# Analysis of Vegas Lines and Predictions of Spread and Over Wagers

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# Project Overview

## A.1. Research Question or Organizational Need

This project will utilize machine learning algorithms to analyze historical Vegas sports betting lines for NCAA college football games and compare them against the actual game results and come up with a model to predict whether the favorite or underdog in a college football contest will win or cover the spread, whether the over/under total will be reached, or whether the betting underdog will win. It will create a Python application that will make a machine learning model that will be used for prediction. Ideally, the project would fit the informational needs of individual sports bettors as they consider their wagers.

## A.2. Context and Background

Sports betting has become a multi-billion-dollar industry in Las Vegas and other states where sports wagering has become legal. Sports books have countless experts whose sole purpose is to set and adjust point totals, money lines, and final-score spreads to entice (relatively) equal amounts of betting on both sides of each line. Their goal is to be able to make a profit by taking a vigorish (“vig”, or “juice”) on each wager. This comes in the form of a built-in percentage (usually 9-10%) of the odds to ensure they make a profit regardless of which team comes out on top. For example, if a sports book’s betting lines show a team with a money line of “-110”, that means for a bettor to win $100 on that bet, they must bet $110. The sports book’s “vig” on that bet is $100/$110 or ~9%. They get $110 from the bettor, pay them $100 if they win, and keep $10 in profit.

A bettor will bet on a particular contest when they “believe the current line does not accurately reflect what the information available suggests it should be”. (Metcalf). Like any other type of wager, a bettor's goal is to guess right and take a little money from the house.

College football is one of the largest sports for eager bettors to place wagers on. Countless books and websites have been written trying to develop strategies to predict the outcome of any of these sports book wagers. Because of how much revenue is generated for sports books, they are unwilling to divulge their formulas or the built-in experience and intelligence of the human oddsmakers who set and adjust these lines. Bookmakers want to find a number on each contest where they believe no one will bet on it or will have an (roughly) equal number of bets on both sides.

The goal is to have a solid prediction model that a sports bettor can use to predict the outcome of these betting lines and confidently place a bet, knowing they have received a confident prediction of the outcome.

## A.3. Summary of Published Works

**How Lines Are Set: An Oddsmaker's Perspective** (written by Matt Metcalf, Circa Hotel and Casino, Las Vegas)

The article explains how Vegas lines are set, the history of setting opening lines, and how opening lines are set today. Bob Martin was the one who started the Las Vegas Line at Churchill Downs and the Plaza in Las Vegas. From there, it migrated all over the country and even overseas to various sportsbooks and bookies (both legal and illegal) for use in their odds making. It’s important to note that the opening lines are just jumping-off points to entice the bettors to start wagering. From there, as action is placed on one side or the other, the oddsmakers “move” the line to keep the action as equal on both sides as possible. In essence, it’s the professional bettors who move the line, not the sportsbooks. (Metcalf) Depending on the sport, one sportsbook will open the betting lines for one sport while another will open the lines for another. Other sportsbooks will see the opening lines and decide how to adjust them. Over time, experience with the sports, lines, and results will help oddsmakers feel more comfortable with the opening lines they wish to set.

Since I will use these lines in my analysis and prediction, how they are initially set and evolve is key. However, I will only analyze the final line before game time and not consider the opening line.

**Stadium size, ticket allotments, and home field advantage in college football** (published by Steven B. Caudill and Franklin G. Mixon, Jr., 26 November 2007, ScienceDirect)

The article analyzes how stadium capacity, ticket allotment (to the visiting team), and fan attendance affect home-field advantage in college football. College football success has shown an increase in the ability of a university to attract “blue-chip” high school football players to help ensure their winning success continues. (Caudill & Mixon, Jr., 2007). A university’s success rate on the football field directly correlates to alums giving and graduation rates of its student-athletes. This equates to one of my sayings: “Success builds upon itself”. If a team was established early in college football history, it most likely has been successful and will continue to be successful. Universities like the University of Southern California, Alabama, Ohio State, and Michigan are considered the “blue bloods” of the sport.

A 1996 study by the same authors on the Alabama-Auburn football rivalry analyzed relative fan attendance and the probability of winning. The study states that the higher the attendance of the home team’s fans, the more they exert their enthusiasm, the more difficult it is for the opposing team to concentrate on executing their plays, the higher the probability of the home team being victorious. In some cases, especially with universities that are not quite as “blue blood” as other schools, they may resort to offering free tickets in the less desirable sections of the stadium, hoping to fill their stadiums and gain more of a home-field advantage, especially if the visiting team is one of the “blue bloods”.

