

PassPredictR: Contextualizing NFL Throwing Decisions By Modeling Receiver Choice



Lou Zhou
Rice University

Zachary Pipping
University of Florida

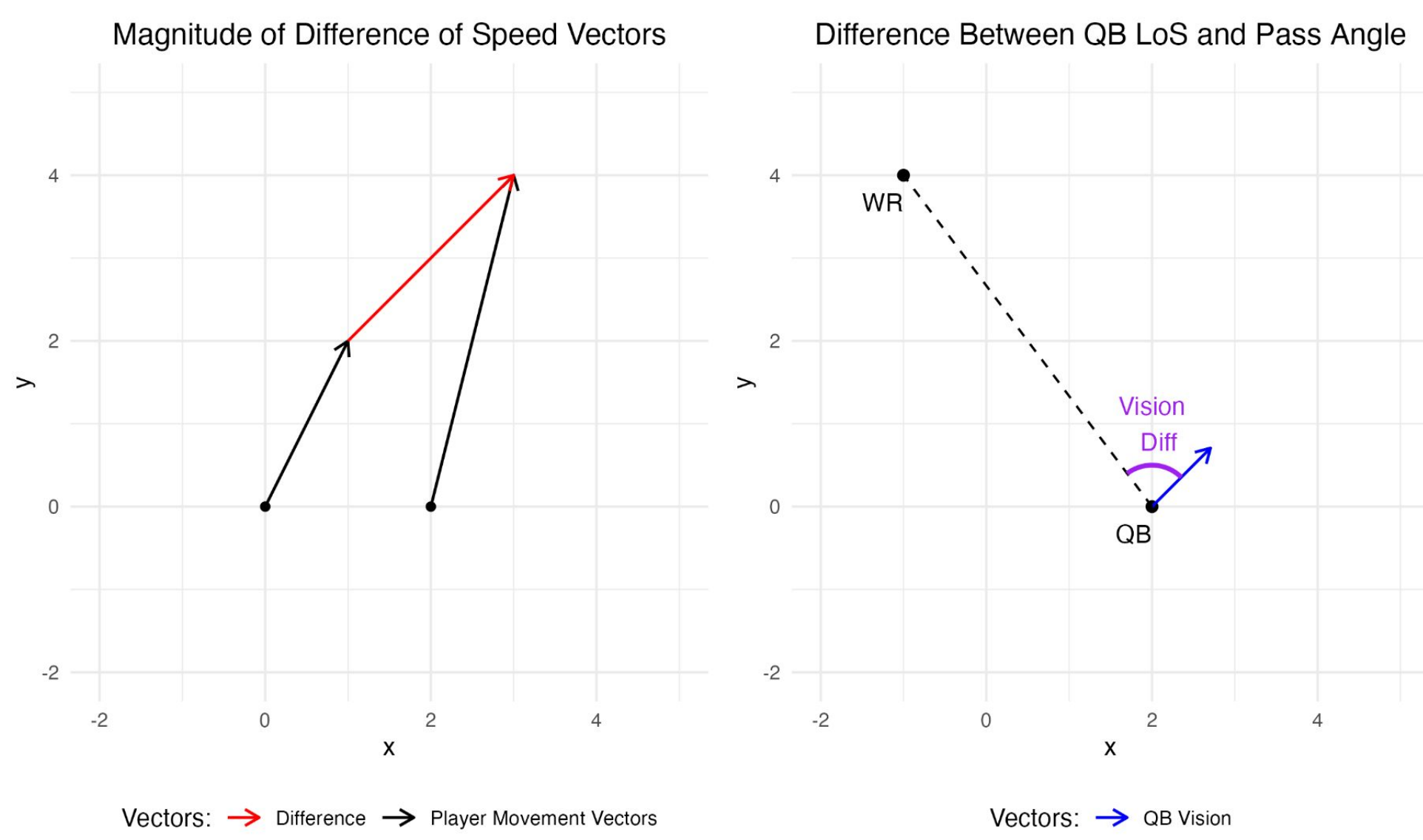
Carnegie Mellon University
Statistics & Data Science

Motivation

- Choice of receiver can be the difference between a touchdown or interception during a throwing play in football
 - A quarterback's decision-making ability is extremely important to the success of a team
- Therefore, it is important to contextualize throwing decisions by comparing with the expected decision
- This work provides this contextualization by building a model which predicts the likely throwing decision
 - Using tracking and event data from the 2024 NFL Big Data Bowl,¹ describing the first 9 weeks of the 2022 season

Methodology

- Like similar approaches in soccer,² we model receiver targeting as a learning-to-rank(LTR) problem using an XGBoost model on hand-crafted features:
 - Full feature set and methods can be found in presentation (see *Further Information*)
- Separation: Magnitude of the difference of speed vectors at throw as a proxy for future separation
 - Strong correlation with future separation (0.81)
- QB Vision: Derived estimate of QB's center line of sight (LoS), difference between LoS and pass angle



- After random search tuning and 5-fold cross-validation, with folding along games, the model yields 59.9% top-1 accuracy, significantly outperforming both a naive guess (20%) and a separation-based heuristic (31.6%)

