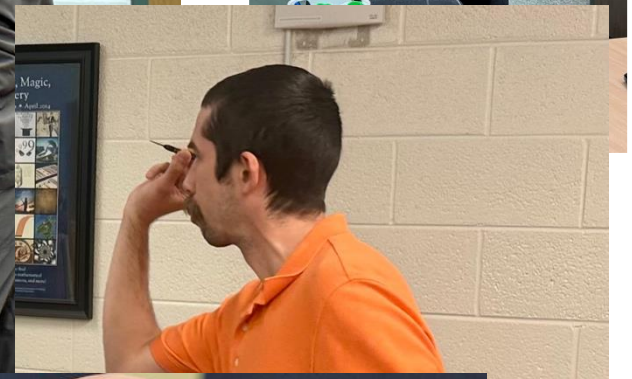
Darts Analysis

Ayham Makhamra – Roanoke College ‘26

Mike Weselcouch – Roanoke College


USA

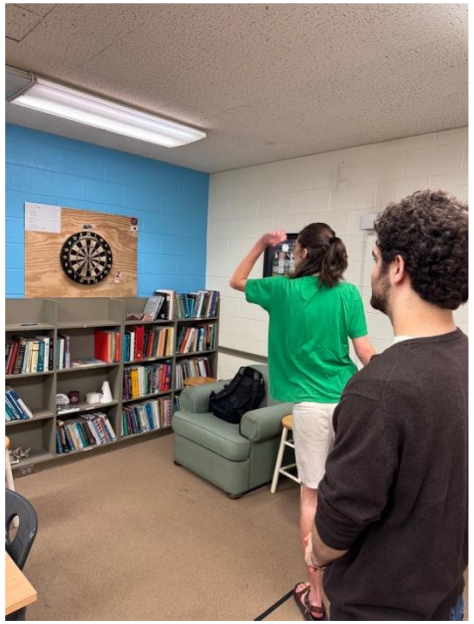

PRESTIGE
BUILDING SUPPLIES LTD

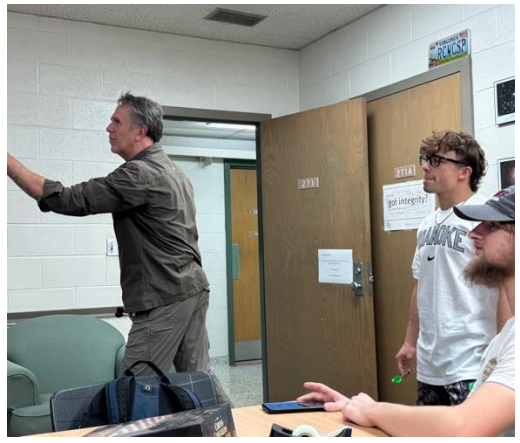


TARGET


WINMAU

Students Yearn for Community!





Darts 271

- Head-to-head matches.
- Throw 3 darts per round.
- Each throw is worth the number of points of its section with outer ring doubling and inner ring tripling the number of points.
- Games end when a player is leading after 271 points.
- No set schedule so players choose who they play and when.

Round	Mike Weselcouch	Ayham Makhamra
1	0	0
2	55	57
3	128	109
4	204	171
5	233	200
Final	285	257

ROANOKE COLLEGE

MCSP Darts

Submit Score

Second Minton Invitational

Player 1

Michael Weselcouch

Total - 0 (271 to go)

19	57	19

Player 2

Ayham Makhamra

Total - 0 (271 to go)