The article goes on to analyze the unique case of the Alabama-Auburn football rivalry because after a 40-year hiatus of the rivalry, the rivalry was renewed and played at a neutral site (Legion Field in Birmingham, Alabama), with the tickets being split 50-50, instead of alternating between playing at Bryant-Denny Stadium (Alabama) and Jordan-Hare Stadium (Auburn).

Stadium capacity, attendance size, and percentage of capacity are statistics I will be including as part of the model.

**Machine Learning in Sports Betting: How Will This New Technology Impact Sports Betting?** (OddsMatrix, 23 June 2025)

The article explains how machine learning is becoming more prevalent in sports betting because it can be “used to predict the outcome of matches more accurately than a human analyst (oddsmaker)”. (OddsMatrix, 2025)

Many use cases for machine learning in sports are not just related to betting on contests, “as most teams have taken to basing their tactical decisions on data” (OddsMatrix, 2025). If you watch any major sport in the United States, you’ll likely hear the term “analytics” frequently thrown out. That’s a shorthand term saying they’re using machine learning and modeling.

A study was done in 2021 analyzing more than 39,000 men’s and women’s tennis matches and found the rate of success from the model was not more than what was predicted by a human oddsmaker, who was right about 65% of the time. This is because even though the world outside the sportsbooks has evolved in adopting machine learning, so have the sportsbooks’ uses of machine learning, since data is their bread and butter. They’ve even made their algorithms open source because they don’t want the technologies that are so vital in their success to be used against them. (OddsMatrix, 2025). Bookmakers are not working alone, either. Companies like OddsMatrix work in step with bookmakers to provide them with vital technology to be more efficient.

In addition to using machine learning to create their prediction models and set odds, sportsbooks use machine learning to analyze their customers’ behavior: what sports they bet on, how often, how much, and on what lines (futures, money line, spread, etc.). This can help them evolve their marketing and sales efforts for their customer base and individual bettors’ preferences.

The remainder of the article highlights the use cases for machine learning in sports betting and how OddMatrix’s value benefits bookmakers and individual bettors, including real-time odds optimization, automating tasks, and fraud detection (among others).

My whole goal with this project is to use machine learning to develop a prediction model to help decide the best features for predicting the lines.

## A.4. Summary of Data Analytics Solution

This project aims to develop predictive models to determine whether the favorite will cover the spread, whether the total points will result in an over or under outcome, and whether the betting underdog will win outright.

The first analytical output will be the three machine learning models corresponding to each betting line (spread, over/under, underdog wins). Each model will be evaluated using accuracy and F1 scores to assess performance and determine whether the RandomForestClassifier or LogisticRegression provides better predictive results for each case.

The second analytical output will be the results of one-sample binomial proportion tests conducted for each model. These tests will evaluate whether model accuracy significantly exceeds relevant baseline thresholds (i.e., 50% for spread and over/under predictions, and over 25% for underdog win predictions). It will result in a p-value that I will compare against my predetermined significance level (α = 0.05) to determine whether the model’s performance is statistically significant.

These betting lines were chosen because they’re the most popular and the simplest lines for sports bettors to wager on, as one of two choices has to be picked with each line.

## A.5. Benefit to the Organization and Decision-Making Process

The objectives of creating the models are to allow sports bettors to see the confidence level of the models’ predictions and use that to determine if the probability is significant enough to bet on one side or the other, instead of taking a random guess. The goal is to have enough confidence in the prediction that it outweighs the risk of placing the wager.

# Data Analytics Plan

## B.1. Goals, Objectives, and Deliverables

### B. 1. A. Goals:

Create models to predict the outcome of the three most common Vegas lines (spread, over/under, money line)

### B.1.B. Objectives

Objective A: Use various scoring methods to select an ideal machine learning algorithm to use to create and train a model for each of the three Vegas lines I am analyzing (spread, over/under, underdog winning)

Objective B: I will utilize a statistical test to calculate a p-value for each prediction model. This will be vital in determining if there is statistical significance in each model to use it over using the base criteria (coin flip guess).

