Rough Draft

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Abstract

This project investigates college football team performance, ranking biases, and predictive legitimacy from 2014 to 2025, with the primary goal of developing a "Fraud Score" to identify discrepancies between subjective perceptions and objective on-field results, thereby promoting fairer evaluations in a bias-prone system. Data is sourced from the College Football API and Sports Reference, featuring over 10,000 games with metrics such as scores, ELO ratings, excitement indices, attendance, and aggregated team-season statistics like Win Percentage (WinPct), Margin of Victory (MOV), Simple Rating System (SRS), and Strength of Schedule (SOS). Methods encompass data processing and exploratory data analysis (EDA) using Pandas, NumPy, and Seaborn for visualizations; clustering via KMeans and visualization using PCA to group teams into tiers; Fraud Score computation through threshold-based features and AP Rank; and Random Forest Classifier to evaluate the Fraud Score as well as evaluation for the Random Forest Classifier model itself.

Preliminary results reveal recurring patterns of overrating among historical dominant teams, which support the claims of prestige and regional bias in college football rankings. These findings not only demonstrate the validity of the proposed Fraud Score but also emphasize its potential role in enhancing transparency and fairness.

1 Introduction

1.1 Introduction

College football is one of the most followed sports in the United States, drawing millions of fans, media attention, and significant financial stakes for universities and athletic programs. College football rankings such as the Associated Press (AP) Poll and College Football Playoff (CFP) committee selection serve as the primary influence over evaluating teams and determining post-season opportunities. These rankings can actually do more than reflect team success, they can influence bowl invitations, playoff participation, recruiting power, and institutional prestige.

However, rankings are not strictly based on performance. Rankings often reflect perceptions shaped by brand recognition, historical success, media narratives, and preseason expectations. As a result, there are consistent divergences between how strong a team appears in polls and how well it actually performs according to efficiency metrics and outcomes. This concept of divergence of a team formed the foundation of our study of "fraud teams" - teams whose poll rankings and reputations exceed their true on-field performance.

This project investigated college football teams performance, ranking biases, and predictive legitimacy from 2014 to the present with a primary goal of developing a Fraud Score: a metric to identify discrepancies between subjective perceptions such as the AP polls rankings and CFP

selections, and performance-based metrics from the on-field results in order to perform a non-bias evaluation. By creating this score, we seek to quantify perception–performance gaps and test whether certain teams are consistently overrated. For example, debates over Florida State's undefeated 2014 season or TCU's 2022 national championship appearance reflect broader questions about whether polls and the CFP committee accurately identify the "best" teams.

This project also speaks to broader concerns in the literature. Scholars have documented voter bias in the AP Poll [1], structural advantages embedded in the Bowl Championship Series [2], and favoritism toward "power programs" with large fan bases and media profiles. By building a replicable Fraud Score framework, our work contributes to this line of research by offering an applied tool for detecting overrated teams.

1.2 Methodologies in Literature

College football rankings, particularly the Associated Press (AP) poll and the College Football Playoff (CFP) committee, play an important role in determine playoff access, financial allocations, and program reputations. However, decades of scholar research show that these systems are vulnerable to biases and begin to question their reliability. Coleman et al. (2010) documented systematic voter bias in the AP poll, with prestige and regional favoritism influencing rankings more than team quality [1]. Eckard (2011) critiqued the Bowl Championship Series as cartel-like, structurally privileging power conferences over outsiders [2]. Other empirical studies also illuminated these flaws: Witte and Mirabile analyzed AP and Coaches Polls from 2004–2008, uncovering regional favoritism where voters inflate rankings for local teams, leading to inefficiencies in predictive accuracy [3]. Hensley (2015) [4], in a University of California, Berkeley honors thesis, quantified state-level bias in AP ballots, showing voters rank in-state teams ∼2–3 spots higher on average. Stone and Rod (2016) [5] critiqued the CFP in the *Marquette Sports Law Review*, arguing that subjective "eye test" criteria foster inconsistencies. Other research explored private incentives among coaches, uncovering evidence that coaches inflate the rankings of their own conference peers [6]. Collectively, these works establish the ethical and structural rationale for seeking more data-driven, bias-resistant evaluation methods.

Efforts to correct such distortions have produced several objective, quantitative ranking systems. Colley (2002) introduced the Bias-Free Colley Matrix, a method that uses linear algebra to generate team ratings based solely on win-loss outcomes and strength of schedule, avoiding human input entirely [7]. The Simple Rating System (SRS), developed by Drinen (2006) for Pro-Football-Reference [8] and adapted for college by Sports Reference, rates teams via average MOV adjusted for SOS. It solves linear equations: for team i, SRSi = average MOVi + average SRS of opponents, normalized to mean 0 (average team). In college, MOV caps at 24 points curb blowout inflation against FCS foes, and non-D1 games aggregate as one "opponent" for balance. SRS is retrodictive, explaining past results (e.g., correlating highly with win totals) but less predictive due to equal weighting, ignoring recency or injuries [9].

The Elo system, original developed by Elo [10] for chess and adapted to football by Silver [11], provides dynamic ratings.

- Teams start at ∼1500 (average)
- Post-game: $R' = R + K(S - E)$

With K (20–30) for volatility, S as outcome (1/0.5/0), and $E = 1/(1 + 10^{(R_{opp}-R)/400})$.

College adaptations add HFA (+55–65 points) and inter-season regression (∼33% toward mean) for turnover [12]. Parallel developments in predictive modeling have leveraged machine learning to improve ranking accuracy. Caballero and Zhao (2024) [13] used Elo for CFP analysis, differing from committee picks, capturing the dynamic evolution of team strength across the season.

In the broader sports analytics field, the push for data-driven alternatives is also rising, coming from sports analytics literature emphasizing quantitative precision over human judgment. Berrar et al. (2019) used K-Means clustering to classify soccer tactics [14], identifying archetypes that enhance outcome prediction. In multisports contexts, Deb et al. (2024) [15] clustered progressive passes in football, while a scoping review by and Fernandez et al. (2024) [16] in the *Electronic Journal of Applied Statistical Analysis* surveyed 278 sports science articles, revealing their ability to categorize play styles, team strengths, and competitive tiers when combined with appropriate validation measures such as silhouette scores. Wang and Huang (2025) clustered tennis matches via deep learning as a proxy for tactical grouping, which is adaptable to college football for performance tiers [17]. Home-field advantage (HFA), a key confounder, is well-documented by Pollard and Pollard (2005) [18] quantified 55–60% home win rates across sports, attributing them to crowd noise and travel. In college football, Risser et al. (2011) [19] used multilevel models to estimate 4–6 point edges varying by venue, while Inan (2020) [20] linked crowd support to outcomes. Boudreaux et al. (2017) [21] noted HFA's decline in replay eras, and Nichols 2014) [22] tied travel to NFL biases, extendable to college.

Ethically, these analytical shortcomings amplify inequities in college athletics, which raised the demands of improving ranking fairness. Edelman (2014) and Eckard (2011) both argue that systemic favoritism and inconsistent ranking criteria exacerbate the competitive imbalance between Power Five and Group of Five schools [23, 2]. In a senior thesis at the University of South Carolina, Oplinger analyzed CFP selections, finding personal biases drive mismatches, exacerbating mental health pressures on athletes [24].

1.3 Project Plan

Building from the Literature, our project aims to construct a Fraud Score that distinguishes between perception-driven rankings and efficiency-driven performance. We focus on the seasons from 2014 to 2024, coinciding with the CFP era.

We will combine College Football Data API [25] with Sports Reference data [26]. Exploratory Data Analysis (EDA) will visualize relationships between rankings and efficiency to highlight discrepancies. Next, we will test methods for detecting fraud teams: Clustering to group teams into elite, contenders, and fraud-prone categories; Creating heuristic thresholds to flag elite vs. borderline performance; Construct a fraud score and conduct supervised learning models to validate the Fraud Score's ability to capture overrated programs.

