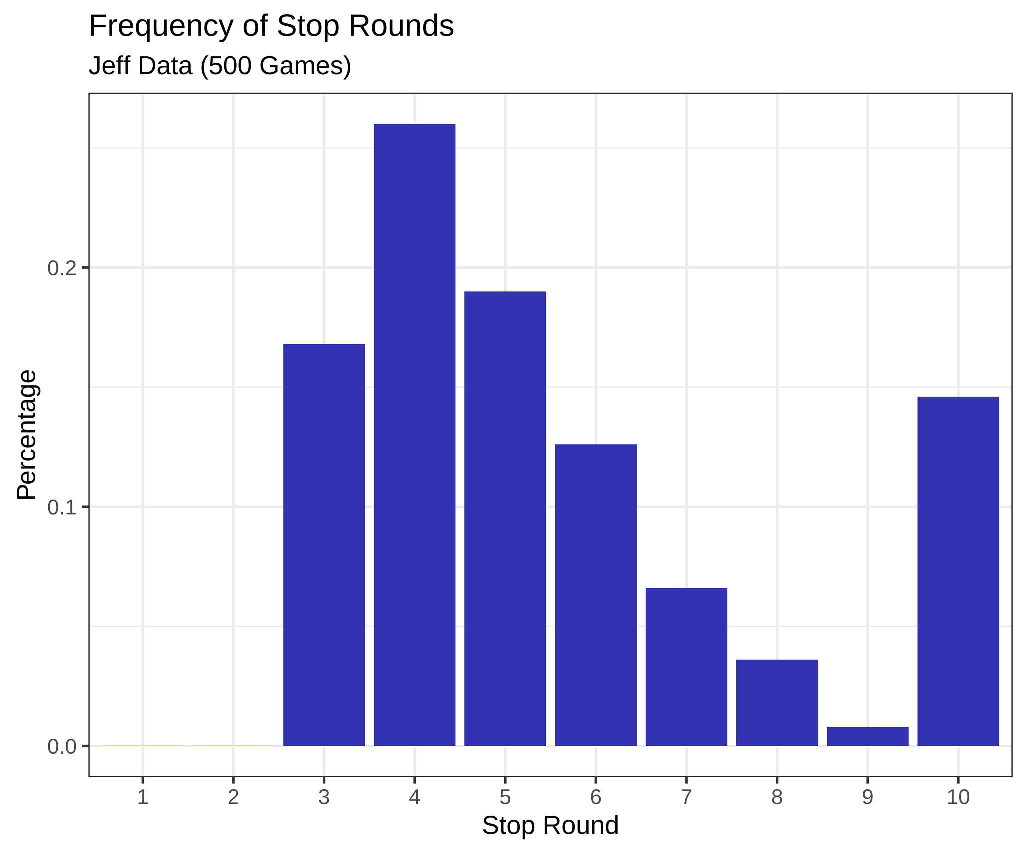
This model beat simulated contestants 42.3% of the time.




## Results




## Future Work and Acknowledgements

- People don't always act rationally; they may choose plays with lower utilities, or trembles.
- Nesting our utility function in a model of stochastic choice can incorporate this behavior into our model and possibly improve the accuracy of our predictions.
- This presentation summarizes the results of the CC-REU NSF summer REU experience (DMS-2050692) where these questions were explored.

## References

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