### B.1.C. Deliverables

|  |  |
| --- | --- |
| **Items** | **Date** |
| Wrangled data from various sports statistics sites | June 25, 2025 |
| Cleaned and processed data | July 5, 2025 |
| Used scoring methods to determine the ideal algorithm | July 8, 2025 |
| Results of statistical tests | July 9, 2025 |
| Trained and tested models | July 11, 2025 |
| Create visualizations | July 14, 2025 |

## B.2. Scope of Project

### B.2.A – Included in Project Scope

The project will include an average historical offensive and defensive statistics analysis before each contest and a prediction model of the likelihood of a team covering the spread, the over/under total reaching the over, and whether the underdog will win a game outright.

### B.2.B – Not Included in Project Scope

I will not be doing any analysis or predictions on any “futures” lines, such as whether a team will achieve more or fewer wins than the Vegas line on predicted wins, or a prediction of who will win the national championship. Those things encompass analyzing different statistics, which I did not have time for, nor are those bets made as often as the weekly spread, over/under, and money line wagers.

## B.3. Standard Methodology

I will use the Waterfall project methodology because I can only train the model in its most correct form after having gathered the data, cleaned, imputed, and preprocessed it. However, after collecting the data, I would not be surprised if the methodology partly becomes Agile, especially if I go back and engineer new features and test those out to make the model as accurate as possible.

## B.4. Timeline and Milestones

|  |  |  |  |
| --- | --- | --- | --- |
| **Milestone** | **Projected Start Date** | **Projected End Date** | **Duration (days/hours)** |
| All data gathered | June 25, 2025 | June 25.2025 | 1 day |
| Data cleaned and preprocessed | June 26, 2025 | July 5, 2025 | 10 days |
| Model development | July 6, 2025 | July 9, 2025 | 4 days |
| Models tested | July 10, 2025 | July 11, 2025 | 2 days |
| Created visualizations | July 12, 2025 | July 14, 2025 | 3 days |

## B.5. Resources and Costs

|  |  |
| --- | --- |
| **Personnel, technology, or infrastructure** | **Cost** |
| Myself as Developer | $0 |
| Data Sources Publicly Available | $0 |
| Visual Studio Code for Development | $0 |
| 30-day free trial to stathead.com | $0 |

## B.6. Criteria for Success

In the first part of my analysis, I will use various scoring methods to determine the ideal machine learning model for each of my prediction models. I will also calculate feature importances to see which features are the most applicable and determine if the prediction results are statistically significant.

In the second part of my analysis, before finalizing the creation of the models, I will run a statistical test to calculate the p-value of each model. I will consider each model successful if the p-value exceeds my predetermined alpha value.

# Design for Data Analytics Solution

## C.1. Hypothesis

**Spread**

**Null Hypothesis(H0)**:

The model’s predictive performance for against-the-spread (ATS) outcomes does not exceed what would be expected by random chance. That is, its classification accuracy is indistinguishable from 50%.

**Alternative Hypothesis (H1)**:

The model’s predictive performance for against-the-spread outcomes exceeds random chance, demonstrating statistically significant accuracy greater than 50%.

*Note:* The 50% benchmark reflects the binary nature of ATS results (cover vs not cover), assuming no prior knowledge or edge.

**Over/Under**

**Null Hypothesis(H0)**:

The model's predictive accuracy in forecasting over/under outcomes equals what would be expected from guessing. That is, performance is not statistically different from 50%

**Alternative Hypothesis (H1)**:

The model achieves statistically significant predictive accuracy greater than 50% in identifying over/under outcomes.

**Underdog Wins**

**Null Hypothesis(H0)**:

The model does not improve upon the expected historical baseline for outright underdog wins. Its accuracy is statistically equivalent to the benchmark win rate of 25%.

**Alternative Hypothesis (H1)**:

The model demonstrates statistically significant improvement over the 25% baseline in predicting underdog wins.

## C.2. Analytical Method

### C.2.A. Justification of Analytics Method

Once the datasets are cleaned, preprocessed, and merged into one, I will need to run OneHotEncoding or Pandas’ get\_dummies function to convert the nominal categorical features into numerical ones for the training of the models. Also, since the ranges of the offensive statistics I will be using in my training will be much different from each other, I will have to use StandardScaler to scale the values of each feature to be consistent.

After creating the models, I will run a binomial proportion test on each trained model to calculate a p-value to compare against my alpha to see if the model’s prediction is statistically significant over the baseline.