2 Methods

2.1 Methods: Data Sources, Preparation, and Cleaning

Most of our data came from College Football API [25], which contains data that started in 2014 up until to the present, with a total of 33 columns and 27873 rows. We obtained this data from the College Football Data website which gives us an API where users can download data from

the games. We gained access to the College Football Data (CFBD) API using the official python client. Authentication was handled using a Bearer API key, stored as an envrionment variable (CFBD_API_KEY) or entered at runtime when unavailable. We then used this API to download the csv file that is usable for our needs.

ColumnName	Count	Datatype
id	27873	int64
season	27873	int64
week	27873	int64
seasonType	27873	object
startDate	27873	object
startTimeTBD	27873	bool
completed	27873	bool
neutralSite	27873	bool
conferenceGame	27873	bool
venueId	27829	float64
venue	27829	object
homeId	27873	int64
homeTeam	27873	object
homeConference	27796	object
homeClassification	27796	object
homePoints	25023	float64
homeLineScores	25022	object

(a) CFBD Games columns (part 1 of 2)

ColumnName	Count	Datatype
awayId	27873	int64
awayTeam	27873	object
awayConference	27522	object
awayClassification	27522	object
awayPoints	25023	float64
awayLineScores	25022	object
highlights	3391	object
attendance	10038	float64
homePostgameWinProbability	11682	float64
homePregameElo	9539	float64
homePostgameElo	8918	float64
awayPostgameWinProbability	11682	float64
awayPregameElo	9057	float64
awayPostgameElo	8436	float64
excitementIndex	11644	float64
notes	889	object

(b) CFBD Games columns (part 2 of 2)

Figure 1: Description of CFBD Games (2014–2025 API).

The data consists of about 1600 games per year primarily from September to November, since with the start of the 2020 season, the games increased to over 3000 per year due to the addition of lower division games being included. Some of the columns need to be clarified in order to make predictions. The first is total points which is home_points + away_points and the second is margin which is home_points - away_points. Additionally, we created two columns, both for win rate by location, whether the home or away team won. The homeWon column was created by comparing if the homePoints column was higher than the awayPoints column, and storing the value as being an integer with one being a win and zero being a loss. The same was conducted for the awayWon column, except this time comparing if the awayPoints column was greater than the homePoints column. Lastly, we also created an elo difference column which takes homePregameElo - awayPregameElo to calculate a difference in the two.

Our second data source we used is Sports Reference College Football [26]. Sports Reference provides both results stats (wins, losses, points scored) and perception measures (AP poll rankings). It also offers advanced summary ratings: the Simple Rating System (SRS), which adjusts for opponent quality and scoring margins. In this data source, we analyzed a decade of data from 2014 to 2024.

In the Sport Reference Data Source, we used annual team ratings and team standings tables. In order to extract these tables, we used the "Share & Export" feature on Sports Reference website. The feature provided the option of "get table as CSV". The CSV formatted texts were then saved into CSV files. The raw CSV exports contained two-row headers, repeated header rows, and embedded citation text. Several cleaning steps were performed. For the two-row headers such as Scoring – Off/Def, Rushing – Off/Def, we converted them into one-row and changed the name to Scoring_Off, Scoring_Def and relevance. Sports Reference often repeats the header row inside the table so we got these removed as well. Since the data came in separate years, for easier working,

we merge all 11 csv files of each ratings or standings into one and added a column of Season.

For the team ratings table, we created derived metrics to enhance comparability across teams and seasons. The Win Percentage (WinPct) is computed as:

$$\text{WinPct} = \frac{\text{Overall\_W}}{\text{Overall\_W} + \text{Overall\_L}}$$

and the Margin of Victory (MOV) is calculated as:

$$\text{MOV} = \text{Scoring\_Off} - \text{Scoring\_Def}$$

For the team standings table, we created two additional metrics. The Conference Strength Differential identifies whether a team struggled within its conference despite padding its record with out-of-conference games, defined as:

$$\text{ConfStrengthDiff} = \text{Conference\_Pct} - \text{Overall\_Pct}$$

The Poll Overperformance / Underperformance Gap, which measures the discrepancy between preseason and final poll rankings, is computed as:

$$\text{PollRankGap} = \text{Polls\_AP\_Pre} - \text{Polls\_AP\_Rank}$$

```
Data columns (total 20 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Rk           1432 non-null   int64
 1   School       1432 non-null   object
 2   Conf         1432 non-null   object
 3   AP_Rank      275 non-null    float64
 4   Overall_W    1432 non-null   int64
 5   Overall_L    1432 non-null   int64
 6   SRS_OSRS     1430 non-null   float64
 7   SRS_DSRS     1430 non-null   float64
 8   SRS_SRS      1430 non-null   float64
 9   Scoring_Off  1430 non-null   float64
 10  Scoring_Def  1430 non-null   float64
 11  Passing_Off  1430 non-null   float64
 12  Passing_Def  1430 non-null   float64
 13  Rushing_Off  1430 non-null   float64
 14  Rushing_Def  1430 non-null   float64
 15  Total_Off    1430 non-null   float64
 16  Total_Def    1430 non-null   float64
 17  WinPct       1430 non-null   float64
 18  MOV          1430 non-null   float64
 19  Season       1432 non-null   int64
dtypes: float64(14), int64(4), object(2)
```

(a) Ratings

```
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Rk                   1432 non-null   int64
 1   School               1432 non-null   object
 2   Conf                 1432 non-null   object
 3   Overall_W            1432 non-null   int64
 4   Overall_L            1432 non-null   int64
 5   Overall_Pct          1430 non-null   float64
 6   Conference_W         1378 non-null   float64
 7   Conference_L         1378 non-null   float64
 8   Conference_Pct       1373 non-null   float64
 9   Points_Per_Game_Off  1430 non-null   float64
 10  Points_Per_Game_Def  1430 non-null   float64
 11  SRS_SRS              1430 non-null   float64
 12  SRS_SOS              1430 non-null   float64
 13  Polls_AP_Pre         275 non-null    float64
 14  Polls_AP_High        520 non-null    float64
 15  Polls_AP_Rank        275 non-null    float64
 16  Polls_Notes          5 non-null      object
 17  ConfStrengthDiff     1373 non-null   float64
 18  PollRankGap          157 non-null    float64
 19  Season               1432 non-null   int64
dtypes: float64(13), int64(4), object(3)
```

(b) Standings

Figure 2: Column names, non-null counts, and data types of season 2014 ratings and standings tables from Sports Reference

2.2 Methods: EDA/Visualization

Our first endeavor into exploratory data analysis with this project started with the College Football Data and plotting win rates for home teams vs away teams to see if there is a homefield advantage using a bar plot. We also created a histogram of the excitement index across all games as well as construct a distribution to see how excitement index can vary throughout each season.

We next ventured into the Sports Reference Standings and Ratings and plotted AP Poll ranking against win percentage. We also wanted to examine if there is a correlation between AP Poll rankings and two different measures: win percentage and SRS(Simple Rating System). SRS combines offensive (OSRS) and defensive (DSRS) efficiency while adjusting for strength of schedule, offering a more robust indicator of true team strength than just win-loss records. For each season, we calculated Pearson's correlation between inverted AP Rank (since lower rank = better) and each performance metric. We also plotted PollRankGap against actual win percentage for the first season we had available, 2014.

We also decided that it would be important to see if pregame ELO has any correlation with win rates and to do so we plotted the results for games for both home and away teams with 0 being a loss and 1 being a win. We also applied a logistic regression to this in order to visualize how win rates and pregame ELO are correlated.

2.3 Methods: Clustering Analysis

To identify groups of teams with similar performance and perception levels, we applied K-Means Clustering on the features of each season. Before clustering, we excluded nonnumeric columns such as Team, School, Conference, and Season. All remaining numeric columns were then standardized using z-score scaling. Clustering was performed separately for each season, and we experimented with different values of k (number of clusters) and evaluated cluster quality using the silhouette score and inertia.

After determining the number of clusters using the elbow method (inertia) and silhouette analysis, we generated cluster summaries by computing average values of key performance indicators (SRS, WinPct, MOV, SOS) for each cluster. Using the summaries, we can interpret the clusters in terms of elite performers, solid performers or potential fraud teams, which had strong perception metrics but weaker performance metrics.

