Projecting NFL Wide Receiver Touchdowns Using Linear Regression: A Data-Driven Approach for Fantasy and Betting Insights

**1. Abstract**

We present a linear regression model to project NFL wide receiver (WR) touchdown (TD) totals by utilizing a broad set of temporal and contextual features spanning multiple seasons. Using data from 1990 to 2024, I constructed a robust dataset that includes lagged statistics, rolling averages, player age and experience, team offensive strength, and additional ‘efficiency’ metrics. The model is trained on 1990–2010 player-seasons and tested on 2011–2024, with careful prevention of data leakage through time-bounded feature engineering. Despite the inherent volatility of touchdown scoring, the model achieves meaningful predictive performance, yielding interpretable coefficients and practical insight into WR TD scoring trends. We conclude with TD projections for the upcoming NFL season, offering actionable guidance for fantasy football participants, bettors, and analysts alike.

**2. Introduction**

Touchdowns are a key driver of value in fantasy football, Daily Fantasy Sports (DFS), and player prop betting markets. Yet among all wide receiver (WR) statistics, touchdowns are the most volatile. As a result, analysts and bettors often times find TD to be the hardest statistic to predict due to its inherent volatility.

This paper introduces a linear regression model designed to project wide receiver touchdowns using a multi-season dataset with both player-level and team-level features. Unlike models that rely solely on prior-year performance, we incorporate lag features, two-year rolling averages, age and experience indicators, and contextual team metrics such as offensive scoring and pace. This richer feature set allows the model to better account for nonlinear career arcs, regression to the mean, role changes within an offense, and changes in structure of the offense itself

The model is trained on NFL player-seasons from 1990 to 2010 and tested on data from 2011 through 2024. Our approach emphasizes temporal integrity to avoid lookahead bias: all engineered features respect chronological boundaries. Despite the simplicity and transparency of a linear model, our results show it captures meaningful signal in a noisy domain and yields actionable projections. We conclude by applying the model to 2024 data to forecast 2025 WR touchdown outcomes.

**3. Data Collection**

To build a model capable of projecting wide receiver touchdowns, I assembled a comprehensive dataset of NFL WR performance spanning over three decades. The dataset aggregates information from multiple sources and levels — including individual player statistics, rushing contributions, and team-level context.

**3.1 Sources**

The core data were scraped from Pro-Football-Reference.com, including:

* **Receiving stats** (e.g., targets, receptions, yards, touchdowns, yards per reception)
* **Rushing stats** (for WRs with occasional carries)
* **Team stats** (e.g., points scored, total offensive plays, yards per play)

These were compiled into season-level records for every wide receiver from 1990 through 2024.

**3.2 Feature Engineering**

To support more accurate modeling, I constructed a variety of derived features:

* **Age-based indicators** (e.g., Prime\_Age, Rookie\_Sophomore, Age\_Squared)
* **Team strength metrics**, like Team\_Offense\_Strength (points per game)
* **Efficiency metrics** such as:
  + Target\_Share (targets per game)
  + Catch\_Rate (receptions per target)
  + TD\_Per\_Reception, TD\_Per\_Target
* **Temporal features**, including:
  + Previous season stats (TD\_Prev, Yds\_Prev, etc.)
  + Two-year rolling averages (TD\_Avg2, Rec\_Avg2, etc.)
  + Career Experience (seasons active)

All temporal features were carefully bounded by year to prevent data leakage. For instance, rolling averages for a given season only use information from past seasons.

**4. Methodology**

This section describes the process used to model and project wide receiver touchdown totals. The approach involves preparing the dataset, training a linear regression model, and evaluating it under strict temporal validation to ensure real-world applicability.

**4.1 Problem Framing**

We frame WR touchdown prediction as a supervised regression task. For each player-season, the goal is to predict the number of receiving touchdowns (TD) a player will score based on a variety of contextual and historical features. The modeling target is continuous (TD ∈ ℝ⁺), and we use a linear regression framework for its transparency and interpretability.