## C.3. Tools and Environment of Solution

The project will be developed using Python in Jupyter Notebooks and the Microsoft Visual Studio IDE, supported by various Python libraries, including Pandas and NumPy, with version control managed by Git and hosted in GitHub.

## C.4. Methods and Metrics to Evaluate Statistical Significance

### C.4.A. Justification of Methods and Metrics

**Model (Spread)**: RandomForestClassifier, LogisticRegression

**Metrics**: accuracy\_score, f1\_score

**Benchmark:** Whichever model results in a higher accuracy score with less computing time

**Model (Over/Under)**: RandomForestClassifier, LogisticRegression

**Metrics**: accuracy\_score, f1\_score

**Benchmark:** Whichever model results in a higher accuracy score with less computing time

**Model (Underdog Wins)**: RandomForestClassifier, LogisticRegression

**Metrics**: accuracy\_score, f1\_score

**Benchmark:** Whichever model results in a higher accuracy score with less computing time

**Statistical Tests:**

**Spread**

**Null Hypothesis(H0):** The model’s predictive performance for against-the-spread (ATS) outcomes does not exceed what would be expected by random chance. That is, its classification accuracy is indistinguishable from 50%.

**Plan:** Calculate the accuracy or F1 scores to determine if there is statistical significance of using the model over the base prediction methodology (coin flip)

**Metric:** p-value from binomial proportion tests

**Alpha:** 0.05

**Over/Under**

**Null Hypothesis(H0):** The model's predictive accuracy in forecasting over/under outcomes equals what would be expected from guessing. That is, performance is not statistically different from 50%

**Plan:** Calculate the accuracy or F1 scores to determine if there is statistical significance of using the model over the base prediction methodology (coin flip)

**Metric:** p-value from binomial proportion tests

**Alpha:** 0.05

**Underdog Wins**

**Null Hypothesis(H0):** The model does not improve upon the expected historical baseline for outright underdog wins. Its accuracy is statistically equivalent to the benchmark win rate of 25%.

**Plan:** Calculate the accuracy or F1 scores to determine if there is statistical significance of using the model over the base prediction methodology (coin flip)

**Metric:** p-value from binomial proportion tests

**Alpha:** 0.05

## C.5. Practical Significance

Creating models that are statistically significant from the baseline is the most important to make successful wagers on the betting lines that the models will be trained to predict. The goal is for the models to replace the baseline of simply guessing which option is correct (flipping a coin).

## C.6. Visual Communication

I will use multiple visualizations to illustrate the significant statistical features in the project. I will create histograms showing the distribution of the spread lines and the over/under lines. I will also make a correlation heatmap to show which features are more relevant to my outcome variables than others. Additional visualizations will be included to contextualize model performance across spread tiers.

# Description of Datasets

## D.1. Source of Data

Sportsbook Reviews - <https://www.sportsbookreviewsonline.com/scoresoddsarchives/ncaafootball/ncaafootballoddsarchives.htm>

Stathead Football - <https://stathead.com/football/>

OddsRank - <https://www.oddsshark.com/>

2024 FBS Attendance Trends | College Athletics News | DI Ticker - <https://www.d1ticker.com/2024-fbs-attendance-trends/>

NCAA College Football Predictive Rankings and Ratings - <https://www.teamrankings.com/college-football/ranking/predictive-by-other>

List of American football stadiums by capacity - <https://en.wikipedia.org/wiki/List_of_American_football_stadiums_by_capacity>

The above dataset sources are publicly available because the statisticians who recorded and published the statistics (both pregame and postgame) had no ownership of the data, as the data is publicly available on any sports-related website (NCAA.com, ESPN.com, etc.). The datasets consist of over 12,000 college football contests and over 30 features.

## D.2. Appropriateness of Dataset

The features in the final dataset will be collected from the above websites, and the pre-game Vegas betting lines (spread, over/under, money line) will be recounted. The features that will be used in the model are as follows:

\*(comp = completions, att = attempts)