Results

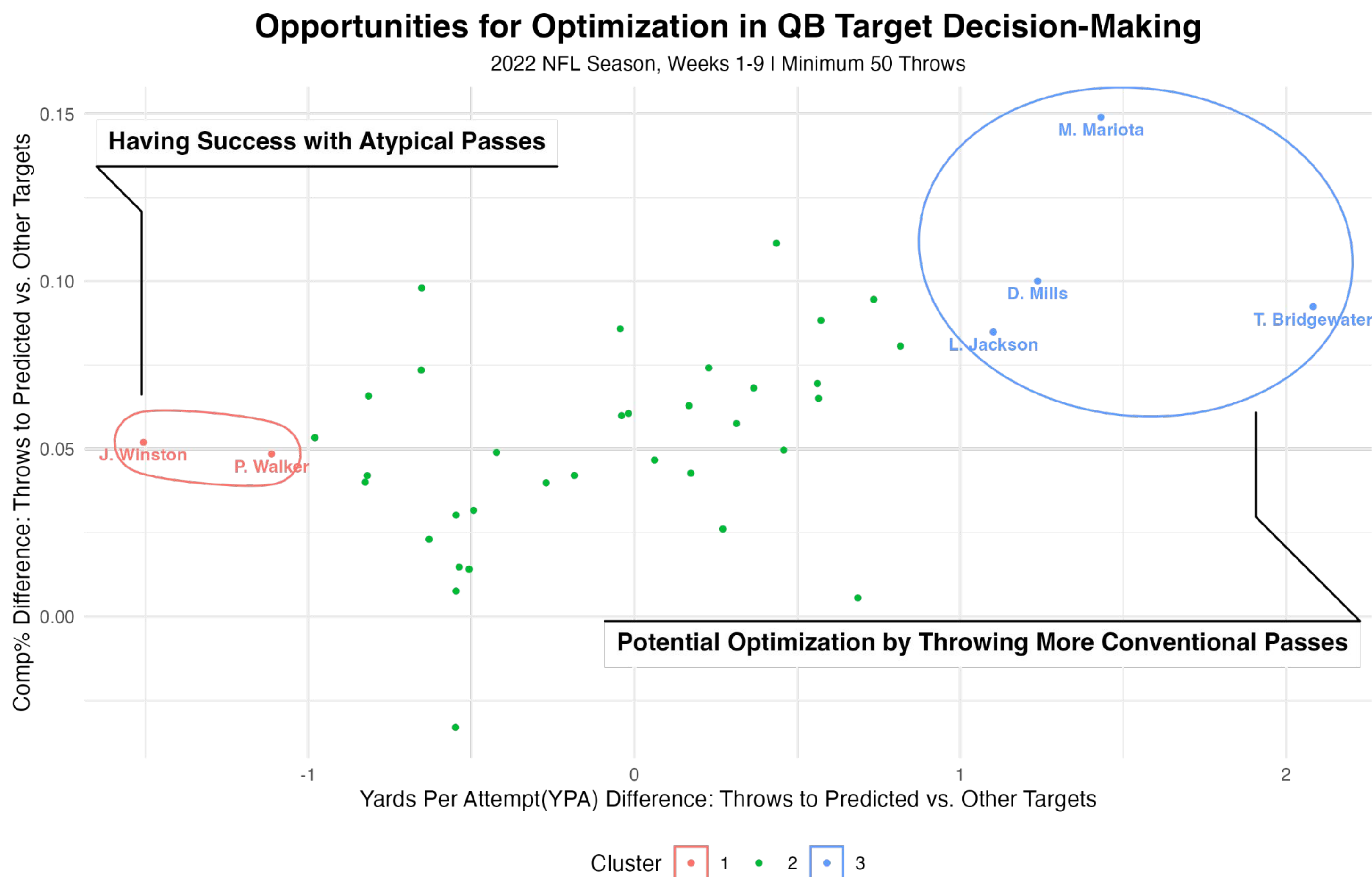


Fig. 1 - Differences in YPA and Completion % between model-agreeing throws and other receivers. Some QBs perform better when aligned with the model, indicating potential opportunities to optimize by favoring expected targets

| Top 10 Least Predictable QBs | | | | |
|--|------|--------------|--------------------------------|--|
| 2022 NFL Season, Weeks 1-9 - Minimum 50 Throws | | | | |
| Quarterback | Team | Total Throws | % Throws to Predicted Receiver | |
| Tua Tagovailoa | MIA | 205 | 52.680 | |
| Jameis Winston | NO | 105 | 59.050 | |
| Dak Prescott | DAL | 74 | 60.810 | |
| P.J. Walker | CAR | 86 | 66.280 | |
| Tom Brady | TB | 359 | 66.300 | |
| Josh Allen | BUF | 262 | 68.700 | |
| Derek Carr | LV | 255 | 69.020 | |
| Davis Mills | HOU | 236 | 69.490 | |
| Joe Flacco | NYJ | 138 | 70.290 | |
| Andy Dalton | NO | 177 | 70.620 | |

