Machine Learning in Sports Betting Final Presentation

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Problem Definition

- Due to its wide availability of data, we chose the NBA
  - 82 regular seasons games a year (not including covid year)
  - Limited number of players limits a little bit of the variation
  - Many datasets are available with in depth advanced metrics
- Initially want to predict wins and losses before looking at spreads
  - Want to see an accuracy that is significantly better than flipping of a coin or home/away win percentage
    - Over the last 10 or so years, win % of home teams is around 58%, but only about 55% for the 2023 season
- We want to see if we can create a model to meet or exceed an accuracy of 53% for spreads
  - We want to see success over past and current seasons
  - Will track our success using a unit size of 10 dollars
- Want to combine sentiment analysis with traditional box score analysis to predict outcomes

Datasets

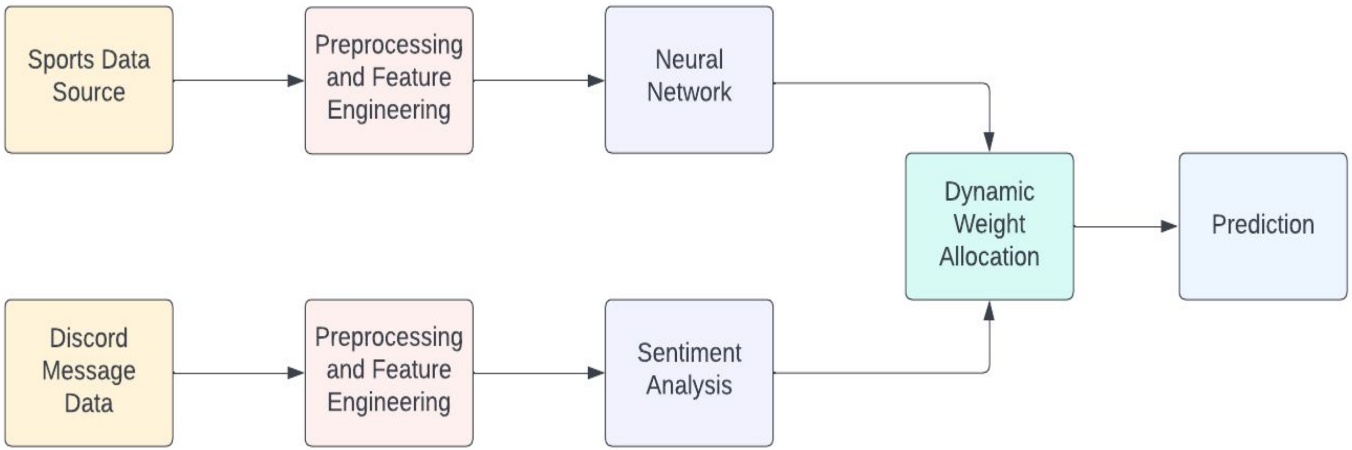
OffPoss	Opp_OffPoss	Points	Opp_Points	FG2M	Opp_FG2M
106.0	106.0	117.0	107.0	38.0	33.0
104.0	103.0	112.5	102.5	32.5	29.0
103.0	102.333333	111.333333	110.333333	32.0	31.333333

- Focusing on PBP Stats, Basketball Reference, and ESPN to pull our data
  - Box scores/statistical information from PBP/Basketball Reference and lines/home team data from ESPN
- A kaggle dataset was combined with ESPN data to grab lines
  - ESPN only had lines from 2021 on, while the Kaggle dataset has data from offshore sites up until 2018
  - Removed the Covid season to account for missing lines and variance from the season as a whole
- Calculated statistics pertaining to last five game averages and full season averages
  - Used to help see how a team is currently playing and how they have played over the year
- Information such as Home/Away, Win/Loss and Cover was converted to categorical data so it could be used
- Data needed to be normalized
- NLP parses the data, tags parts of speech, utilizes Name-entity recognition and adapts TF_IDF
  - Goal of finding correlation between sentiment and game results
  - Use of discord to gather sentiment for teams

Feature Engineering

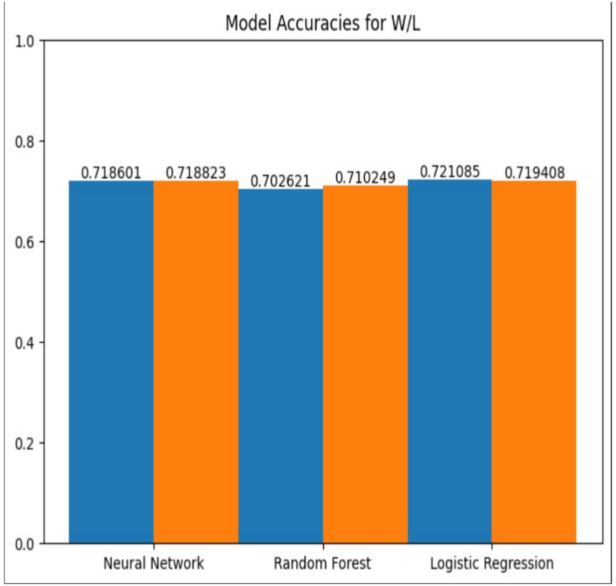
- Converted spread results, home/away, and win/loss into categorical data
- Added extra features such as Assist to turnover ratio to try to add more advanced metrics
- Win/loss percentage over the last five games was calculated to see how a team is playing at the moment
- 5 day, 10 day, and season averages were calculated to help account for changes for a team throughout a season and over seasons
  - The 5 day averages showed to be the most effective when predicting wins and losses and spread results

