Draft Hype vs. Reality:
The Limited Predictive Power of NBA Scouting Report Sentiment

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Outline:
Project Details, Initial Analysis, Sentiment Analysis Refinement, Correlation Analysis, Results & Conclusion, Limitations & Next Steps

Project Details

Motivation and Context:

Statistics like PER, Win Shares, and Plus-Minus are widely used to measure a player's performance on the court, but scouting reports offer qualitative evaluations that capture traits/intangibles/potential like basketball IQ, work ethic, clutch, coachability, and instincts—attributes that don't always show up in box scores. Despite their importance in draft decisions, little research has tested whether the sentiment in pre-draft scouting reports can actually predict rookie performance in the NBA.

Hypothesis

- Pre-draft scouting report sentiment correlates with rookie performance.

Research Question:

- Do the sentiment scores of the 2023 NBA rookie pre-draft scouting reports correlate with the players' performance metrics in their rookie season?

Modeling Approach:

- Scrape text data from various reputable scouting report pages for the 2023 NBA Draft.
- Apply the VADER and TextBlob sentiment analysis package in Python to compute sentiment scores ranging from -1 to 1, where scores between -0.05 and 0.05 are considered neutral.
- Use a combination of correlation tests to assess the relationship between sentiment scores and rookie performance metrics.
- Define rookie success using measurable criteria such as rookie team awards, minutes played during the season, and win shares.

Data Dictionary:

Column	Description	Potential Responses
Player Name	Name of NBA Player	Victor Wembanyama, Brandon Miller
Scouting Report	Full text of pre-draft scouting report	Athletic player with some strengths and some weaknesses
Compound Sentiment Score	Overall sentiment score of the report	Range from -1 to 1
Positive Sentiment Score	Score that was of positive sentiment	Percentage positive
Negative Sentiment Score	Score that was of negative sentiment	Percentage negative
Neutral Sentiment Score	Score that was of neutral sentiment	Percentage neutral
Player Plus Minus	Player's overall contribution to team success	The number can be positive or negative depending on scoring while the player is on the court
Player Minutes Played	Total minutes played during rookie season	Total number of minutes the player was on the court
Player PER	Player efficiency rating, for the overall efficiency of a player	The number can vary, league average is around 15
Player WS	Win shares, showing a player's contribution to wins	Number showing contribution to a number of games
Player VORP	Value over replacement player, showing a player's overall value	Number quantifying how much better a player is than a replacement
Player Awards	Any award received during the rookie season	All rookie first team, rookie of the year, etc.

Data Acquisition & Explanation

Acquisition:

- Collected pre-draft scouting reports from ESPN, Sports Illustrated, and NBADraft.net using a combination of manual copy-and-paste and a Python web scraper.
- Gathered rookie performance statistics from the NBA website and Basketball-Reference.
- No licensing or ethical concerns were encountered.

Data Integration:

- Combined the scouting reports and performance stats by merging on the "Player Name" field.
- Cleaned the data to remove missing and duplicate entries.

Dataset Summary:

- The dataset contains 46 NBA rookies from the 2023 draft class, with each row representing a unique player.
- Data types include text (scouting reports) and numerical performance metrics.