| Top 10 Most Predictable QBs | | | | |
|--|------|--------------|--------------------------------|--|
| 2022 NFL Season, Weeks 1-9 - Minimum 50 Throws | | | | |
| Quarterback | Team | Total Throws | % Throws to Predicted Receiver | |
| Justin Fields | CHI | 171 | 80.700 | |
| Ryan Tannehill | TEN | 128 | 80.470 | |
| Jared Goff | DET | 249 | 79.520 | |
| Matt Ryan | IND | 270 | 78.890 | |
| Trevor Lawrence | JAX | 274 | 78.830 | |
| Jalen Hurts | PHI | 215 | 77.210 | |
| Bailey Zappe | NE | 86 | 76.740 | |
| Baker Mayfield | CAR | 146 | 76.710 | |
| Kyler Murray | ARI | 321 | 76.640 | |
| Geno Smith | SEA | 232 | 76.290 | |

Fig. 2 - Quarterback "predictability", measured by proportions of throws to the expected targets

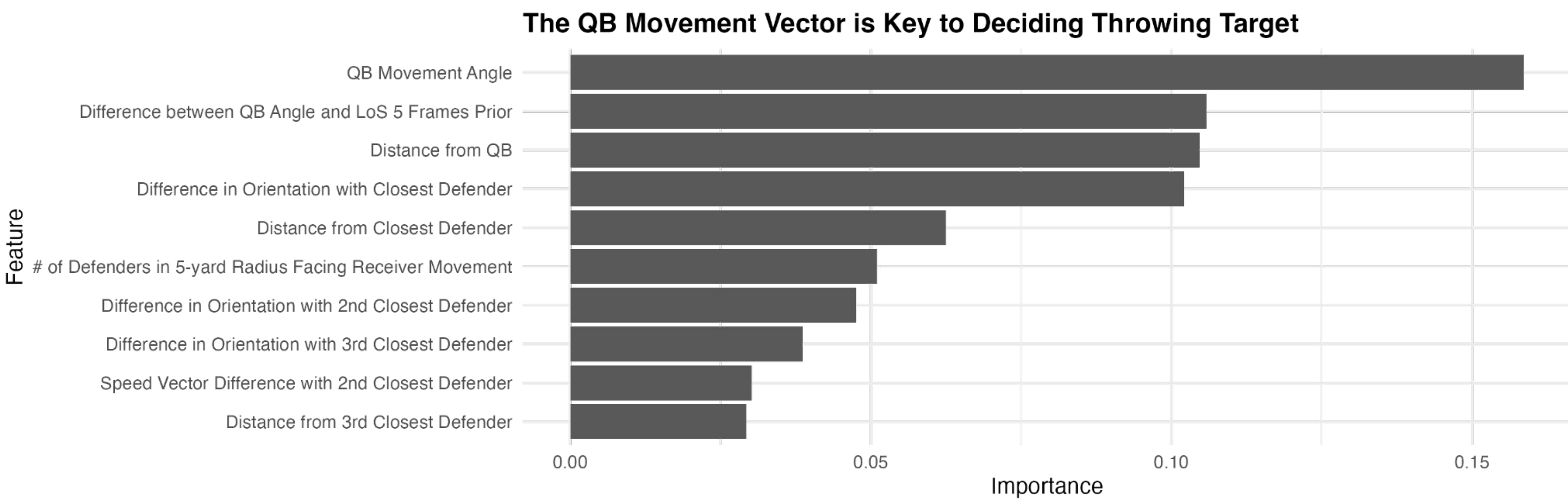


Fig. 3 - Variable Importance for the XGBoost Model, determining the expected throw target

Discussion

- This work builds an XGBoost learning-to-rank model with handcrafted features to predict the likely target of a typical quarterback
 - We can then contextualize individual QB decisions by comparing them to model-predicted choices.
- By analyzing YPA and completion rate by model agreement, we can highlight QBs who succeed with unconventional pass options or might benefit from more conventional throws
- However, quarterbacks will encounter different game states, so some may have more opportunities to make more typical throws
 - To better evaluate QB decisions, future work should estimate yards and completion probability for receivers to find the optimal decision
- Additionally, future work includes pre-snap factors (coverage mismatches, motions, receiver skill) to update target probabilities from the snap to the pass

Acknowledgements

The authors of this work would like to thank Dr. Karim Kassam, Quang Nguyen, and Dr. Ron Yurko for their guidance, as well as the CMU Statistics Department for providing the opportunity and support to conduct research throughout the summer

References

- Michael Lopez, Thompson Bliss, Ally Blake, Andrew Patton, Jonathan McWilliams, Addison Howard, and Will Cukierski. NFL Big Data Bowl 2024. <https://kaggle.com/competitions/nfl-big-data-bowl-2024>, 2023. Kaggle.
- Li, Heng & Zhang, Zhiying. (2019). Predicting the Receivers of Football Passes. 10.1007/978-3-030-17274-9_15.

Further Information

Presentation and Code:



Contact:

Lou Zhou
lz80@rice.edu
lou-zhou.github.io
Zachary Pipping
zrpipping@gmail.com
zachbtw.github.io