20	60	18

Update Totals

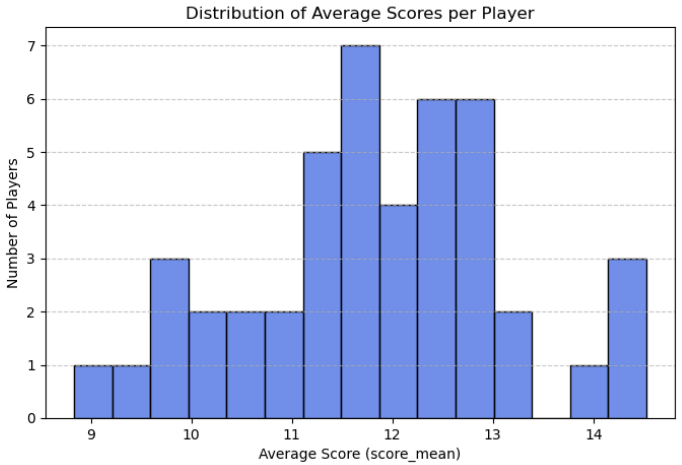
Join Discord Server

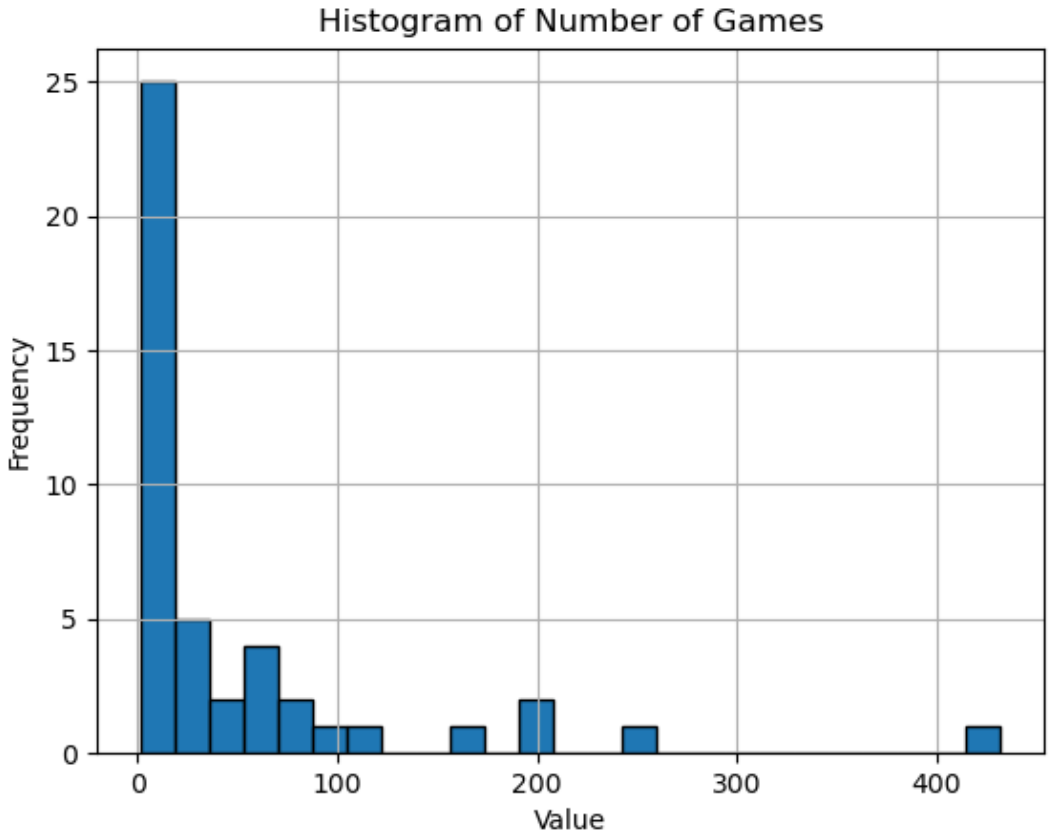
Our Data Set

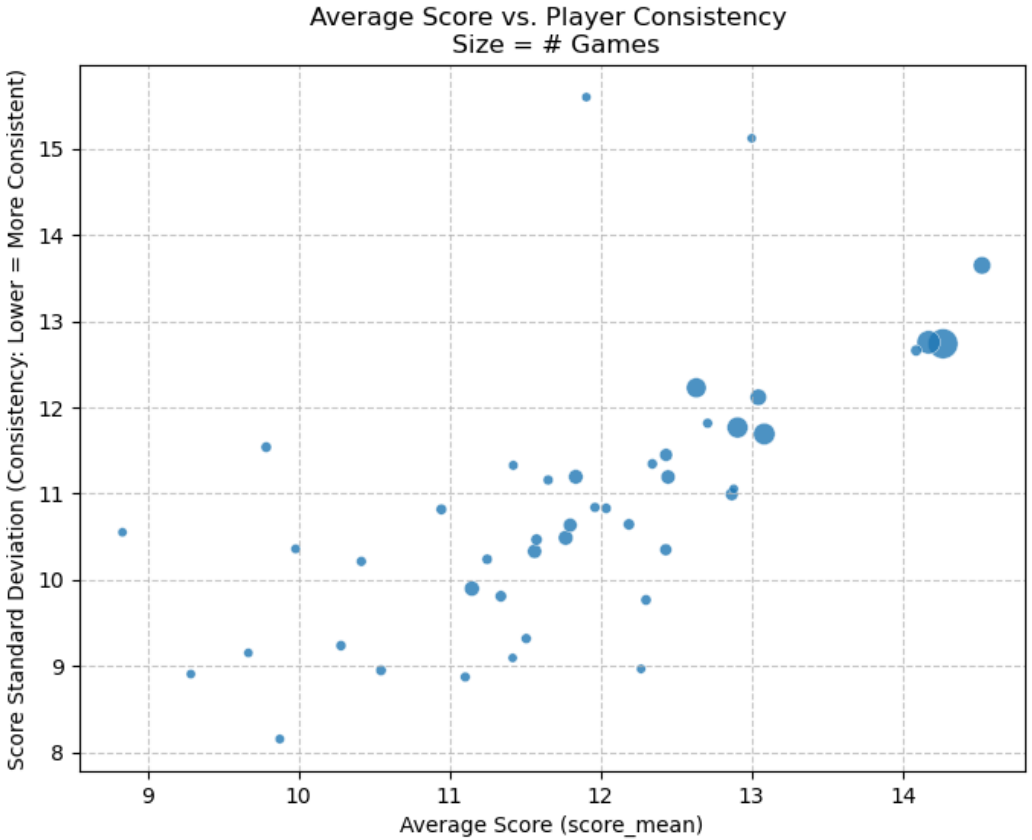
- App was created by RC Math+CS Major, Liz Satynska.
- For each throw, app records:
  - Start Time of Game
  - Game ID
  - Player ID
  - Opponent ID
  - Round Number
  - Points Scored
- Doesn't have:
  - Multiplier (triple 6 and single 18 are same)
  - Which player throws first.
  - Correct order of throws in round.

