Cleveland Browns Field Goal Kicking Analytics: What Makes the Perfect Kick?

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Abstract

This project analyzes the NFL's Cleveland Browns' practice field goal data to examine how factors such as Ball Speed, Launch Angle, and Apex affect kick success. Using linear regression, Random Forest models, and XGBoost, we predicted make probabilities across conditions and distances. These were scaled with in-game Expected Points Added (EPA) values from nflfastR to estimate the game impact of each practice kick. A bin-by-bin EPA breakdown revealed where kickers underperform in games relative to practice, informing targeted coaching. We also used league-average scaling curves to compare Browns kickers' transition to games with the rest of the NFL. Results show that mechanical adjustments—like increasing ball speed on long kicks—can significantly boost projected game EPA, supporting data-driven performance optimization.

Objectives

- Develop predictive models to estimate field goal success based on key metrics such as ball speed and attempt distance.
- Use model outputs and visualizations to identify optimal kicking conditions and inform coaching decisions.

Methods

A dataset of over 3,800 NFL practice field goal attempts collected with Trackman was analyzed to study kick performance under various conditions (launch angle, ball speed, kick distance, venue type, etc). The data was cleaned by filling missing values and assigning a binary success label.

Modeling:

- **Linear Regression:** Estimated continuous success probabilities to reveal trends kick outcomes.
- **Logistic Regression**: Served as a baseline for classifying kicks as made or missed.
- **Random Forest & XGBoost:** Used class balancing (SMOTEENN and SMOTETomek), threshold tuning, and hyperparameter optimization to improve recall and overall predictive performance.

Models were evaluated using precision, recall, accuracy, and confusion matrices. Tree-based models importance revealed the metrics most predictive of field goal success.

Findings

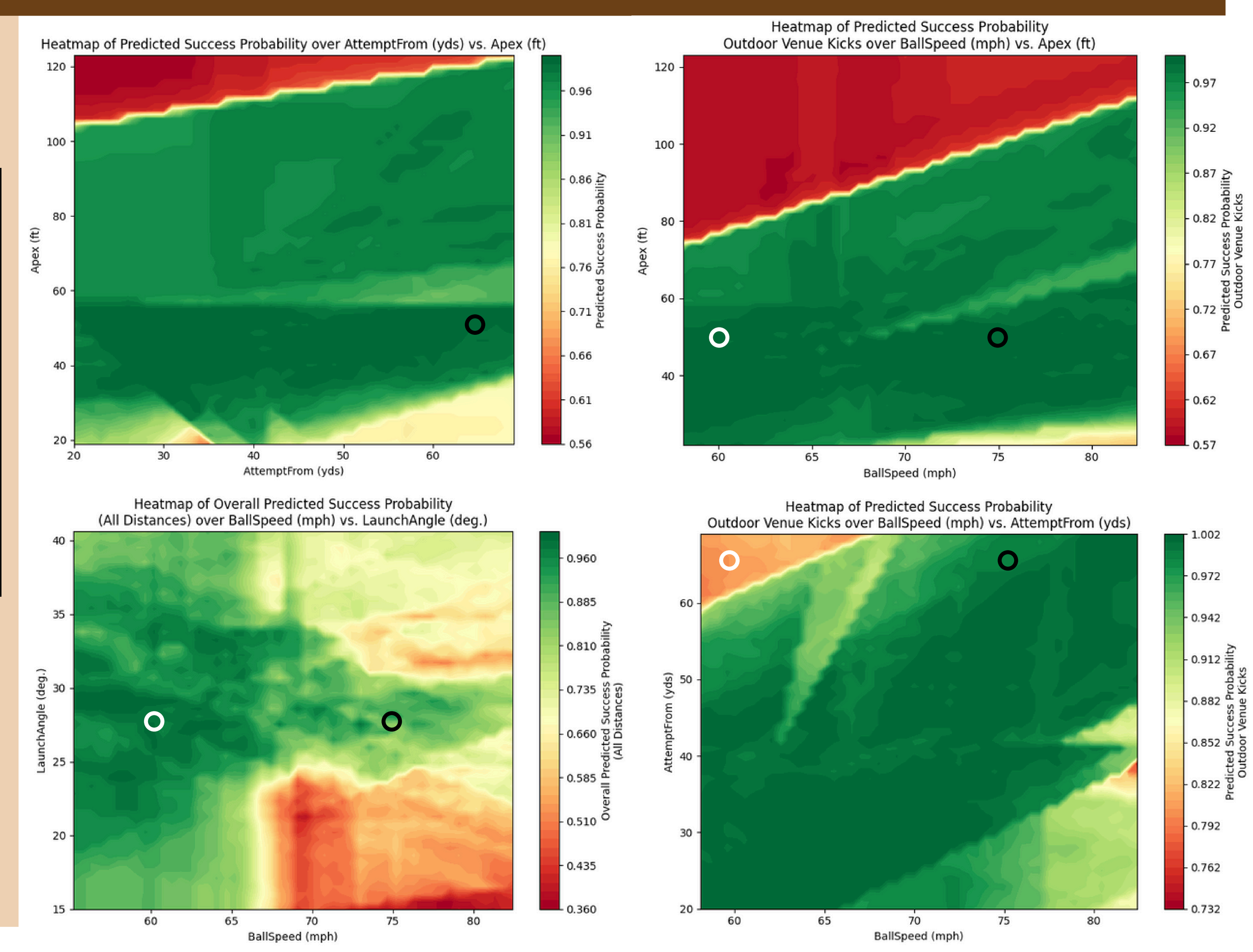
Isolated Metric Impact on Make Probability

