PassPredictR: Contextualizing NFL Throwing Decisions By Modeling Receiver Choice



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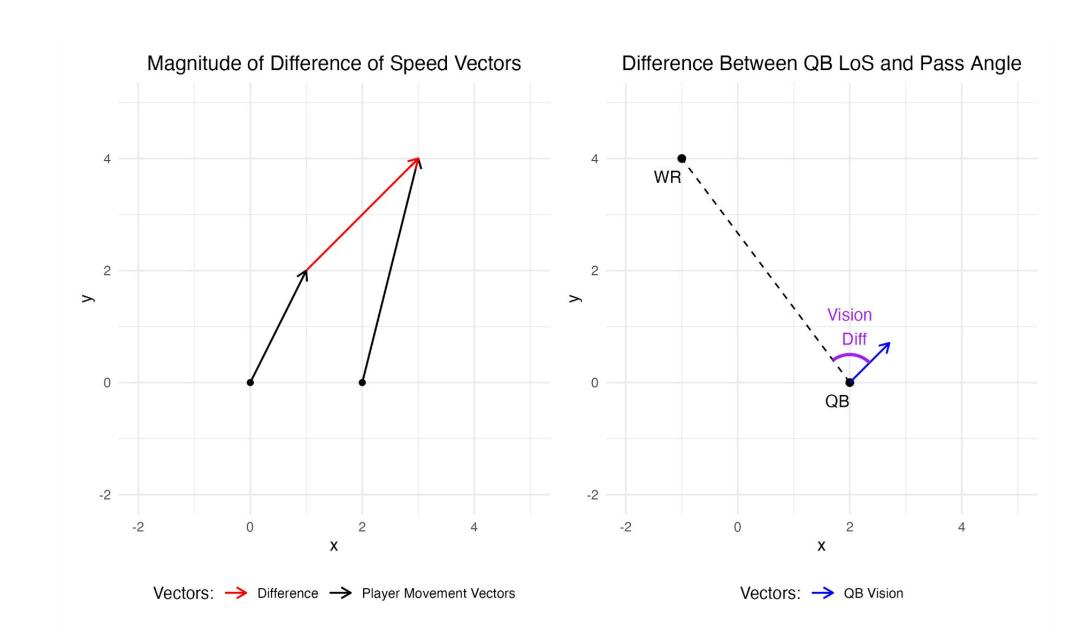
Statistics & Data Science