Overview

- 1131 total games & >40,000 throws
- 45 players
- 157 player vs player matchups.

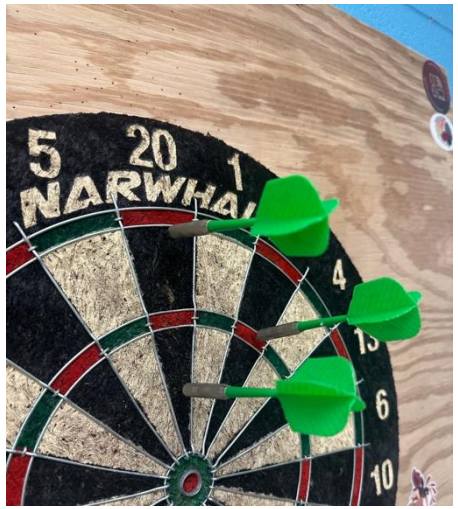


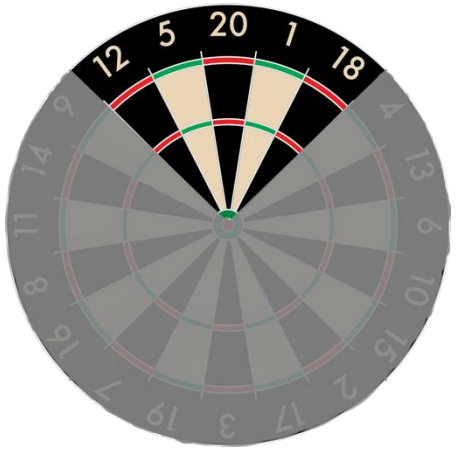




Basic Strategies

- Aim for triple 20 (highest possible score)
- Aim for triple 19 (more points for misses)
- Aim for the board (anything is better than nothing)





A Statistician Plays Darts

Ryan J. Tibshirani* Andrew Price† Jonathan Taylor‡

Abstract

Darts is enjoyed both as a pub game and as a professional competitive activity. Yet most players aim for the highest scoring region of the board, regardless of their skill level. By modeling a dart throw as a 2-dimensional Gaussian random variable, we show that this is not always the optimal strategy. We develop a method, using the EM algorithm, for a player to obtain a personalized heatmap, where the bright regions correspond to the aiming locations with high (expected) payoffs. This method does not depend in any way on our Gaussian assumption, and we discuss alternative models as well.