We also applied Principal Component Analysis (PCA) to reduce the high-dimensional feature space to two components for visualization. PCA does not affect the clustering itself but allows us to represent multidimensional similarities in a two-dimensional scatterplot. Each point corresponds to a team in the 2019 season, colored by its assigned cluster.

This approach aligns with past literature that emphasizes the gap between human poll rankings and statistical metrics or efficiency metrics in college football rankings [1, 2]. We did the clustering analysis across all numeric features and avoided bias toward teams grouping. This allowed the data to naturally form groups itself.

2.4 Methods: Threshold Construction and Fraud Labeling

The purpose of introducing thresholds is to establish a consistent benchmark for what makes up "elite" or "borderline" performance across seasons. These thresholds allow us to compare teams not only within a given year but also within several years. The thresholds are one of the two core components of our fraud score framework.

We derived our thresholds by analyzing the top ten teams in each metric (e.g., SRS, MOV, WinPct) for every season from 2014–2024. For each metric, we calculated the mean performance of those top ten teams and set the threshold slightly above that mean, which shows in table 1. Teams meeting the threshold were flagged with an "EliteHit," while those near the cutoff were marked as "BorderlineHits." A team meeting or exceeding the threshold is therefore performing above the historical average of top-ten teams in that category, approximating what "elite" performance looks like. At the same time, it helps identify teams that may be overrated in polls despite failing to reach elite statistical levels.

Table 1: Key Metrics and Thresholds for Elite/Borderline Classification

Metric	**Elite Threshold**	**Borderline Threshold**
Simple Rating System (SRS)	> 15	$10 \leq x \leq 15$
Margin of Victory (MOV)	> 20	$15 \leq x \leq 20$
Win Percentage (WinPct)	> 0.85	$0.75 \leq x \leq 0.85$
Strength of Schedule (SOS)	> 5	$2 \leq x \leq 5$
Elo Rating (PostgameElo_End)	> 1700	$1600 \leq x \leq 1700$
Elo Delta (season improvement)	> 100	$50 \leq x \leq 100$
Total Wins	> 11	$9 \leq x \leq 11$

In order to create fraud label for our dataset, we combined perception-based and performance-based indicators. Specifically, AP Rank served as a proxy for perception, while the EliteHits threshold represented objective statistical performance. This approach balances subjective voter evaluations with objective statistical metrics. By combining these two dimensions, we created a binary fraud label that could later be validated and refined through machine learning classifiers.

2.5 Methods: Random Forest Classifier to evaluate Fraud Labeling

To evaluate the Fraud Label we just created for our data, we used Random Forest Classifier model. The model was trained on independent performance-based features such as win percentage, strength of schedule (SOS), SRS, MOV, and Elo metrics. Threshold-derived variables (EliteHits, BorderlineHits) were excluded from the input to avoid circularity. Evaluation was performed using accuracy, F1-score, and ROC-AUC, metrics that balance overall classification performance with the ability to distinguish true "fraud" cases from legitimate contenders. Additionally, feature importance values were conducted as well to identify which variables most strongly influenced the classification.

2.6 Methods: Rationale for Using Random Forest Classifier

We selected the Random Forest Classifier as our primary machine learning model due to its robustness, interpretability, and ability to handle nonlinear relationships among performance metrics.

Random Forests, as an ensemble of decision trees, mitigate overfitting through bootstrap aggregation (bagging), where each tree is trained on a random subset of data and features. This not only improves predictive stability but also ensures generalization across seasons, an essential property for longitudinal sports data. Compared to single decision trees, which tend to overfit, or linear models, which assume additive relationships, Random Forests strike an effective balance between flexibility and reliability.

Another advantage of this approach is its interpretability through feature importance metrics. By quantifying each variable's contribution to model accuracy, we were able to validate that intuitive predictors of team quality—such as Margin of Victory (MOV), Simple Rating System (SRS), and end-of-season Elo—were indeed the most influential. This transparency supports the model's face validity and aligns with existing literature emphasizing the importance of efficiency and dominance metrics in distinguishing elite teams.

Alternative models such as logistic regression and gradient boosting were considered. Logistic regression was ultimately rejected due to its limited ability to model nonlinearities and feature interactions, while gradient boosting (e.g., XGBoost) was deemed less suitable for our project scope, as it required more extensive hyperparameter tuning and introduced interpretability challenges. The Random Forest model, by contrast, provided strong out-of-sample performance with minimal tuning, achieving high accuracy and AUC values while maintaining interpretability—a key goal for ensuring that the "fraud" designation remains explainable and data-driven.

3 Results

3.1 Results: EDA/Visualization

Our first figure resulting from the College Football API is Figure 3 which shows Win Rate by Location as a barplot, whether the winning team was home or away. What it shows us is that there is a clear advantage in being the home team, with the home team having a 52.6% win rate compared to away teams having a 37.0% win rate.

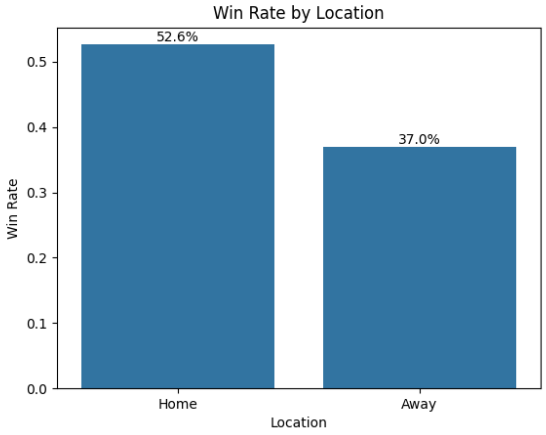


Figure 3: Win Rates by Location(Home vs. Away)

Figure 4 takes the pregame Elos, how strong the team is expected to be before the game and compares it to win rates for both home team and away teams. It also creates a logistic regression

line predicting the probability of a team winning given their pregame elo. What it shows is in line with what one might expect for the data, which is that as pregame elo increases so does the winrate. Also notable is that for all elos it appears that the predicted probability of winning for a home team is always greater than that of the away team.

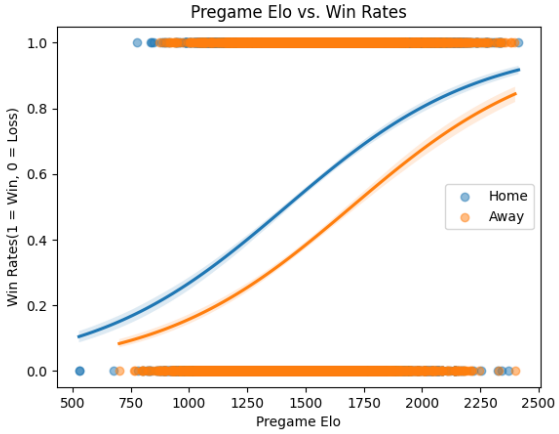


Figure 4: Pregame Elo vs Win Rates

Figure 5 has a similar concept to the previous figure, although this time we took the difference in elo between the home team and away team and compare that to the win rate for just the home team. Again, we created a logistic regression line predicting probability of a home team winning given the difference in their elo compared to the away team. It is also in line with what one might think would happen in the sense that as the elo difference increases so does the win rate and when it is lowest the win rate is lowest.

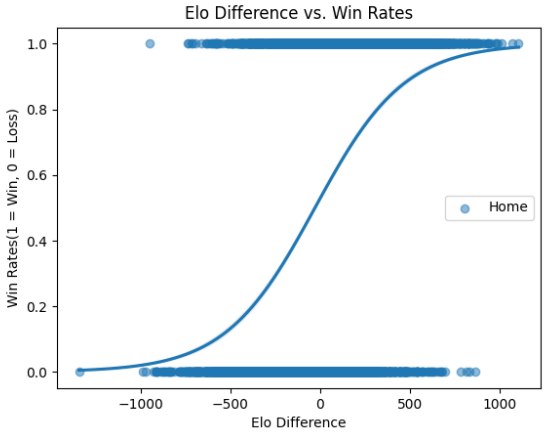


Figure 5: Elo Difference vs Win Rates

The histogram in Figure 6 illustrates the distribution of the Excitement Index across all games in the dataset from 2014 to 2024. The histogram is right-skewed with the majority of games cluster around lower excitement scores. However, the long right tail highlights that a handful subset of games reached very high excitement levels, for example overtime thrillers, rivalry games, and upsets that captured attention nation-wide.