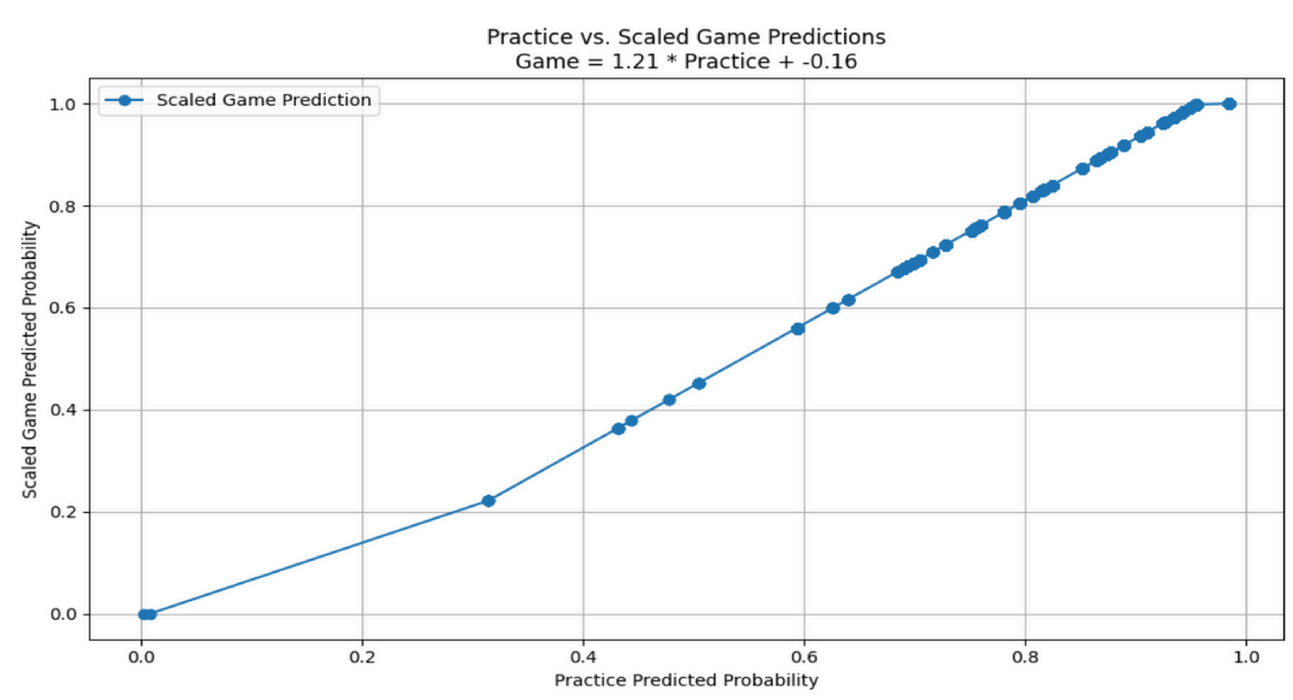
The heat maps illustrate how small changes in ball speed can greatly affect kick success. Both kicks (black vs. white circles) have the same distance, apex, and launch angle.

High confidence make:
- **Attempt From:** 65 yds
- **Apex:** 50 ft
- **Ball Speed:** 75 mph
- **Launch Angle:** 27.5 deg

Lower confidence make/miss:
- **Attempt From:** 65 yds
- **Apex:** 50 ft
- **Ball Speed:** 60 mph
- **Launch Angle:** 27.5 deg

However, the faster kick (75 mph) lands in a high-probability zone, while the slower one (60 mph) falls in a low-probability zone. This shows how targeted mechanical tweaks can turn a likely miss into a make, helping coaches prioritize the most impactful adjustments.





Regression of Practice vs. Game Success

A linear regression model was used to relate practice predictions to scaled in-game performance, producing the equation:

Game = 1.21 × Practice +/- 0.16.

Expected Points Added (EPA)

EPA=i∑(ATTi×(a · PRAC_PROBi+b)×EPA_VALUEi)

EPA measures how much a play increases or decreases a team's expected points by comparing the situation before and after the play. It captures the true impact of a play—showing whether it helped or hurt the team's chances of scoring.