Keywords: *EM algorithm, importance sampling, Monte Carlo, statistics of games*

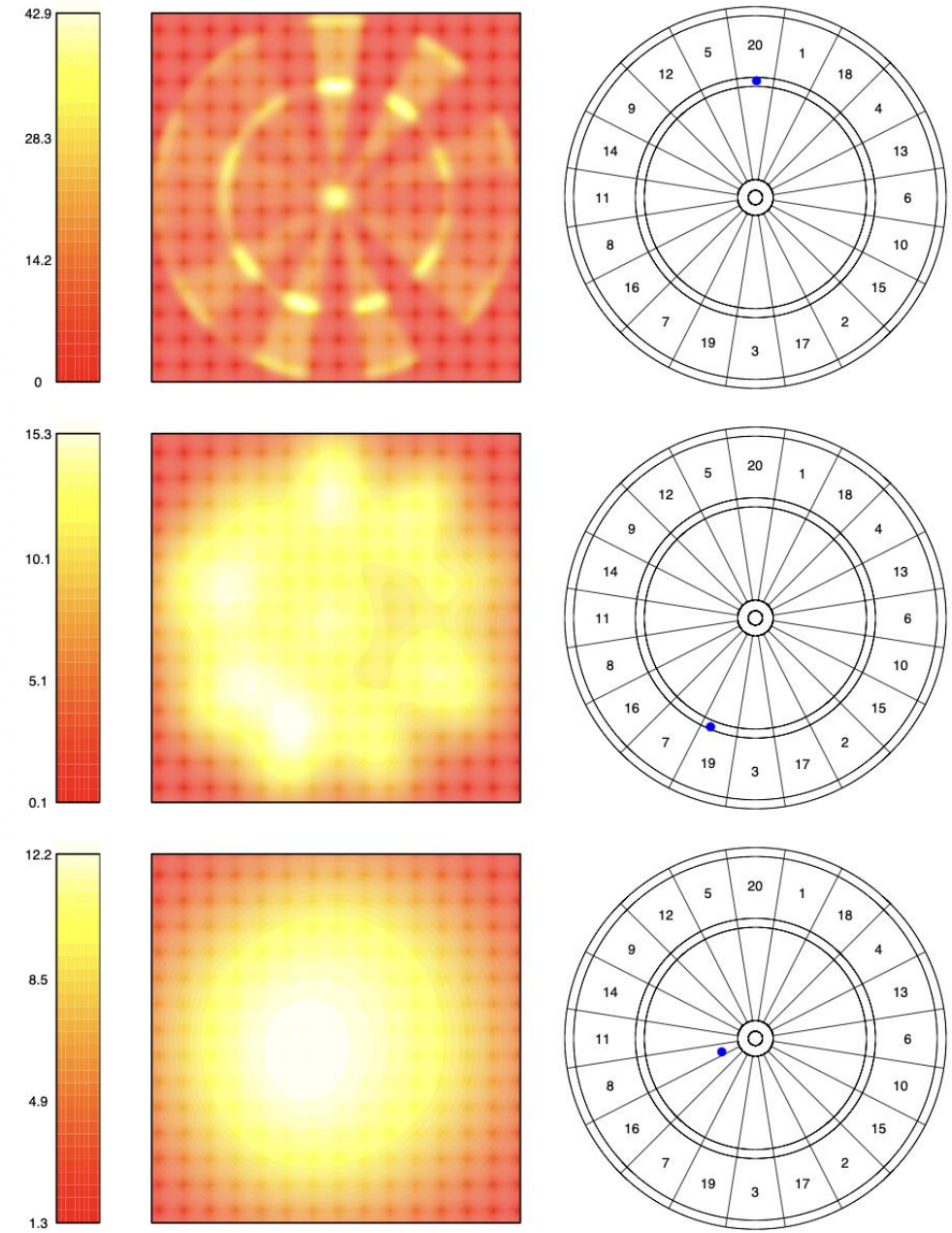
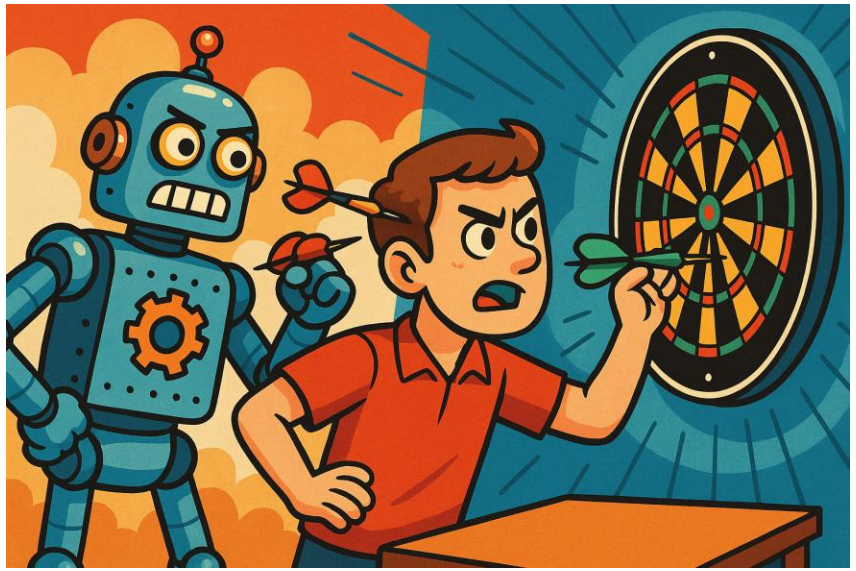


Figure 2: *Heatmaps of* $\mathrm{E}_{\mu,\sigma^2}[s(Z)]$ *for to* $\sigma = 5, 26.9,$ *and* 64.6 *(arranged from top to bottom). The color gradient for each plot is scaled to its own range of scores. Adjacent to each heatmap, the optimal aiming location is given by a blue dot on the dartboard.*

Brier Score

$$BS = \frac{1}{N}\sum_{t=1}^{N}(f_t - o_t)^2$$



Thank you ChatGPT for the image.

- Measures accuracy of a model.
- 0 = perfect, 1 = awful
- Model with lower BS is better.
- N = the number of predictions.
- f_t is the forecast probability (i.e. 25% chance),
- o_t is the outcome (1 if it happened, 0 if it didn't).

Our two models

1. **Logistic Regression Model (Cut-off Date Model)**

Training: Data before April 1st

Testing: Data after April 1st

Pros:

- Machine automatically detects patterns
- Can handle many variables and interactions

Cons:

- Less intuitive—"black box" nature
- Hard to explain why the model predicts a winner

2. **Simulation Model (Intuitive Model)**

Build **player scoring distributions**: e.g., probability of throwing 0, 1, …, 60