Pipeline


Sports Data Source
Preprocessing and Feature Engineering
Neural Network
Dynamic Weight Allocation
Prediction
Discord Message Data
Preprocessing and Feature Engineering
Sentiment Analysis

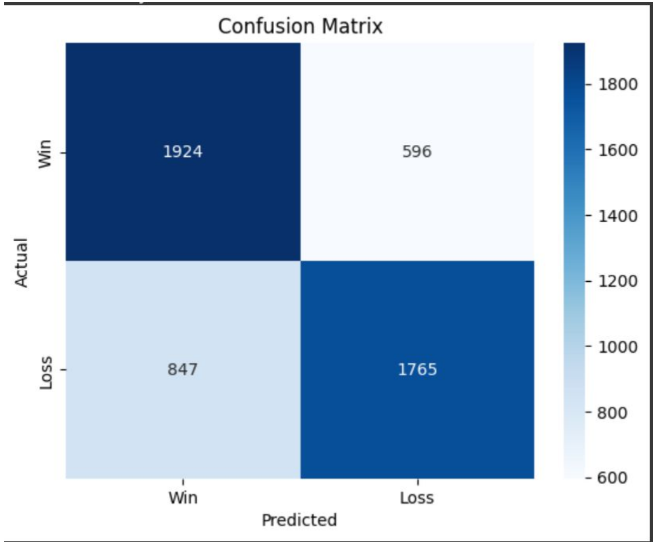
Final Models (Traditional Box Score)

- Looked at both classification and regression when approaching our problem
    - Classification was far more effective, with regression staying at an RMSE of around 11 and a spread result prediction accuracy hovering around 50%
- Trained Neural Network, Logistic Regression, Random Forest, Linear Regression, and XGBoost
- Used GridSearchCV to tune hyperparameters
    - Improved accuracy for logistic regression spread prediction and wins and losses around 3%
- Neural Network consists of 3 dense layers
    - Adam optimizer and binary cross entropy loss



Final Models (Traditional Box Score)

- Saw the most success with our Neural Network for both wins and losses and spread results
  - ~72% for W/L and ~60% for spread results
- Very similar success for the 2023 season compared to previous seasons
- Some of the most influential features consisted of assists, defensive rebounds, and field goal percentage defense



Final Model (Sentiment Analysis)

$$\frac{|team1polarity| + |team2polarity|}{2}$$

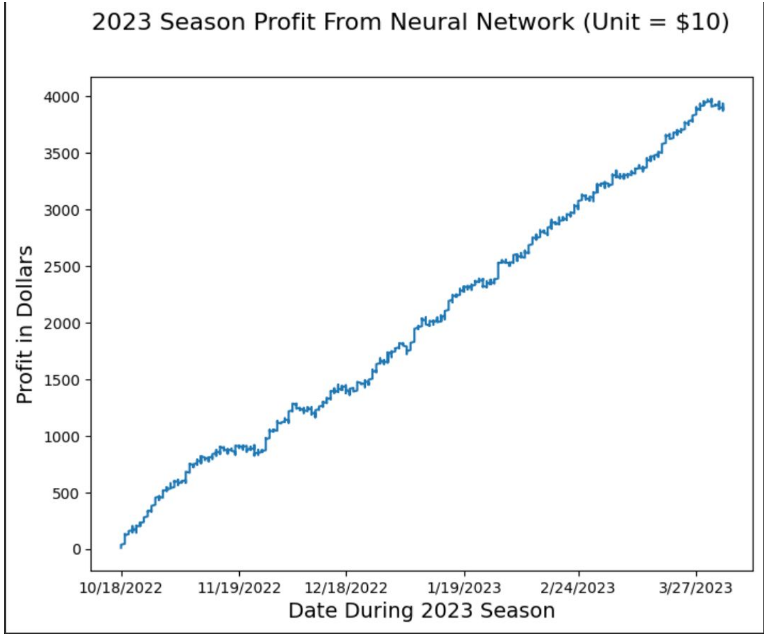
- We output a decimal point number to represent polarity
    - This number goes from -1.0 to 1.0, where 0 represents fairly neutral sentiment
    - Scores are inverted based on team viewpoints
        - We then average them out
- This number is then compared to the EV of a given line to see if there are any profitable lines
    - If positive odds, the formula is EV = 1/(1 + x/100)
    - If negative odds, the formula is EV = 1/(1 + 100/|x|)
    - So if EV is 55% team A and we have score of 0.85, betting on team A would be +EV
    - Model on its own loses $0.08 per $1 wagered over 433 games