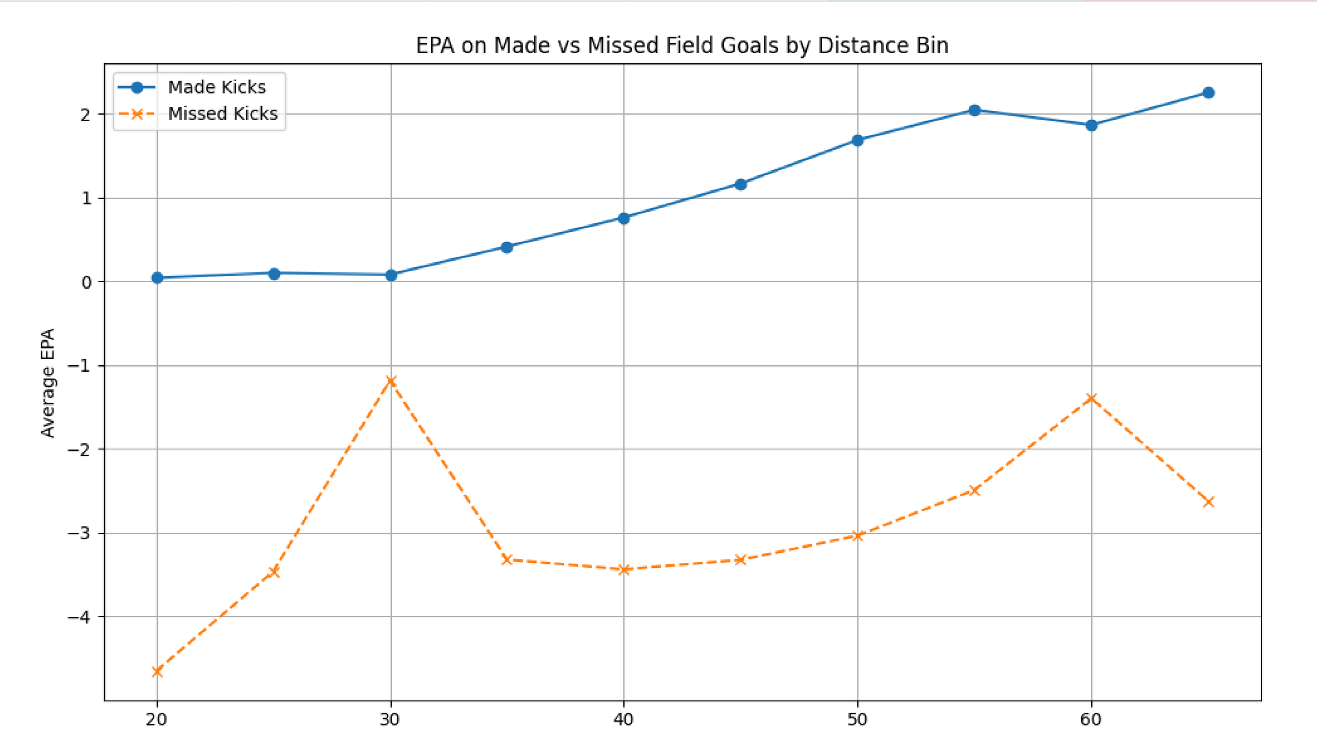
A regression model converted practice success probabilities into projected game outcomes, matched with in-game EPA values from nflfastR. This translation helps the Browns determine which kickers to use in specific situations. Bin-by-bin EPA breakdowns expose performance drop-offs—such as a 0.15 EPA loss on 40-yard kicks—guiding targeted training. League-average scaling curves enable comparisons of Browns kicker development to the rest of the NFL. The anonymized practice leaderboard, using player IDs, highlights high-impact kickers for strategic decisions.

Game Data

Kicker	EPA/Att	Total EPA	Attempts	Makes 40yd	Misses 40yd
B. Aubrey	0.44	16.31	37	2	0
D. Hopkins	0.16	25.47	162	32	6
R. Patterson	0.09	6.17	69	9	3

Practice Data

Player ID	EPA/Att	Total EPA	Attempts	Makes 40yd	Misses 40yd
117	0.63	109.78	174	31	3
115	0.59	39.9	68	9	0
137	0.56	15.18	27	3	0



EPA on Make - EPA on Miss = EPA Value

By comparing the EPAs on makes and misses of different kick distances, we can see which kicks may drive a kicker's EPA higher or lower and where they are consistent in makes or misses. It also shows us which kicks have more risk and reward. By combining these two insights, coaches can choose when to attempt a kick at a certain distance or not, and which kicker to use if they do decide to attempt.

97% Model Accuracy

Recall achieved by the Random Forest model when predicting successful field goal attempts — correctly identifying nearly all makes

Conclusion

This analysis shows how player tracking data and predictive modeling can uncover trends in field goal performance. By linking practice metrics with in-game EPA, it offers a framework for evaluating kicker effectiveness beyond basic stats. These findings can support data-driven coaching decisions, with future work exploring added factors like weather or game context.

References