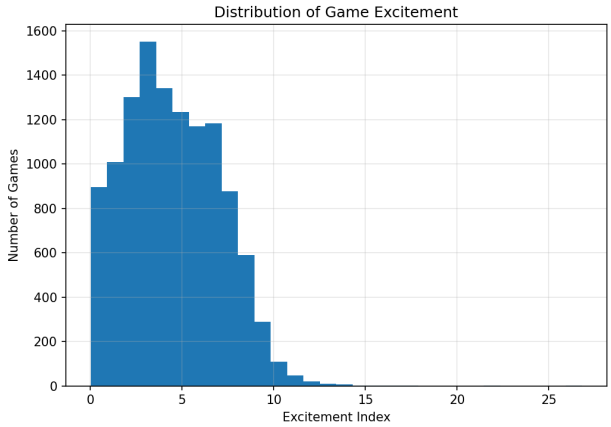


Figure 6: Distribution of the Excitement Index across all games

The boxplot in Figure 7 compares the distribution of the excitement of the game across 2014-2025 seasons. Median values remain fairly stable, but certain years have wider spreads and more frequent high-excitement outliers. Outliers in excitement may help explain why polls overreact or underreact in certain years. If a season produces many high-drama games, poll rankings may reward teams for the hype and popularity rather than consistent efficiency, contributing to fraud risk.

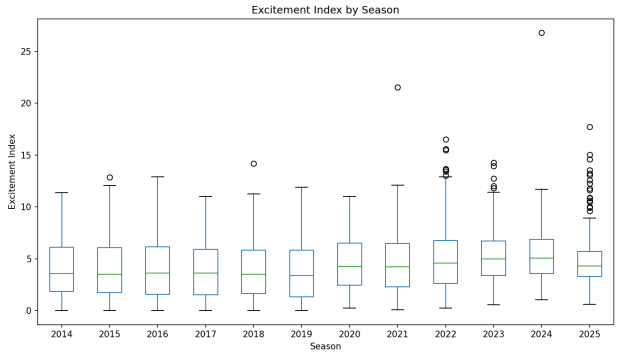


Figure 7: Distribution of game excitement across different seasons

Figure 8 plots the final ranking of the AP Poll against the win percentage. The overall trend shows that stronger ranked teams tend to win more games, but several outliers are noticed. For example, Georgia was highly ranked in the polls despite only a moderate win percentage, suggesting perception exceeded on-field performance. In contrast, Marshall achieved a strong record of Win Percentage despite a lower AP ranking, suggesting a possible underrating. These mismatches highlight where polls can overvalue or undervalue teams and similar patterns which that appear in multiple seasons (2014-2014) can be found in Appendix B. This supports the idea that "fraud teams" are not isolated anomalies but a recurring feature of college football rankings.

Figure 9 shows the correlation between AP Poll rankings and two performance measures: win percentage and SRS (Simple Rating System). SRS combines offensive (OSRS) and defensive (DSRS) efficiency while adjusting for strength of schedule, offering a more robust indicator of true team strength than just win-loss records. For each season, we calculated Pearson's correlation

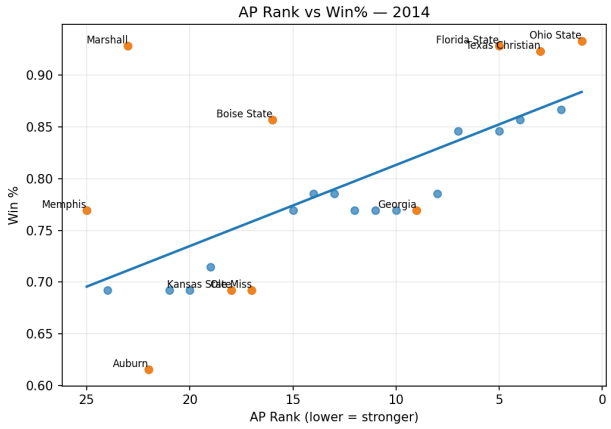


Figure 8: Relationship between final AP Poll ranking and Win Percentage in the 2014 season

between inverted AP Rank (since lower rank = better) and each performance metric. The results indicate that the poll rankings track the win percentage moderately well, but their correlation with SRS is consistently weaker. This suggests that while polls reward teams for accumulating wins, they often overlook efficiency-based measures.

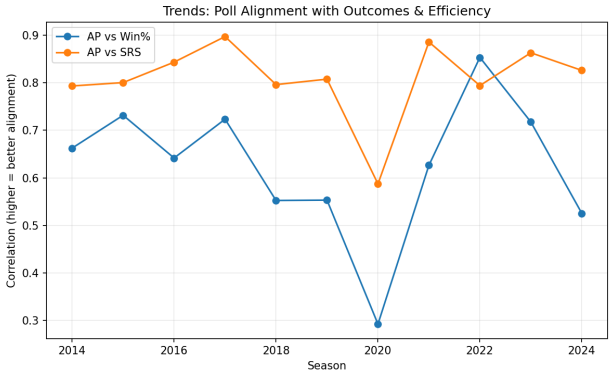


Figure 9: Correlation trend of AP Rank with Win% and SRS (2014–2024)

Figure 10 plots PollRankGap against actual win percentage for the 2014 season. The positive slope indicates that, on average, teams who outperformed preseason polls also won more games. However, significant outliers exist. Auburn and USC illustrate classic "fraud" teams, entering the season with hype but finishing below expectations. In contrast, Oregon, and Ohio State surpassed expectations, demonstrating strong alignment of perception and performance.

3.2 Results: Clustering Analysis

In order to determine the appropriate number of clusters we should use, we evaluated both the silhouette score and inertia across k = 2–10, Figure 11. The silhouette score peaked at k = 2, indicating the strongest separation. However, the solution of 2 clusters might be too simplistic. The inertia curve showed a clear elbow around k = 3 or 4. To balance statistical fit, we selected k = 3 clusters for the main analysis, corresponding to elite, solid, and struggling tiers of teams.

We applied K-Means Clustering Method to the 2019 season with k=3. The result shows three

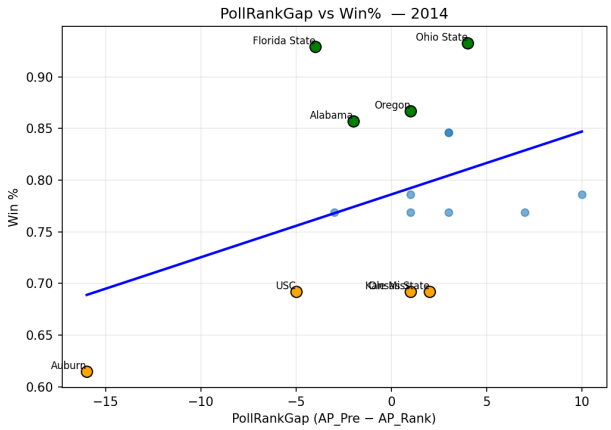
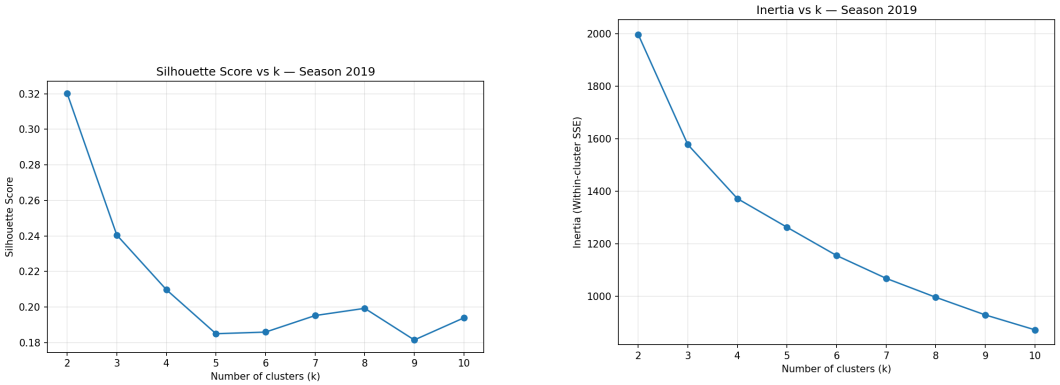


Figure 10: Relationship of Difference between AP Preseason Rank and AP Final Rank and Win Percentage



(a) Silhouette **(b)** Inertia

Figure 11: Elbow Line Charts of 2019 Season

clusters with detailed information explained in the following and table 2.