Weight Allocation

- Since our traditional box score model was already very good at predicting spreads, we decided to simply add the sentiment analysis output as a feature for the model
  - This should help the model in predicting games where certain star players are not playing, showing how most fans believe the other players will step up into their new roles
- Sentiment Analysis is very different from our neural network working with more traditional player data.
  - Experimenting with ensemble learning but currently the model outputs are different

Final Model Results

- The results of the neural network model covering spreads for the 2023 season profited almost $4000 using only $10 bets on every game
- Some of the downturns in profit, such as near the end of the season, can be attributed to star players sitting out games ahead of the playoffs
- Possible quick fix for this could be to stay away from games where top player(s) are injured or resting



Website

Machine Learning in Sports Betting (NBA)

Live Games

Nuggets 33 @ Timberwolves 36

Cavaliers 93 @ Knicks 102

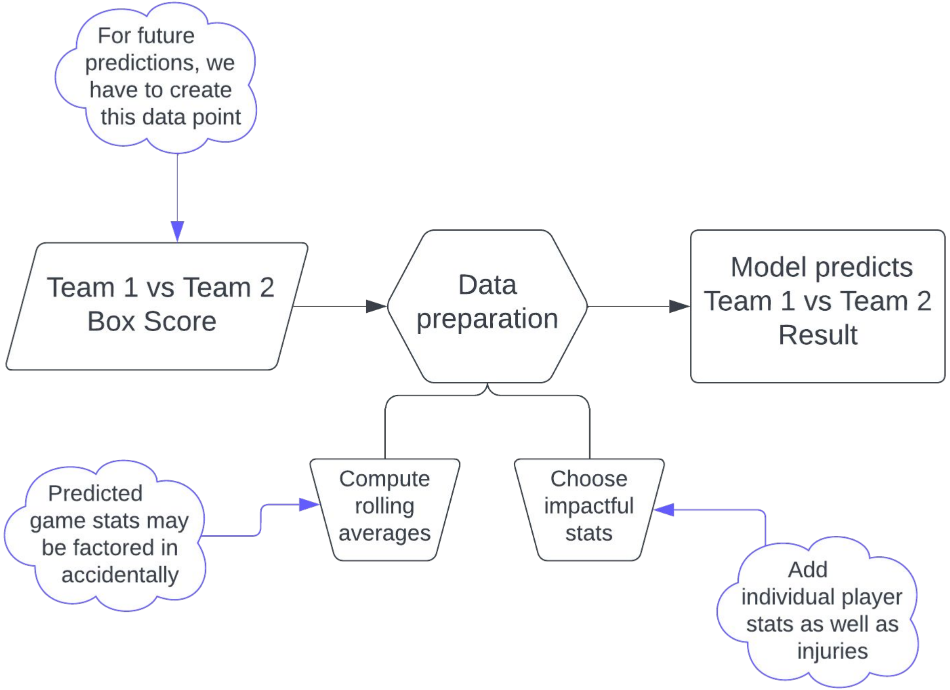
Kings 125 @ Warriors 126

Celtics 129 @ Hawks 121

Future Work and Considerations

- Further evaluate our feature extraction process to make accuracy more realistic
  - Stats from game (to be predicted) are used in prediction
- Continue to fine tune the model to increase accuracy as the season moves along
  - Factor in home team vs away team history
  - Include individual player data to account for injuries and rest days
- Add capability for the model to automatically predict games yet to be played
  - As of now, can only be done manually
- Adjust model for playoffs
  - 7 game series where teams play each other back to back will result in different outcomes from regular season games

Future Work visualized



Accuracy would most likely decrease, but this is intended

Contributions

- Ron - Sentiment analysis
- Austin - Data scraping and preprocessing
- Tyler - Model/Neural network tuning and website building
- Davin - Neural network building and feature extraction

References

[1] Tan, R. J. (2022, March 2). *Breaking down mean average precision (MAP)*. Medium. Retrieved March 13, 2023, from https://towardsdatascience.com/breaking-down-mean-average-precision-map-ae462f623a52

[2] Mishra, A. (2020, May 28). *Metrics to evaluate your machine learning algorithm*. Medium. Retrieved March 13, 2023, from https://towardsdatascience.com/metrics-to-evaluate-your-machine-learning-algorithm-f10ba6e38234

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[4] Culver, J. V. (2021, March 7). *Why 52.4% is the most important percentage in sports gambling.* Medium. Retrieved February 1, 2023, from https://medium.com/the-intelligent-sports-wagerer/why-52-4-is-the-most-important-percentage-in-sports-gambling-16ade8003c04

[5] Dotan, G (2020). *Beating the Book: A Machine Learning Approach to Identifying an Edge in NBA Betting Markets.* Retrieved February 3, 2023, from https://escholarship.org/uc/item/115957mb