Simulate 1,000 games between players based on these probabilities

Win Probability = proportion of wins

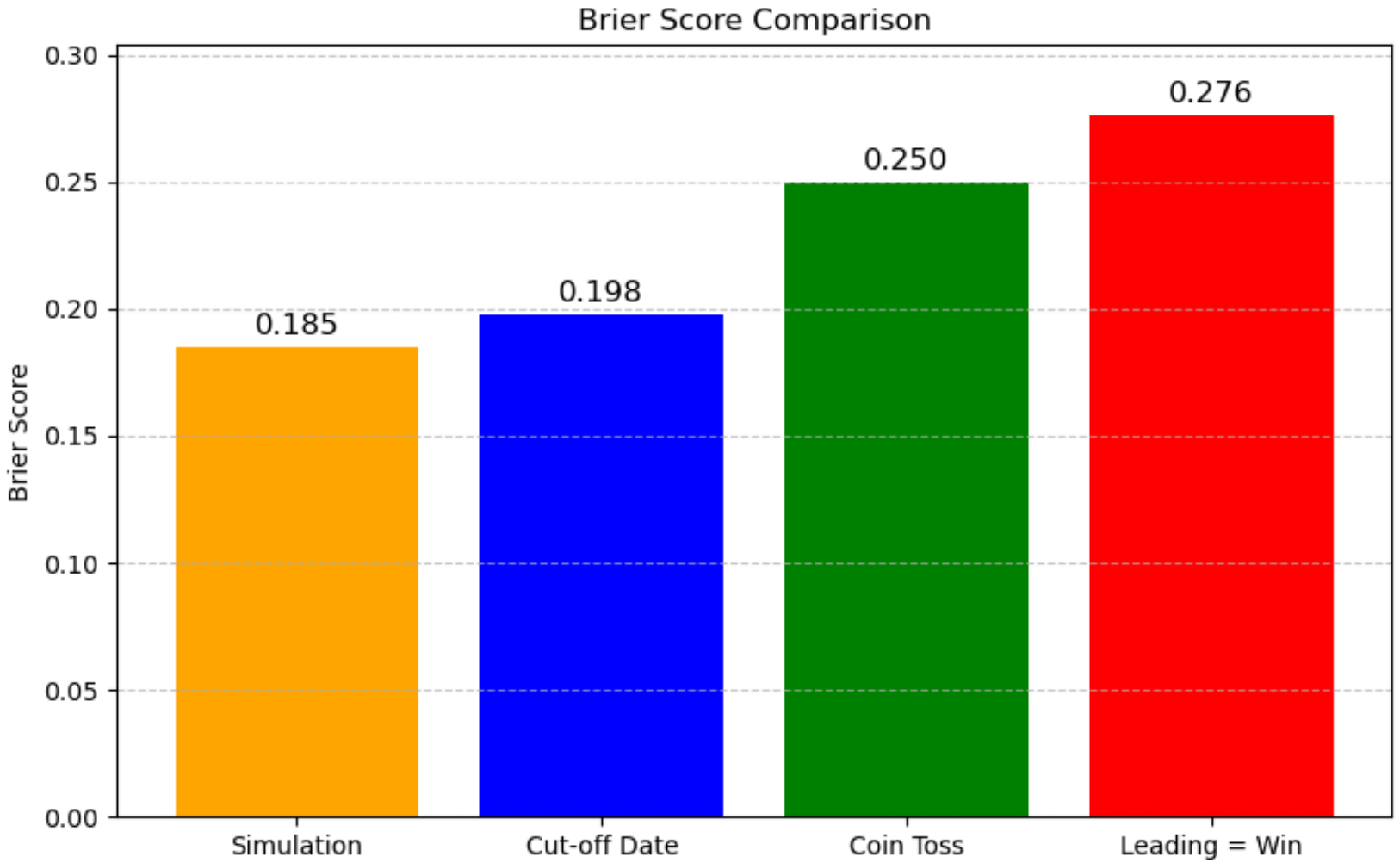
Pros:

- Intuitive and interpretable
- Mirrors human reasoning ("How often would this player likely win?")

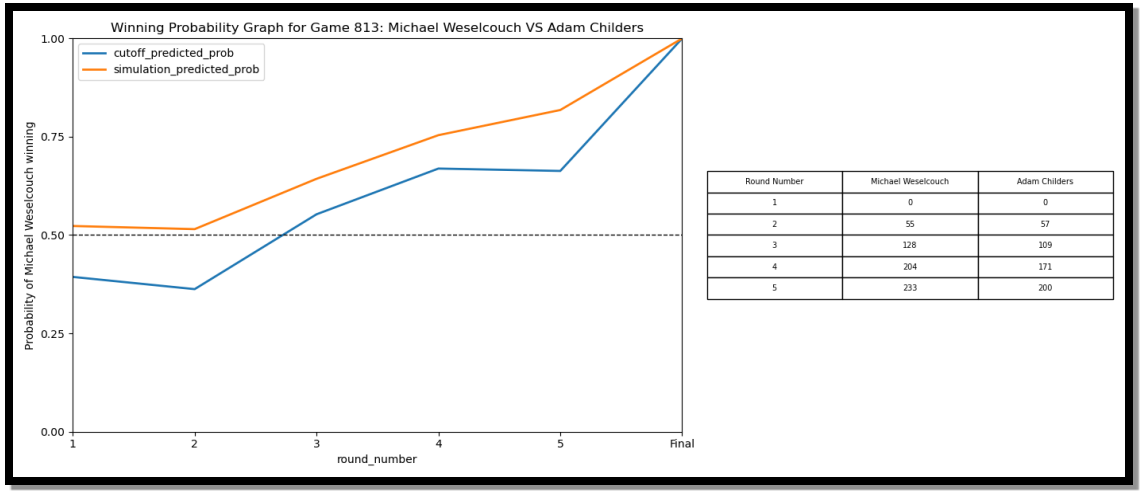
Cons:

- Assumes past scoring patterns fully represent skill

Brier Score Comparison

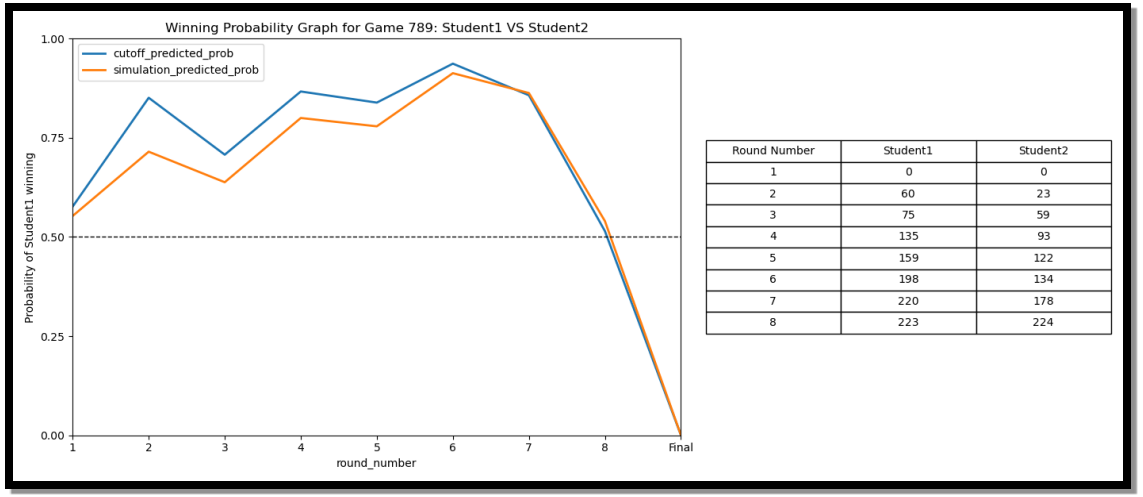


Our two models often agree



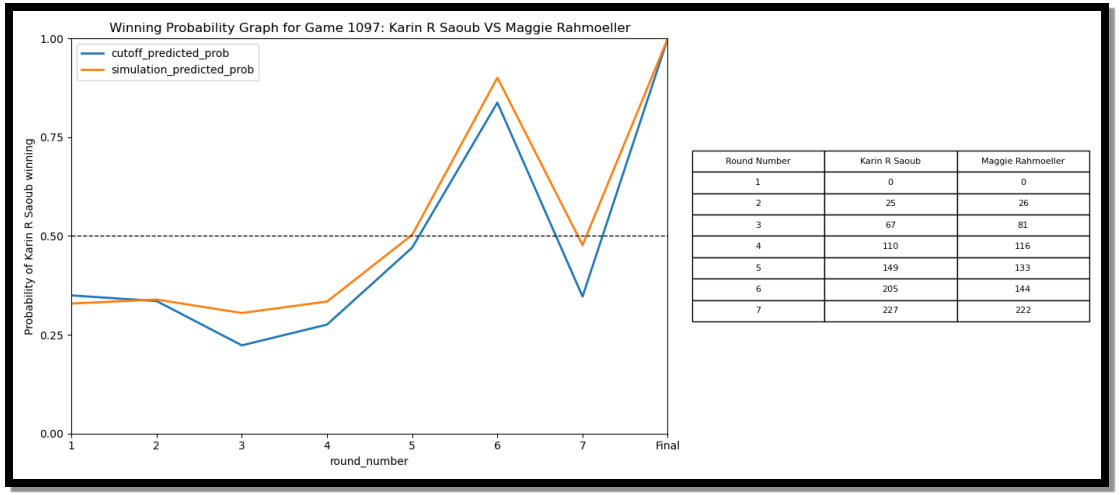
Round Number	Michael Weselcouch	Adam Childers
1	0	0
2	55	57
3	128	109
4	204	171
5	233	200

Figure 1. Both Models Agree



Round Number	Student1	Student2
1	0	0
2	60	23
3	75	59
4	135	93
5	159	122
6	198	134
7	220	178
8	223	224

Figure 2. Both Models Agree, but big surprise



Round Number	Karin R Saoub	Maggie Rahmoeller
1	0	0
2	25	26
3	67	81
4	110	116
5	149	133
6	205	144
7	227	222