- Cluster 0 (27 teams): This cluster contained the majority of elite teams of 2019. These teams have very high Simple Rating System (SRS) values (mean = 15.15), strong win percentage (mean = 0.79) and dominant Margin of Victory (mean = 50.81).
- Cluster 1 (61 teams): This cluster represented the middle tier teams. The large portion of teams fall into this cluster. Teams in this group achieved moderate success, with an average win percentage (mean = 0.52) and moderate Margin of Victory compare to Cluster 0 (mean = 30.8).
- Cluster 2 (30 teams): This cluster contains struggle or lower tier teams. Teams here had strongly negative SRS values (mean = –11.32) and low win percentages (mean = 0.31). Their performance metrics clearly separated them from both middle tier and elite teams.

The PCA visualization of 2019 clusters, in Figure 12 shows three relatively distinct groupings of teams. Cluster 0 (blue) includes elite teams like Ohio State, Clemson, and LSU, consistent with

Cluster	SRS_SRS	WinPct	MOV	SOS
0	15.148148	0.794438	50.808148	3.542222
1	1.285410	0.515237	30.800328	0.384262
2	-11.318667	0.311966	12.677667	-3.505667

Table 2: Cluster means of key stats in season 2019

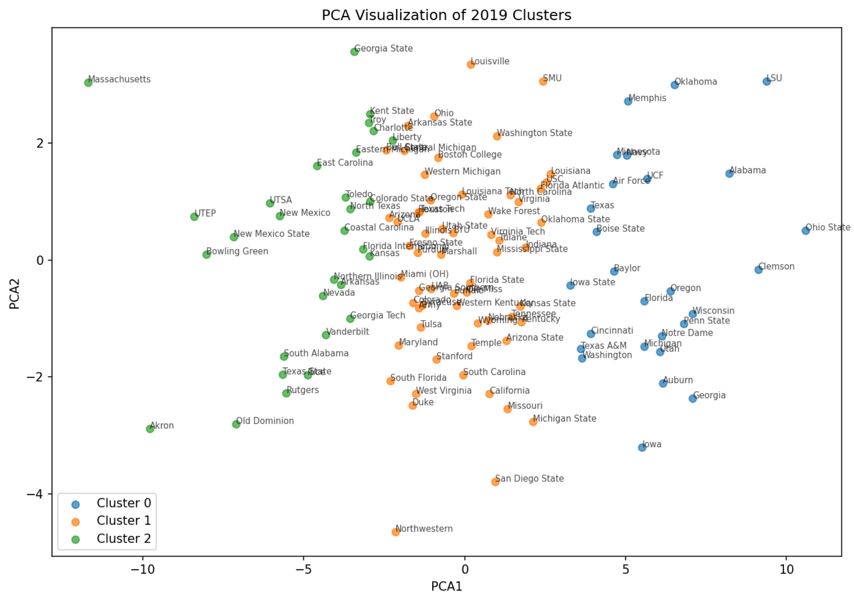


Figure 12: PCA Clustering of 2019 season

their elite performances in both AP polls and efficiency metrics. Cluster 1 (orange) captures middle-tier teams like Michigan State, Missouri, and Arizona State, reflecting strong but not dominant seasons. Cluster 2 (green) consists mainly of struggling or low-performing teams, including Rutgers, UTEP, and Bowling Green, who struggle in both win percentage and efficiency. Although some overlap is visible in the middle clusters, the separation of elite teams from struggling teams is clearly shown.

3.3 Results: Threshold Construction and Fraud Labeling

Using our thresholds, we defined frauds as teams that (1) reached the AP Top 12 at some point in the season, but (2) registered six or fewer elite threshold hits. This cutoff was chosen based on exploratory data analysis, which consistently showed that teams with fewer than six elite hits rarely resembled true national title contenders, despite their ranking. The Top 12 filter also reflects the current College Football Playoff structure, which includes twelve teams. This labeling design allows us to identify teams with high expectations that do not meet the requirements of underlying play-specific metrics.

Accordingly, we created three groups:

- **Frauds (label = 1):** Teams in the AP Top 12 with six or fewer elite hits.
- **Contenders (label = 0):** Teams in the AP Top 12 with more than six elite hits.

- **Irrelevant:** Teams never ranked in the AP Top 12. These were excluded from model training to keep the classification focused on hyped programs, but they are automatically assigned a fraud score of 100 in application since they were never legitimate contenders.

This framework avoids diluting the contender class with unranked teams and ensures that the model focuses on distinguishing between hyped programs that either lived up to expectations or fell short.

Applying the EliteHits threshold together with the AP Rank data, we obtained the Fraud Label column (1 or 0) for each satisfied team with result examples showing in table 3, 4, and 5.

Table 3: Top 5 Fraud Candidates in 2014, Based on AP Ranking and Elite Hits

Team	AP_High	EliteHits	AP_Rank	FraudLabel
Auburn	2	4	22	1
Mississippi St.	1	2	11	1
Georgia Tech	8	5	8	1
Michigan State	5	5	5	1
Wisconsin	11	2	13	1

Table 4: Top 5 Fraud Candidates in 2019, Based on AP Ranking and Elite Hits

Team	AP_High	EliteHits	AP_Rank	FraudLabel
Florida	6	6	6	1
Michigan	7	5	18	1
Auburn	7	6	14	1
Oregon	5	6	5	1
Notre Dame	7	5	12	1

Table 5: Top 5 Fraud Candidates in 2022, Based on AP Ranking and Elite Hits

Team	AP_High	EliteHits	AP_Rank	FraudLabel
Kansas State	11	3	14	1
Penn State	7	6	7	1
USC	4	6	12	1
Oregon	6	0	15	1
Clemson	4	1	13	1

3.4 Results: Random Forest Classifier Model Performance

Our training dataset contained 260 team-seasons, with 192 labeled as frauds and 68 as contenders. The imbalance reflects the frequency with which highly ranked teams fail to live up to contender-level performance. By training only on ranked teams, the model learns patterns in performance associated with fraud outcomes rather than simply reproducing the labeling criteria.

Our Random Forest classifier achieved strong results in distinguishing between contenders (0) and frauds (1). On the holdout test set, the model reached an overall accuracy of 94%, with a precision of 0.949 and recall of 0.974 for fraud cases. This means that nearly all true frauds were

correctly identified while minimizing the risk of mislabeling contenders. The model's ROC–AUC on the test data was 0.987, indicating excellent separation between the two classes.

To ensure these results were not inflated by temporal leakage, we applied season-aware validation using GroupKFold, which ensures entire seasons are kept in either training or testing sets. Performance remained consistently strong, with a mean AUC of 0.982 and mean accuracy of 0.930 across folds. This demonstrates that the model generalizes well across years, rather than memorizing patterns from a single season.

Feature importance analysis confirmed that margin of victory (MOV) and overall SRS were the strongest predictors of fraud status, followed by end-of-season Elo ratings and offensive production metrics (Table 6). This aligns with intuition: true contenders tend to dominate opponents and score highly on efficiency-adjusted systems, while fraudulent teams often lack such statistical dominance despite their poll ranking.