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

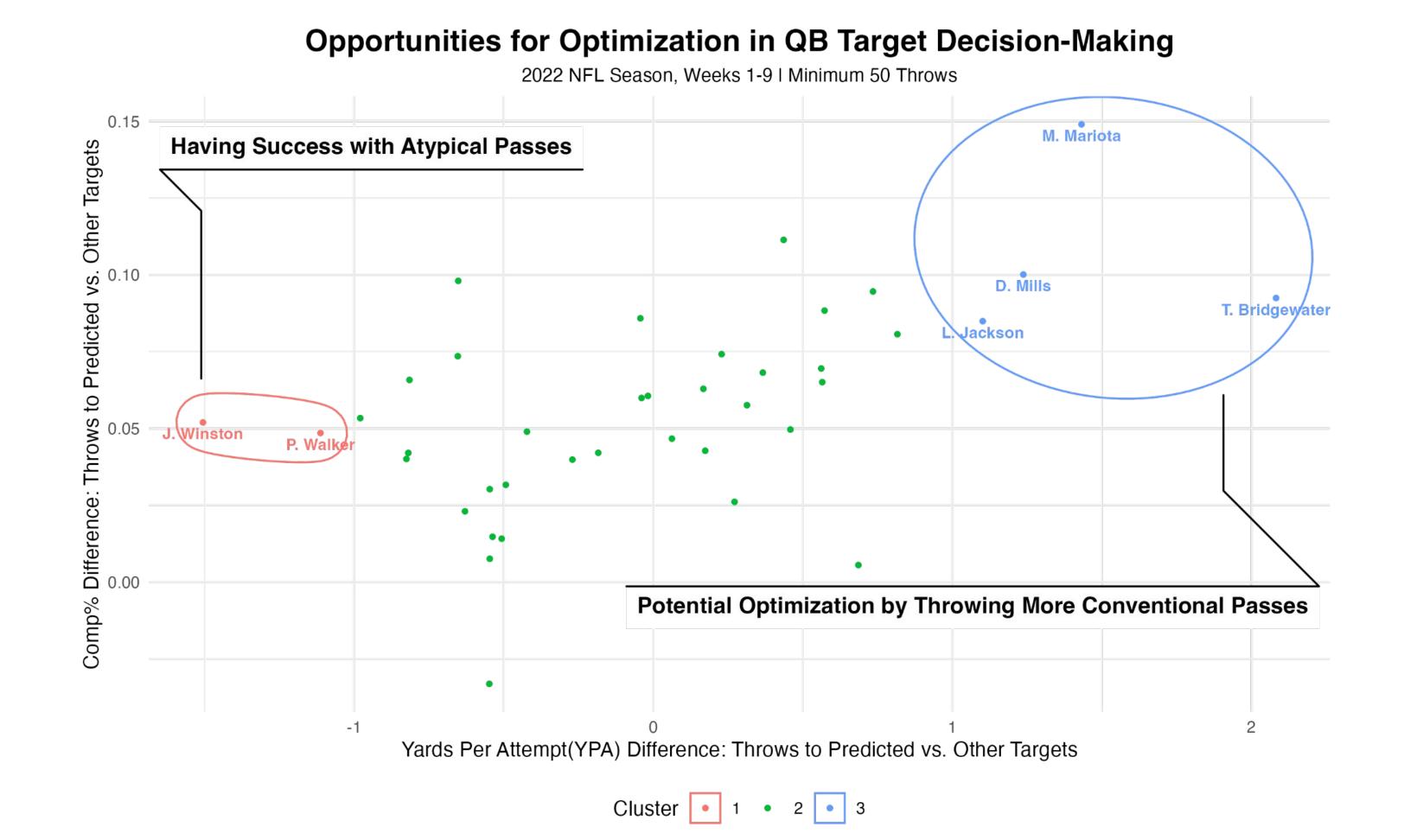
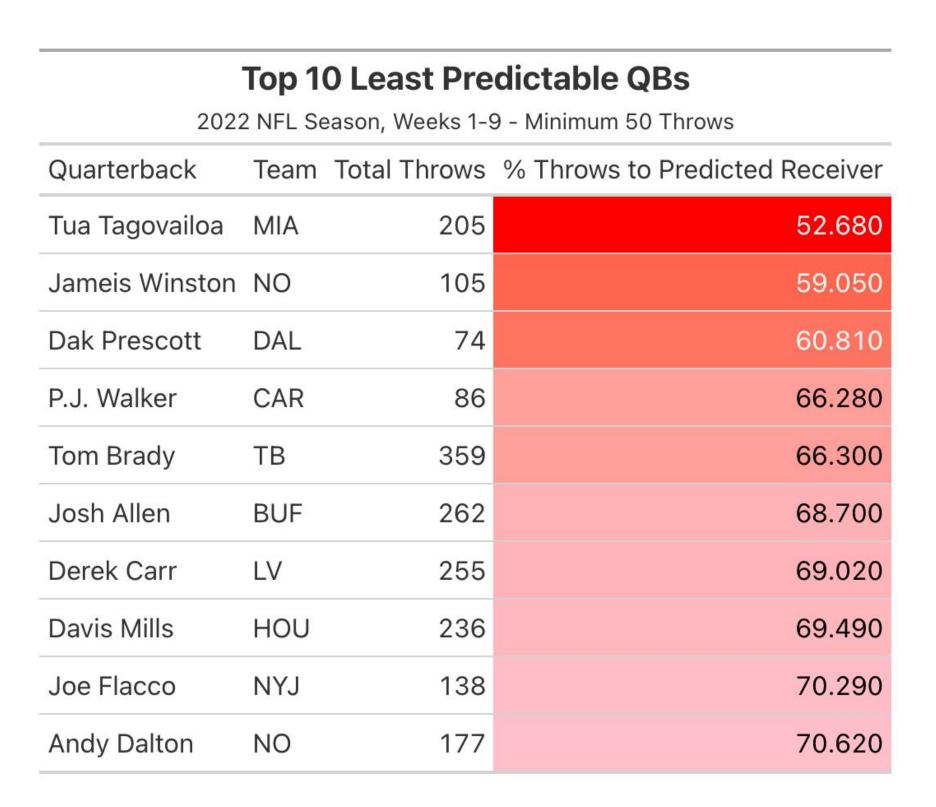