**4.2 Feature Set and Target Variable**

The features used in the model fall into the following categories:

* **Lag Features**: Stats from the previous season (e.g., TD\_Prev, Yds\_Prev, Tgt\_Prev, Y/R\_Prev)
* **Rolling Averages**: Two-year rolling means for TDs, targets, receptions, and yards (TD\_Avg2, etc.)
* **Player Traits**: Age, experience (Age, Age\_Squared, Experience, Prime\_Age, Rookie\_Sophomore)
* **Efficiency Metrics**: TD\_Per\_Target, Catch\_Rate, Target\_Share, Yards\_Per\_Game
* **Team Context**: Offensive output per game (Team\_Offense\_Strength), and scoring environment
* **Durability**: Games played and Games\_Played\_Rate

The target variable is the actual number of **receiving touchdowns** scored by a player in that season.

**4.3 Temporal Validation and Data Leakage Prevention**

To ensure valid backtesting, we implement a **chronologically consistent train/test split**:

* **Training Set**: Player-seasons from 1990–2010
* **Test Set**: Player-seasons from 2011–2024

All temporal features (e.g., lag stats and rolling averages) are computed using only prior seasons up to the year being predicted. This simulates a true forward-looking forecast and prevents leakage from future data.

**4.4 Model Choice: Linear Regression**

We train a **Linear Regression** model using scikit-learn, with the following characteristics:

* No regularization (ordinary least squares)
* Median imputation for missing values
* Standardization applied to numeric features via StandardScaler

This choice was made to prioritize **interpretability**, making it easier to identify which features positively or negatively influence TD outcomes.

**4.5 Training and Evaluation**

We apply 5-fold cross-validation on the training set to assess in-sample error and model variance. Metrics reported include:

* **MAE** (Mean Absolute Error)
* **RMSE** (Root Mean Squared Error)
* **R² Score**

The final model is evaluated on the full test set (2011–2024) to measure out-of-sample generalization.

**4.6 Projections for Upcoming Season**

After evaluation, we apply the trained model to WRs from the 2024 season to generate **TD projections for 2025**. These are sorted, bucketed into performance tiers (e.g., Low, Medium, High, Elite), and used to identify potential over and undervalued players for fantasy and betting applications.

**4.7 Results**

The linear regression model was trained on NFL wide receiver data from 1990 to 2010 and evaluated on a temporally isolated test set spanning 2011 through 2024. Results from the out-of-sample backtest show that the model captures meaningful signal in a high-variance target variable: receiving touchdowns.

**4.7.1 Test Set Performance**

The model achieves the following on the 2011–2024 test set:

| **Metric** | **Value** |
| --- | --- |
| **Mean Absolute Error (MAE)** | 0.82 TDs |
| **Root Mean Squared Error (RMSE)** | 1.29 TDs |
| **R² Score** | 0.803 |

These results indicate strong predictive accuracy for a linear model, especially given the high volatility – and perceived non-linearity. The low MAE suggests most predictions are within ±1 TD of actual outcomes, and the R² of 0.803 implies the model explains over 80% of the variance in WR touchdown totals.

**4.7.2 Top Features**

The most influential features, ranked by coefficient magnitude, include:

| **Feature** | **Interpretation** |
| --- | --- |
| **Catch\_Rate** | Efficiency at converting targets to receptions |
| **Ctch%** | Alternate encoding of catch efficiency |
| **Yards\_Per\_Game** | Volume and role in offense |
| **TD\_Avg2** | Two-year TD average |
| **Yds\_Avg2 / Yds** | Sustained yardage production |
| **Yds\_Prev** | Last year’s yardage |
| **Rec\_Avg2 / Rec** | Rolling and raw reception counts |

Notably, the model emphasizes **efficiency metrics** over raw counting stats like total touchdowns from the prior year, suggesting that sustainable performance indicators matter more than single-season spikes.

**4.7.3 Visualization Summary**

The following visualizations summarize model performance:

* **Bar chart (top-left)**: Shows MAE, RMSE, and R² on the test set
* **Coefficient plots (top-right & bottom-left)**: Reveal most impactful features by direction and magnitude
* **Model summary box (bottom-right)**: Recaps key metrics and modeling rationale

**4.7.4 Cross-Validation (Train Set)**

During training (1990–2010), the model achieved a **cross-validation MAE of 0.45 ± 0.08**, suggesting low variance and good generalization. The consistency between train and test scores supports the model’s robustness and lack of overfitting.