Table 6: Top Feature Importances from Random Forest Classifier

Feature	**Importance**
Margin of Victory (MOV)	0.245
Simple Rating System (SRS_SRS)	0.150
Postgame Elo	0.091
Points For	0.073
Total Offense	0.071
Scoring Offense	0.070
Scoring Defense	0.053
Total Defense	0.043

4 Discussion

4.1 Discussion: EDA/Visualization

Our exploratory data analysis provided foundational insights into the relationship between perception-based measures, such as AP Poll rankings, and performance-based metrics, including Win Percentage (WinPct), Simple Rating System (SRS), and Margin of Victory (MOV). Most notably, the figures we created depicting the relationship between final AP Poll ranking and win percentage for each season was helpful in identifying "frauds" early on in the project. The EDA also helped identify consistent patterns across seasons. For example, teams such as Oklahoma, Clemson, Ohio State frequently appeared near the top of both AP and performance metrics, while others, like UCF or Baylor in certain years, achieved strong records but weaker efficiency scores, consistent with the perception bias documented [1, 5]. This evidence guided the later design of our Fraud Score, which distinguishes between perception and performance to determine these disparities.

4.2 Discussion: Clustering Analysis

The PCA clustering of the 2019 season in Figure 12, when viewed alongside the AP Preseason and Final Rankings in Table 7, highlights both alignment and divergence between perception and performance. Elite teams such as LSU, Ohio State, and Clemson not only clustered in the high-performance group but also finished within the top of the AP rankings. These teams serve as an

example for what a "true contender" looks like in our framework.

However, several divergences exist when comparing AP ranks to cluster placement. For instance, teams such as Texas, Michigan and Texas A&M entered the season highly ranked in the AP poll but were placed close to the mid-tier clusters in the PCA analysis as well as dropping to lower AP Rank at the end of the season. This gap emphasizes the issue of voter bias in preseason polls identified by Coleman et al. (2010), where historical prestige or media may inflate early-season expectations [1].

Table 7: AP Poll Rankings: Preseason, Highest, and Final (2019 Season)

School	AP Pre	AP High	AP Rank
Clemson	1	1	2
Alabama	2	1	8
Georgia	3	3	4
Oklahoma	4	4	7
Ohio State	5	2	3
LSU	6	1	1
Michigan	7	7	18
Florida	8	6	6
Notre Dame	9	7	12
Texas	10	9	25
Oregon	11	5	5
Texas A&M	12	12	–
Washington	13	13	–
Utah	14	5	16
Penn State	15	5	9
Auburn	16	7	14
UCF	17	15	24
Michigan State	18	18	–
Wisconsin	19	6	11
Iowa	20	14	15
Iowa State	21	21	–
Syracuse	22	21	–
Washington State	23	19	–
Nebraska	24	24	–
Stanford	25	23	–
Wake Forest	–	19	–
Virginia	–	18	–
Virginia Tech	–	23	–
Cincinnati	–	17	21
Memphis	–	15	17
Navy	–	20	20
SMU	–	15	–
Baylor	–	8	13
Kansas State	–	20	–
Oklahoma State	–	21	–
Texas Christian	–	25	–

School	AP Pre	AP High	AP Rank
Indiana	–	24	–
Maryland	–	21	–
Minnesota	–	7	10
Boise State	–	14	23
Air Force	–	22	22
San Diego State	–	24	–
California	–	15	–
USC	–	22	–
Arizona State	–	17	–
Missouri	–	22	–
Appalachian State	–	19	19

4.3 Discussion: Real-World Validation for Fraud Score

To validate our fraud score predictions beyond internal performance metrics, we cross-referenced model-identified frauds and contenders with historical outcomes from ESPN and Sports Reference. This provided a means of evaluating whether teams flagged as fraudulent by our model underperformed relative to their poll position and whether low-scoring teams demonstrated true contender status. These case studies ensure that our fraud score is not only statistically grounded but also aligned with historical reality as documented in widely accepted archives [27, 28, 29].

Table 8: Model-Predicted Fraud Scores (2014, 2019, 2022)

Season	Team	FraudScore	AP High	EliteHits	Label
2014	Mississippi State	100.0	1	2	Fraud
2014	Texas A&M	100.0	6	1	Fraud
2014	Notre Dame	100.0	5	0	Fraud
2014	USC	100.0	9	0	Fraud
2014	Arizona State	100.0	7	0	Fraud
2014	Alabama	5.2	1	9	Contender
2014	Ohio State	1.0	1	10	Contender
2019	Texas A&M	100.0	12	0	Fraud
2019	Texas	100.0	9	0	Fraud
2019	Baylor	99.8	8	3	Fraud
2019	Minnesota	95.8	7	2	Fraud
2019	Notre Dame	92.8	7	5	Fraud
2019	LSU	1.8	1	11	Contender
2019	Ohio State	0.2	2	18	Contender
2022	Clemson	100.0	4	1	Fraud
2022	Oregon	100.0	6	0	Fraud
2022	Texas A&M	100.0	6	1	Fraud
2022	BYU	100.0	12	0	Fraud
2022	Florida	100.0	12	1	Fraud
2022	Tennessee	5.0	2	8	Contender
2022	Michigan	4.0	2	9	Contender

2014 – Mississippi State. The model flagged Mississippi State as a top fraud with a Fraud-

Score of 100.0 despite their peak AP ranking at #1. This aligns with reality: Mississippi State's hot start (including a win over Auburn) vaulted them to the top of the polls, but they finished 10–3 with losses to Alabama, Ole Miss, and Georgia Tech in the Orange Bowl, failing to contend for the playoff [27].

2019 – Texas A&M. Texas A&M was also flagged as a fraud with a FraudScore of 100.0. The Aggies were ranked as high as #12 in the AP Poll but stumbled to an 8–5 finish, including losses to Clemson, Alabama, Georgia, and LSU. Despite preseason hype, their metrics revealed that they were overvalued by the polls [28].

2022 – Clemson. Clemson carried an AP high of #4 but was given a FraudScore of 100.0 by our model. The Tigers finished 11–3, but late-season losses to Notre Dame and South Carolina exposed offensive weaknesses, and they were overmatched by Tennessee in the Orange Bowl. Their top ranking was not supported by the statistical dominance seen in true contenders [29].

5 Conclusions

This project was successful in defining and quantifying what a "fraud" team is and creating a systematic way to identify them. By leveraging performance metrics that highlight meaningful differences between perception and reality, we developed a machine learning model capable of distinguishing contenders from frauds with high accuracy. Our framework provides a standardized measure of how teams truly perform relative to historical championship-level benchmarks, offering insights into when hype is justified and when it is misleading.

The model demonstrated strong predictive accuracy across multiple seasons, with temporal validation confirming its generalizability and feature importance rankings aligning with intuitive measures of team dominance. The fraud scores not only separated contenders from frauds statistically but also held up under real-world validation, with case studies highlighting teams such as Mississippi State (2014), Texas A&M (2019), and Clemson (2022) as historically overvalued, while true contenders like Ohio State (2014), LSU (2019), and Michigan (2022) received low fraud scores.

From an ethical standpoint, the project also highlights the continuous disparities by biased ranking systems. As Edelman (2014) and Oplinger (2021) [23, 24] have argued, subjective rankings can reinforce disparities between Power Five and Group of Five programs, influencing recruitment, funding, and bowl access. Our findings of Fraud Score suggest that incorporating transparent, data-driven models could help minimize such biases. This aligns with broader calls in sports analytics for fairness, where algorithmic transparency ensures that evaluative models can be audited and improved over time rather than concealed by subjective judgment.

Taken together, these findings show that the fraud score is both statistically rigorous and contextually meaningful, with potential applications for evaluating standings, informing betting markets, and even improving playoff selection debates. While the current model is robust, it can be further improved by incorporating additional efficiency-based metrics such as SP+ or Massey Ratings. With continued refinement and application to ongoing seasons, this framework has the potential to scale into a comprehensive tool for assessing true team performance year after year.