Fig. 1 - Differences in YPA and Completion % between model-agreeing throws and other receivers. Some QBs perform better when aligned with the model, indicating potential opportunities to optimize by favoring expected targets



Top 10 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

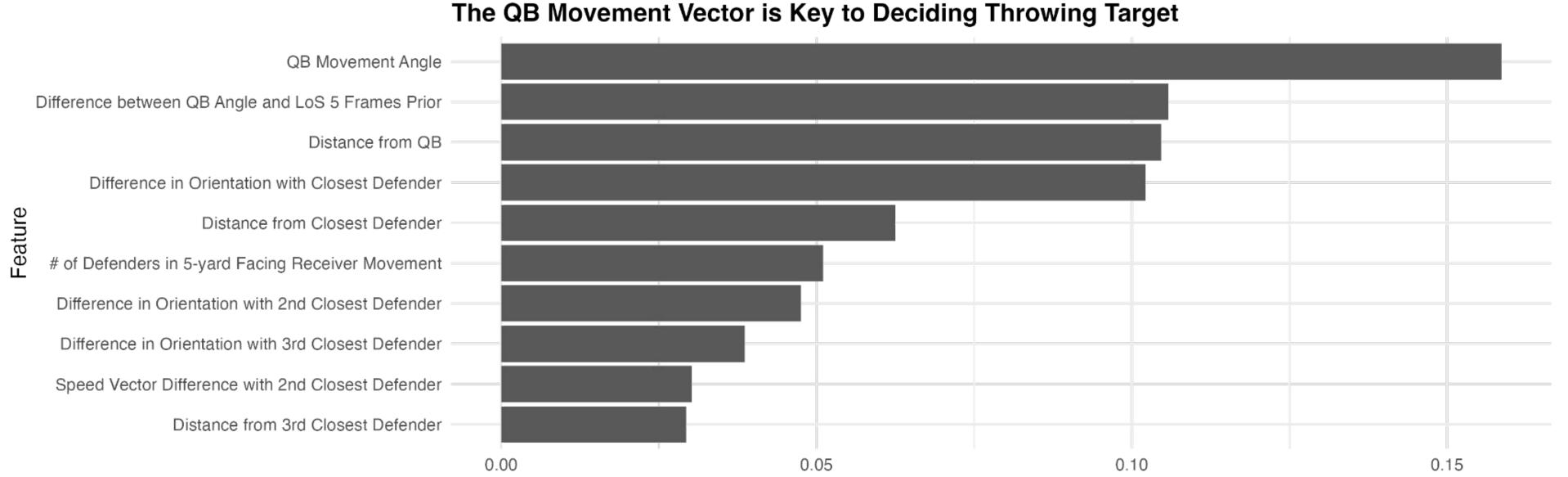


Fig. 3 - Variable Importance for the XGBoost Model, determining the expected throw target

Importance

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

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References

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- **2.** Li, Heng & Zhang, Zhiying. (2019). Predicting the Receivers of Football Passes. 10.1007/978-3-030-17274-9_15.

Further Information

Presentation and Code:



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