1. full\_date
2. away – visiting team
3. home – home team
4. conf\_away – FBS conference of the visiting team
5. conf\_home – FBS conference of the home team
6. score\_away – visiting team’s score
7. score\_home – home team’s score
8. first\_downs\_away
9. first\_downs\_home
10. third\_down\_comp\_away
11. third\_down\_att\_away
12. third\_down\_comp\_home
13. third\_down\_att\_home
14. fourth\_down\_comp\_away
15. fourth\_down\_att\_away
16. fourth\_down\_comp\_home
17. fourth\_down\_att\_home
18. pass\_comp\_away
19. pass\_att\_away
20. pass\_yards\_away
21. pass\_comp\_home
22. pass\_att\_home
23. pass\_yards\_home
24. rush\_att\_away
25. rush\_yards\_away
26. rush\_att\_home
27. rush\_yards\_home
28. total\_yards\_away
29. total\_yards\_home
30. fum\_away – lost fumbles by visiting team
31. fum\_home – lost fumbles by home team
32. int\_away – interceptions by visiting team
33. int\_home – interceptions by home team
34. pen\_num\_away – number of penalties of visiting team
35. pen\_yards\_away – number of penalty yards of visiting team
36. pen\_num\_home – number of penalties of home team
37. pen\_yards\_home – number of penalty yards of home team
38. possession\_away – time of possession for visiting team
39. possession\_home – time of possession for home team
40. rivalry – is the contest considered a rivalry game for both teams?
41. (stadium) capacity
42. attendance
43. ou\_total – closing over/under line
44. spread – closing spread line
45. ml\_fav – closing money line of favorite team (negative amount)
46. ml\_dog – closing money line of underdog team (positive amount)

Since this will be a prediction model and the box score data from each game cannot be used to train the model, I will be engineering features that include the average of each box score statistic of all previous contests in the dataset for each team involved (for both their home and away contests).

The engineered features will be as follows:

1. match\_key – combination of both teams sorted alphabetically and separated by an underscore character (\_) (e.g., Alabama\_Auburn)
2. game\_id – combination of match\_key and the full\_date fields (since one of the datasets had all the games for each team for the 2023 and 2024 seasons, the games were duplicated, and the duplicates needed to be dropped.
3. spread\_away\_cover -
4. spread\_home\_cover
5. favorite\_covered – did the favorite cover the spread
6. ou – were the total points scored more (over) or less (under) the over/under total
7. attend\_percent
8. fav\_side – team that is the betting favorite (home or away)
9. dog\_side – team that is the betting underdog (home or away)
10. home\_avg – average points scored per game by home team in previous contests
11. away\_avg – average points scored per game by visiting team in previous contests
12. home\_yards\_avg – average yards gained by home team in previous contests
13. away\_yards\_avg – average – average yards gained by visiting team in previous contests
14. home\_pass\_yards\_avg
15. away\_pass\_yards\_avg
16. home\_first\_downs\_avg
17. away\_first\_downs\_avg
18. home\_third\_down\_avg
19. away\_third\_down\_avg
20. home\_fumbles\_avg
21. away\_fumbles\_avg
22. home\_ints\_avg
23. away\_ints\_avg
24. home\_pen\_yards\_avg
25. away\_pen\_yards\_avg
26. home\_possession\_avg
27. away\_possession\_avg
28. spread\_bins
29. spread\_labels
30. underdog\_win\_rate (for underdogs based on which spread bin they’re in)

Also, the textual categorical features (conf\_home, conf\_away) will be converted using Pandas’ get\_dummies function to be able to use them in the analysis.

Exploratory data analysis reveals that underdog win rates vary significantly across point spread intervals, with smaller spreads (e.g., 0–3.5) showing disproportionately higher upset potential than larger spreads.

## D.3. Data Collection Methods

The data I will collect is available on the websites I sourced it from in an HTML tabular format, so it will be easiest to copy and paste the content into Microsoft Excel and save the data from the individual sites as CSV files.

## D.4. Data Quality

Since the data I need is not already consolidated in a single dataset, I will have to do a fair amount of cleaning and imputation, followed by merging, to have a single data source from which to perform the statistical tests and train the models that will be involved in the project. I will also need to engineer several features to help complete as much data as possible to train the models.

## D.5. Data Governance, Privacy, and Security, Ethical, Legal, and Regulatory Compliance

### D.5.A. Precautions

The datasets that will be used in these models are publicly available since the sources of the statistics are made available both before and after the contests by the sports outlets that cover the games and are published on countless websites for use in various scenarios (sports betting, statistical analysis, coaching strategies, etc.). There are no restrictions in terms of privacy or regulatory compliance made by any of the sources of the datasets since they do not own the data on which they are reporting. No precautions will need to be taken since the data I will be using is publicly available. The only time security might be an issue is if I want to copyright the model to be used in a business setting and prevent someone from stealing my intellectual property, but that is not a goal now.

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