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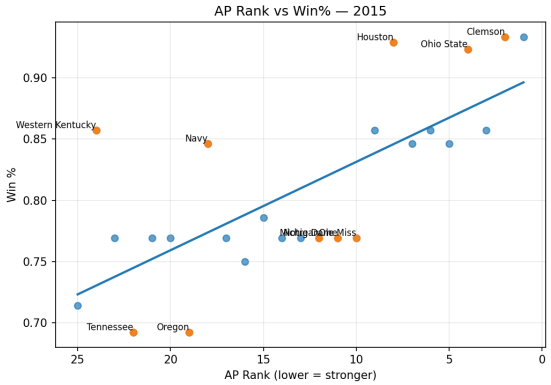
A Code Appendix (Github Reference)

The code repository of this project can be accessed here.

B List of All Teams from Each Cluster in Season 2019

- Cluster 0 teams (27): Ohio State, LSU, Alabama, Clemson, Wisconsin, Georgia, Penn State, Notre Dame, Oregon, Auburn, Oklahoma, Michigan, Florida, Utah, Iowa, Memphis, Navy, Washington, Texas, Baylor, Minnesota, UCF, Cincinnati, Air Force, Texas A&M, Boise State, Iowa State
- Cluster 1 teams (61): SMU, USC, Louisiana, Florida Atlantic, Oklahoma State, Kansas State, North Carolina, Virginia, Michigan State, Kentucky, Indiana, Tennessee, Mississippi State, Arizona State, Tulane, Washington State, California, Virginia Tech, Wake Forest, Louisville, Missouri, Nebraska, Ole Miss, Oregon State, Florida State, San Diego State, Buffalo, South Carolina, Wyoming, Temple, BYU, Tulsa, Western Kentucky, Duke, Colorado, Georgia Southern, Illinois, Boston College, Houston, Purdue, Marshall, UCLA, Texas Tech, Louisiana Tech, Western Michigan, Arkansas State, Utah State, Stanford, Ohio, Syracuse, West Virginia, Central Michigan, Miami (OH), Northwestern, Maryland, South Florida, Ball State, Army, Arizona, Fresno State, UAB
- Cluster 2 teams (30): Kent State, Troy, Liberty, Kansas, Arkansas, Georgia State, Colorado State, Charlotte, Coastal Carolina, Eastern Michigan, Florida International, Georgia Tech, Nevada, Toledo, North Texas, East Carolina, Northern Illinois, Vanderbilt, Rice, Rutgers, South Alabama, Texas State, New Mexico, UTSA, Bowling Green, New Mexico State, Old Dominion, UTEP, Akron, Massachusetts

C AP Poll Ranking vs Win Percentage (2015-2024)



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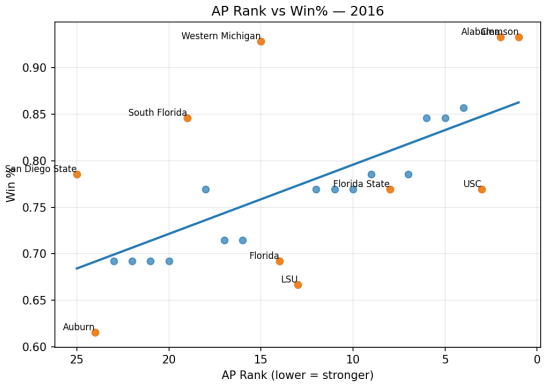

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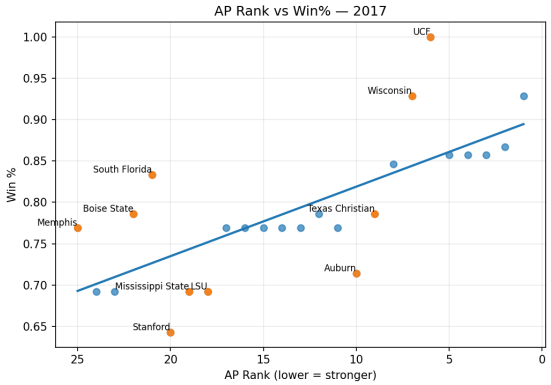
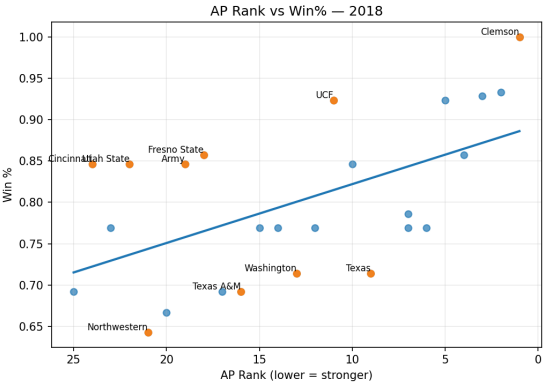
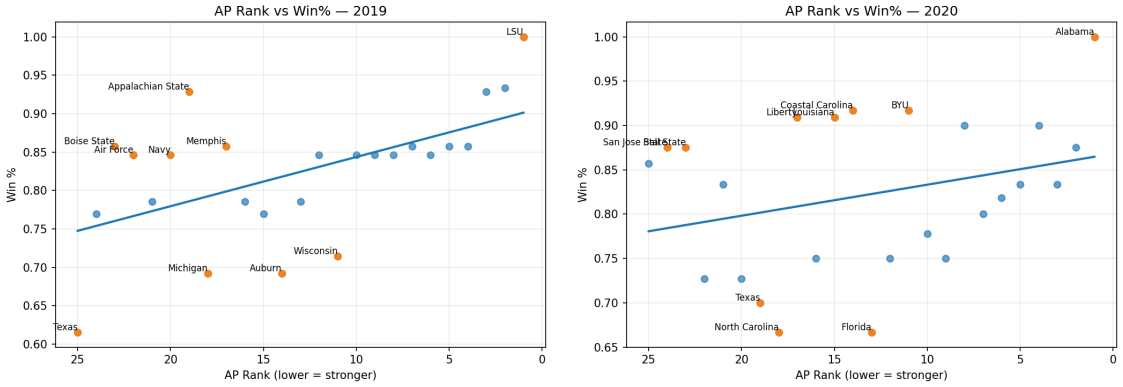


(c) 2017

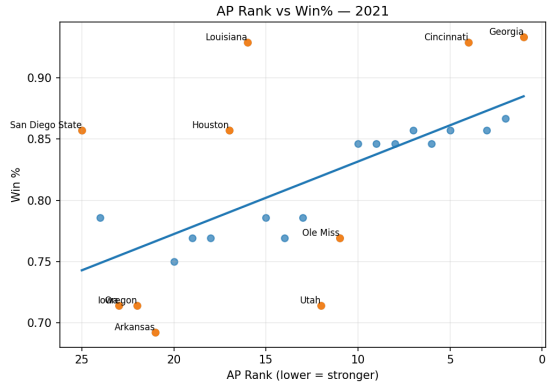


(d) 2018

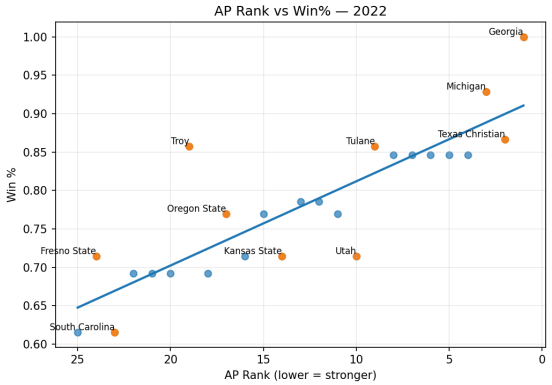


(a) 2019

(b) 2020



(c) 2021



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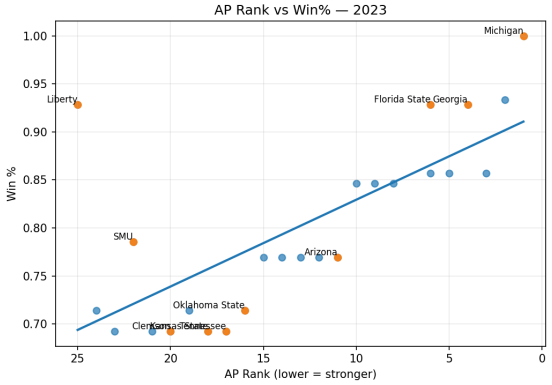