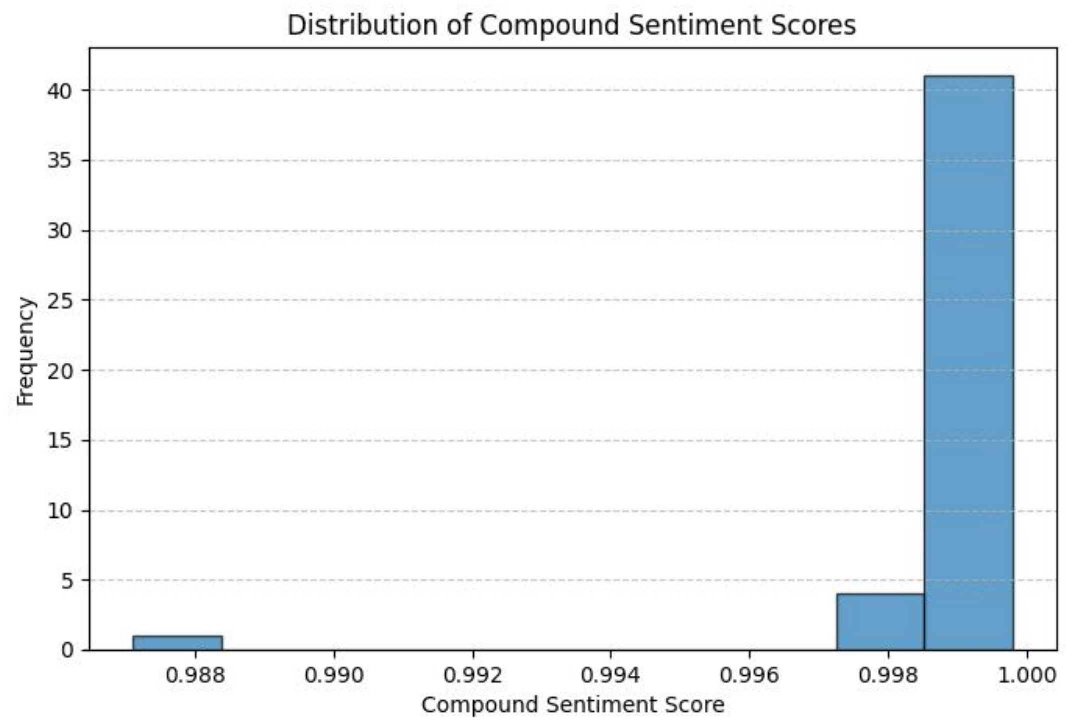
Analysis Plan & Justification

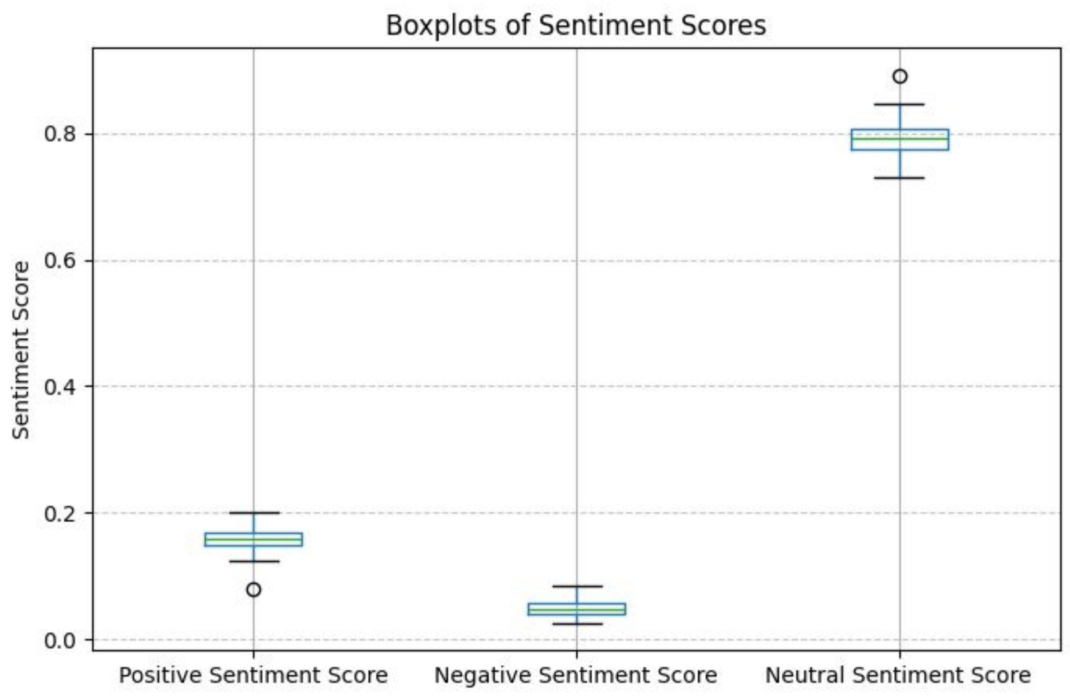
- After cleaning the dataset, we performed an initial EDA to assess the overall distribution of the VADER sentiment scores in scouting reports.

- Our primary question was: "What is the overall distribution of the VADER sentiment scores in scouting reports?"

- Analysis of the compound sentiment scores revealed extremely low variation, indicating that most reports were scored similarly.

- We further examined separate sentiment scores (positive, neutral, and negative), which showed slightly better variation, though we still had concerns about the limited predictive power.





Tricky Analysis Decision

- Noticed that VADER's compound sentiment scores exhibited extremely low variation, limiting their predictive power.

- Determined that the qualitative nature of scouting reports required a sentiment model better suited to formal text.