Figure 3. Both Models Agree, but change a lot

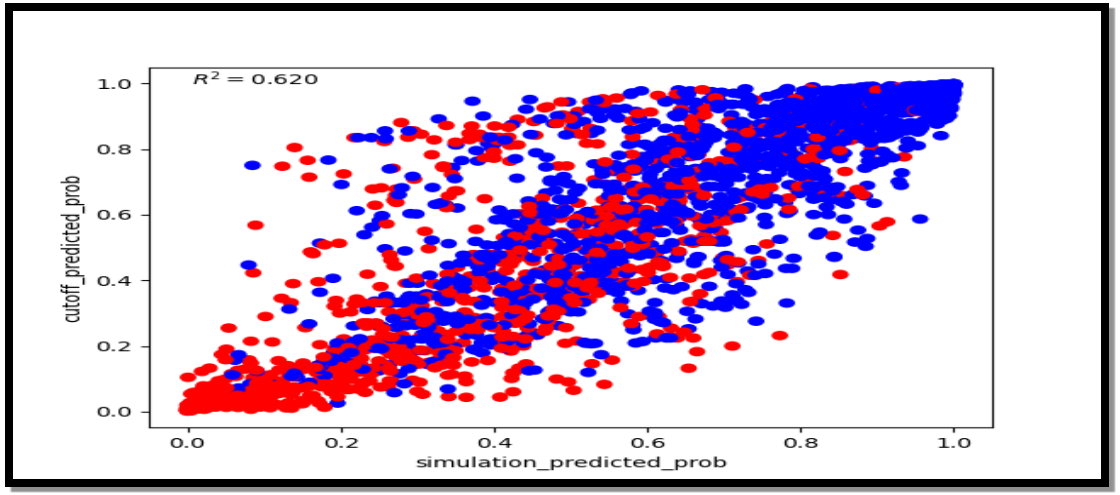
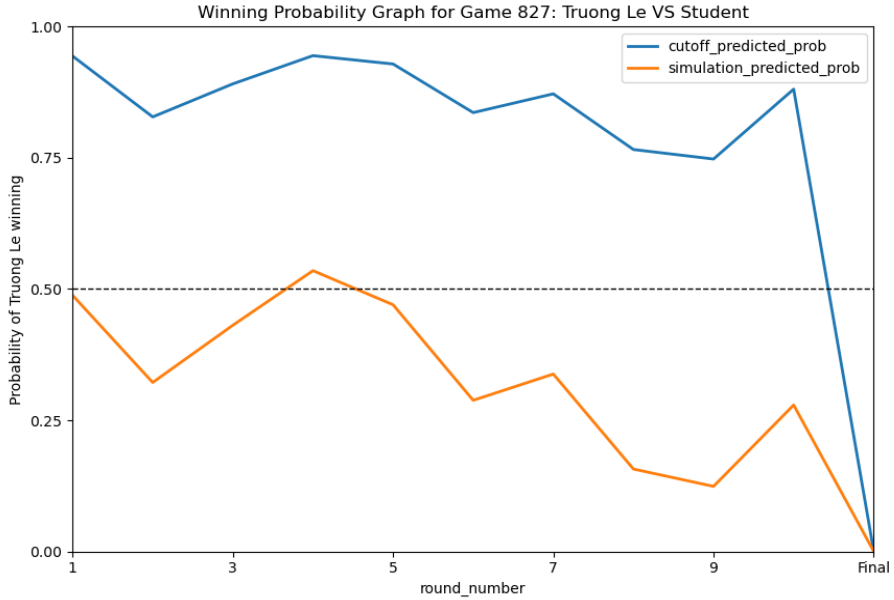