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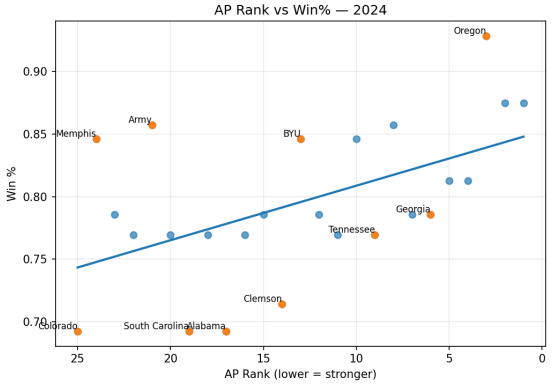
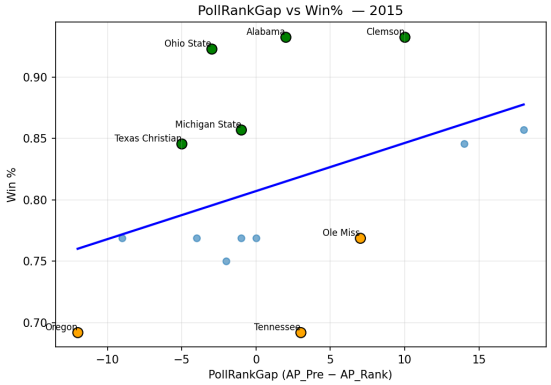


(f) 2024

Figure 14: AP Rank vs Win% scatterplots for the 2015–2024 seasons

D PollRankGap vs Win Percentage (2015-2024)



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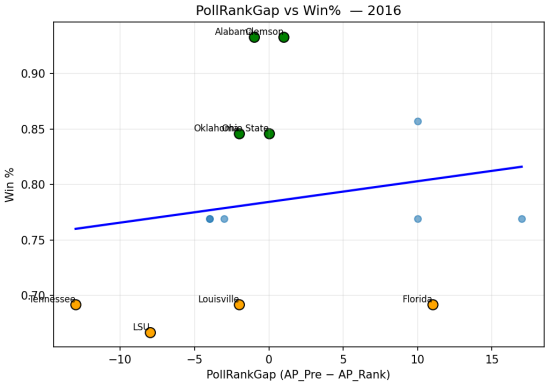

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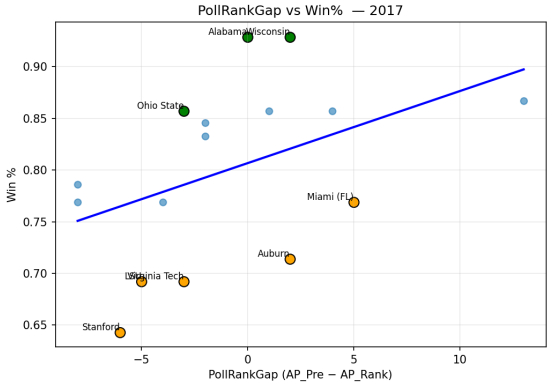
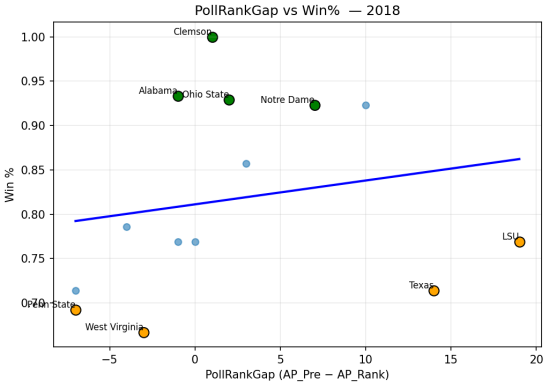
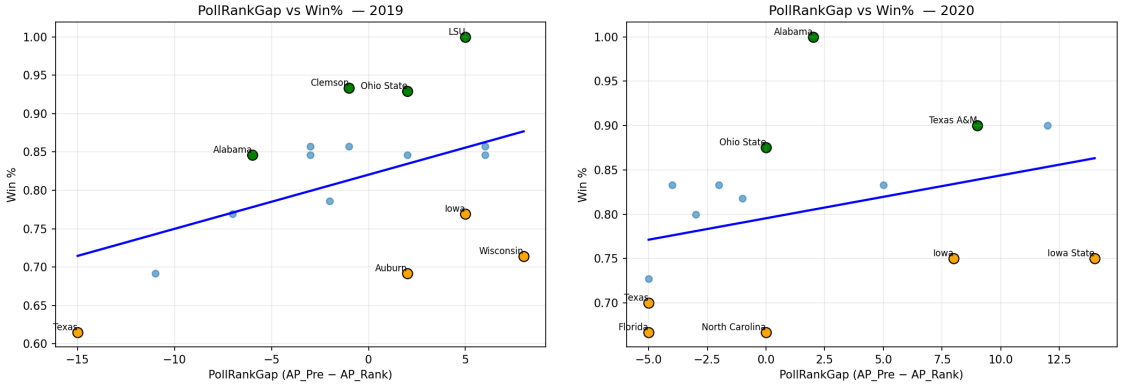


(c) 2017

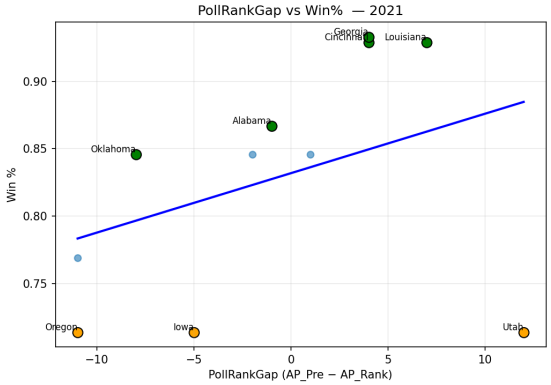


(d) 2018

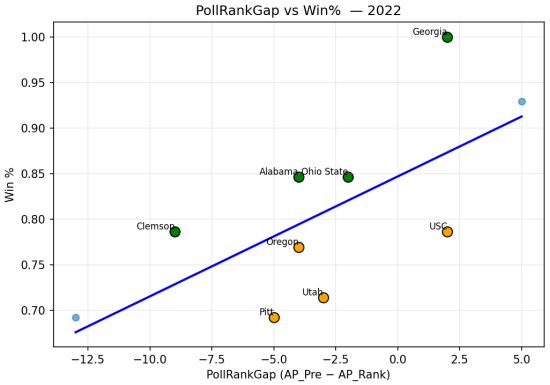


(a) 2019

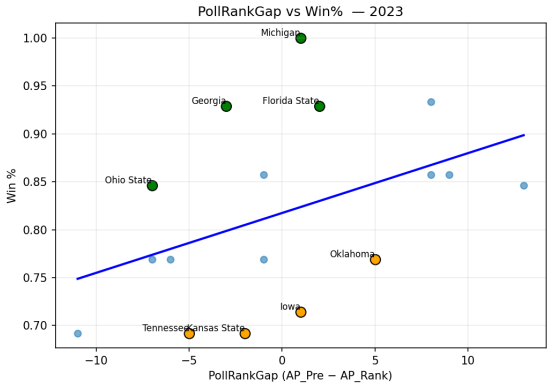
(b) 2020



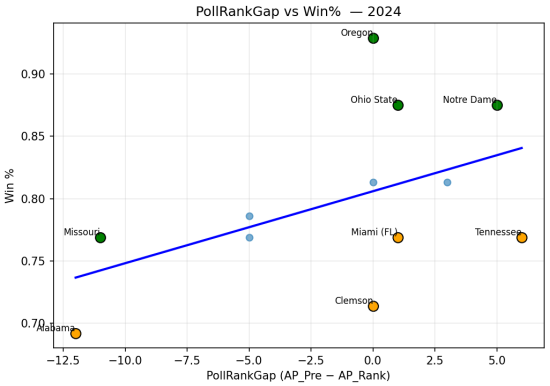
(c) 2021



(d) 2022



(e) 2023



(f) 2024

Figure 16: Poll Gap vs Win% scatterplots for the 2015–2024 seasons