- Switched to using TextBlob, which provided greater variation in polarity and subjectivity scores, thereby offering a more nuanced view.

- This decision, although deviating from our original plan, was crucial to better capture the subtle differences in scouting report sentiment and enhance our correlation analysis.

Bias and Uncertainty Validation

Neutral Tone Dominance:

- Mean Neutral Sentiment Score is ~0.79, indicating that around 79% of words are classified as neutral. This is typical in professional, factual text, resulting in a heavy bias toward neutrality.

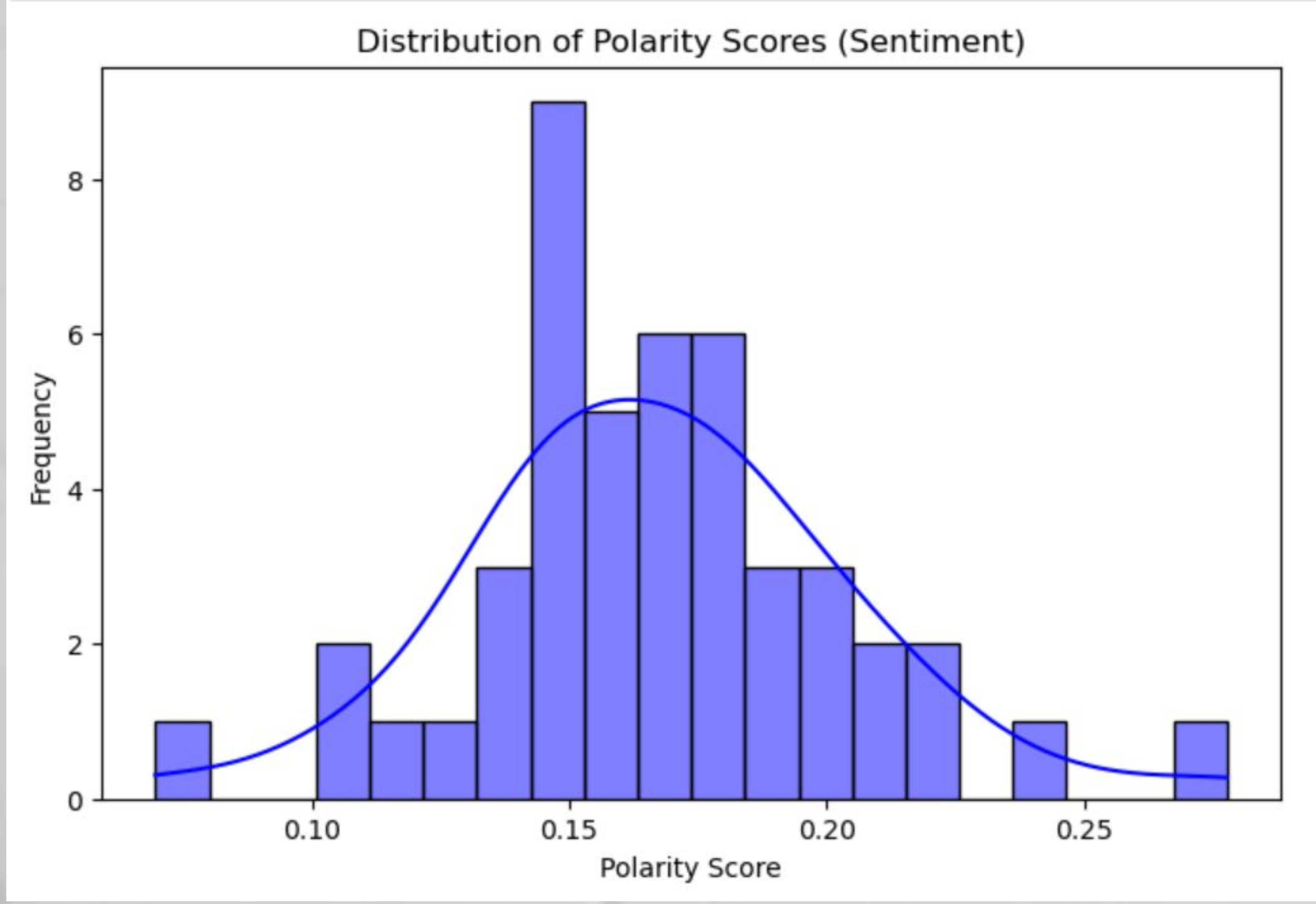
Negation and Context Handling Issues:

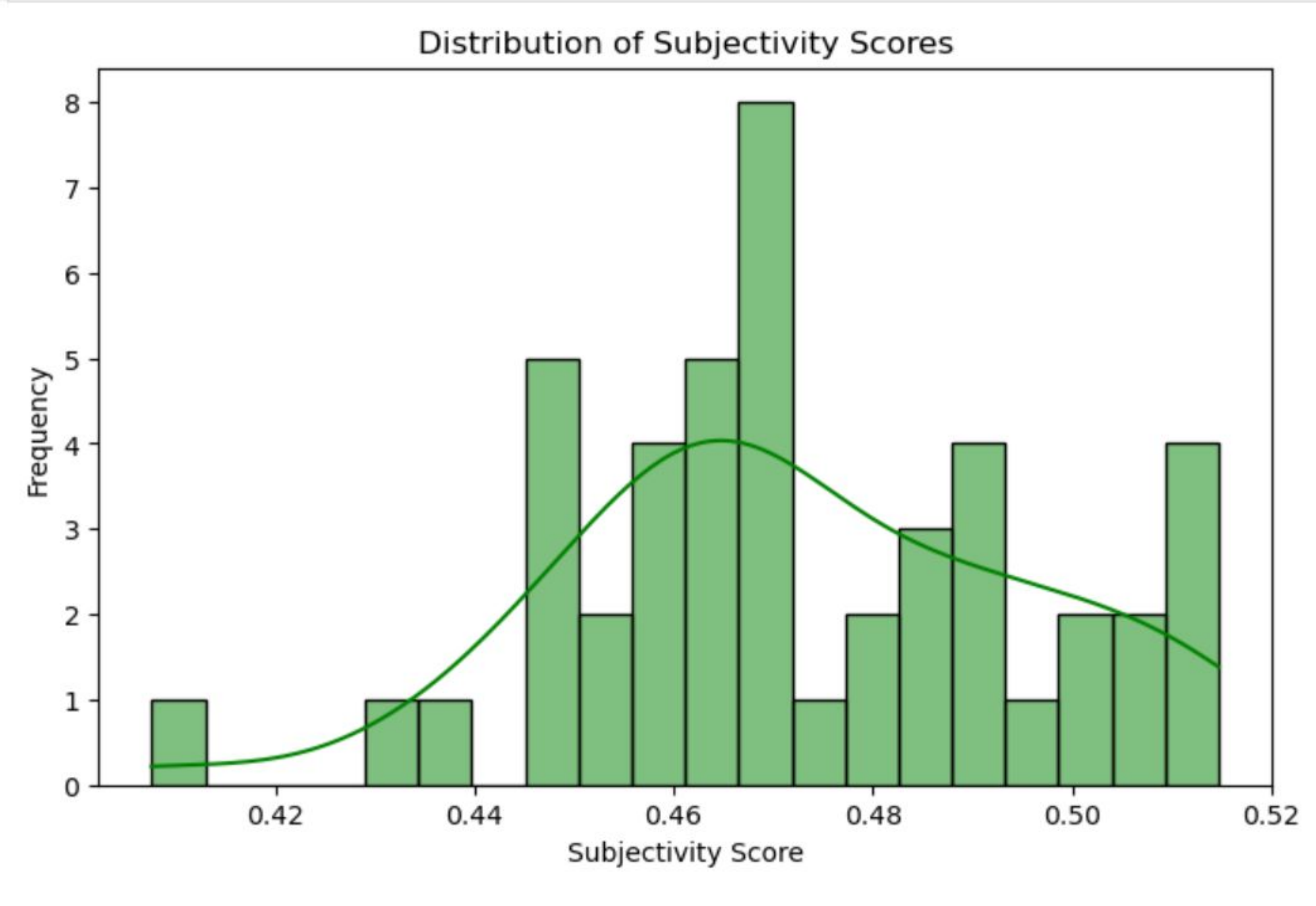
- While VADER handles simple negation (e.g., "not good"), it struggles with subtle critiques where negative comments are immediately balanced by constructive positive statements.
- For example, "While his defense has improved, he still struggles in transition" may be misinterpreted as neutral or slightly positive.