Figure 4. Models Comparison Scatter Plot

Flaws with Black Box

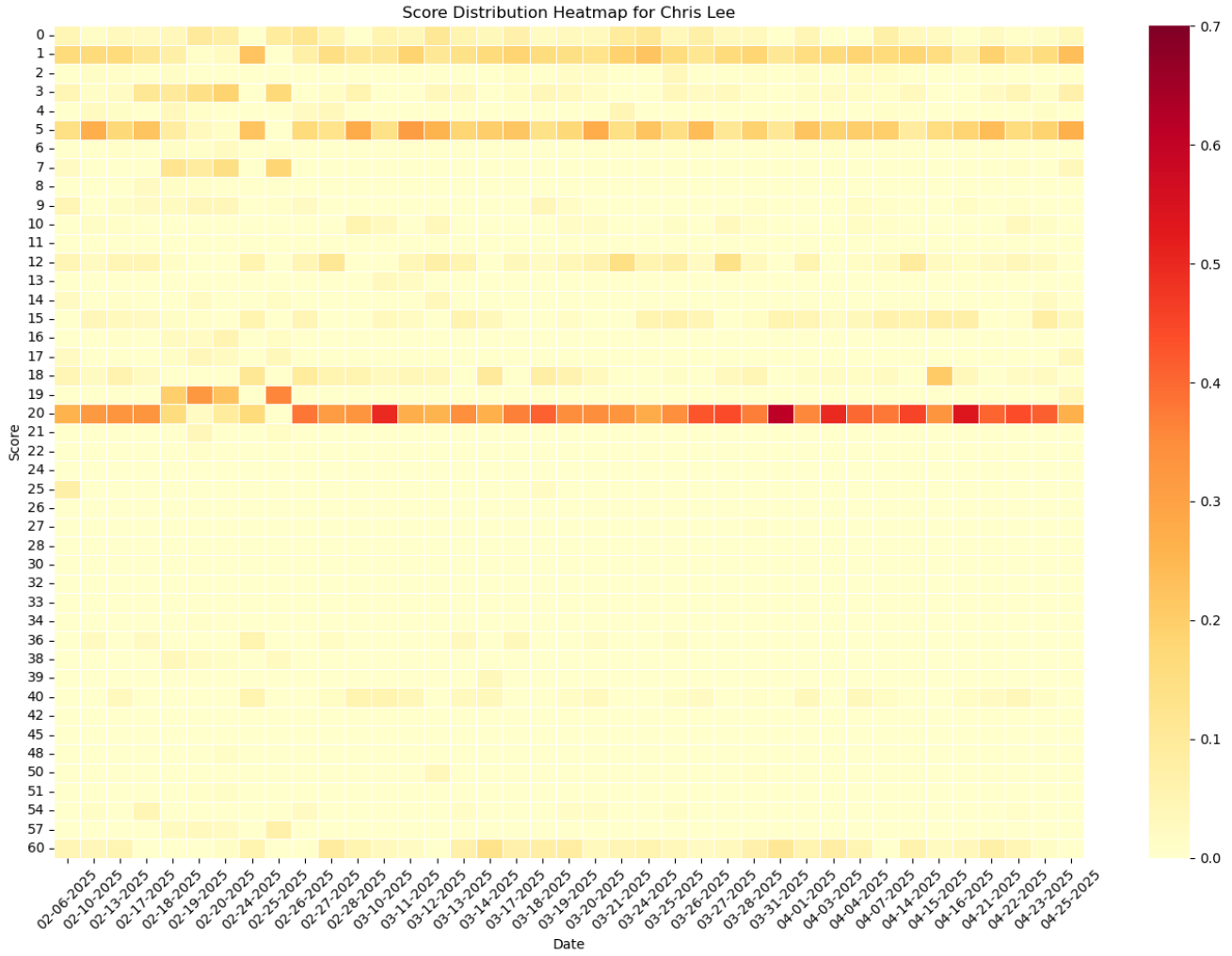


Round Number	Truong Le	Student
1	0	0
2	2	33
3	39	56
4	68	66
5	98	102
6	111	138
7	147	166
8	156	193
9	175	214
10	231	246

- **Overconfidence in Familiar Players:**
- The logistic regression preferred Dr. Le even when losing (175 vs 214)???
  - **Reason – Overfitting / Memorization:**
- After reviewing pre-April 1st training data, we found that:
  - Dr. Le always beat this student.
  - Probably, overfitting.
- **Key Takeaway:**
- Black Box ≠ Game Awareness.

Flaws with Simulation

- Simulation relies on historical throw distributions
- **Problem:** players change strategy in tournaments
- In high-stakes games, players stick to one scoring strategy (often aiming for 19 or 20).
- **Key Takeaway:**
- Simulation is interpretable and intuitive but fails when strategy shifts away from historical averages.

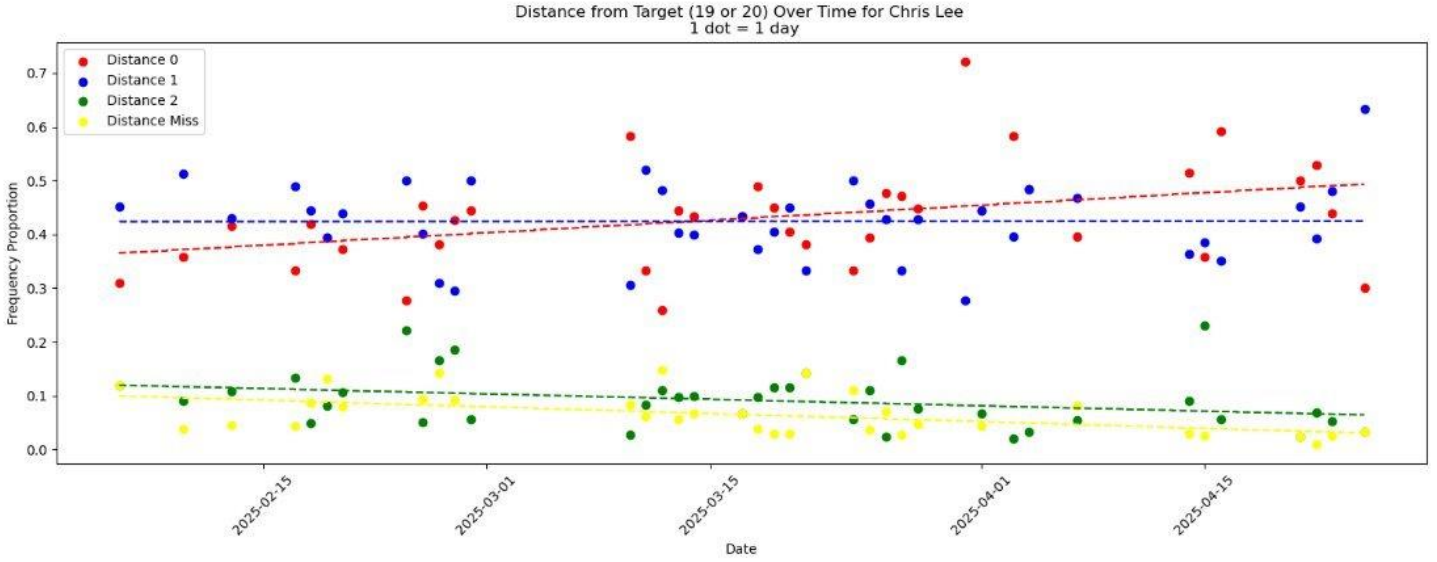


Dist. 0, 1, 2, miss…. New model?

- Introduce a **distance-based distribution** instead of using all raw scores.
- Map scores to distance from target:
- Distance 0 → target/multiples
- Distance 1 → immediate neighbors
- Distance 2 → secondary neighbors
- Miss → everything else

Distance Model

- Use regression to estimate current proportion of Distance 0, 1, 2, and Miss for each player on April 1.
- Use these proportions to simulate games.
  - Dist 0 = ~20 points
  - Dist 1 = ~5 points
  - Dist 2 = ~16 points
  - Miss = ~? Points
- Weights can be player-dependent.



Future Work

- Implement distance model and compare to two other models.
- Score-dependent Massey Method.
- Collect more darts data and test models on new data.

My best round. 133 points!

Thank you!