Mitigation and Uncertainty:

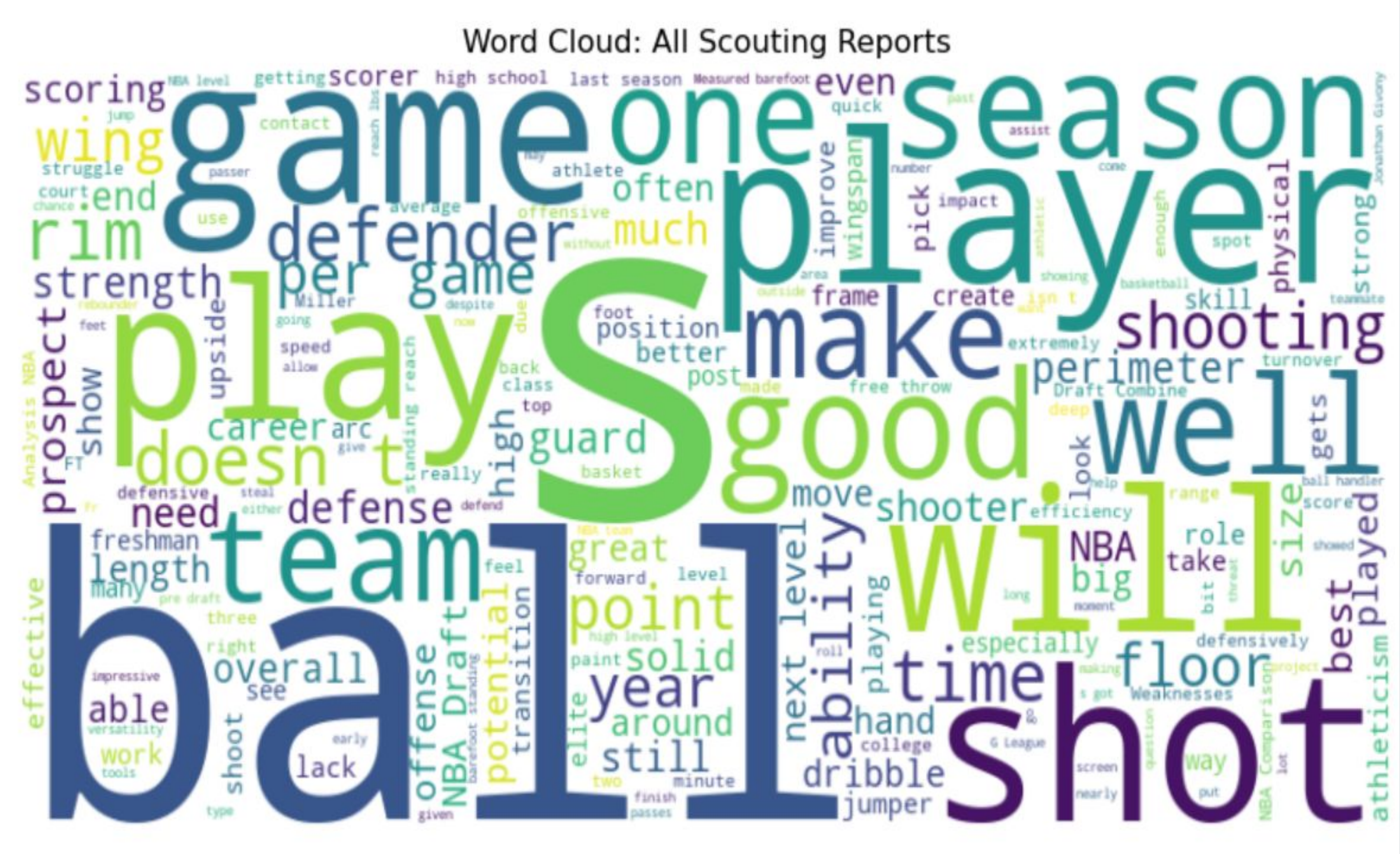
- The technical, descriptive, and objective nature of scouting reports inherently limits the expressive range of sentiment scores.
- TextBlob was used as an alternative since it's more suited to analyze longer, detailed, and formal text such as scouting reports whereas VADER is optimized for shorter, social media-like content. TextBlob also provided a broader range of polarity scores, capturing subtle variations in sentiment.

Pivoting to Textblob





- Textblob was able to measure differences in scouting report sentiment better than VADER with a more normal distribution
- Polarity score: analyzes positive vs negative attitudes (scored from -1 to 1)
- Subjectivity score: analyzes text by opinionated vs factual information (-1 to 1)



Word Cloud

Most popular words used in scouting reports of 2023 NBA rookies

Listed Differences for Textblob

Word Coverage:

- Textblob was trained on large, general purpose lexicon, and is able to capture more sentiment in phrases
- VADER is better suited for social media and short text, and may struggle with nuanced language

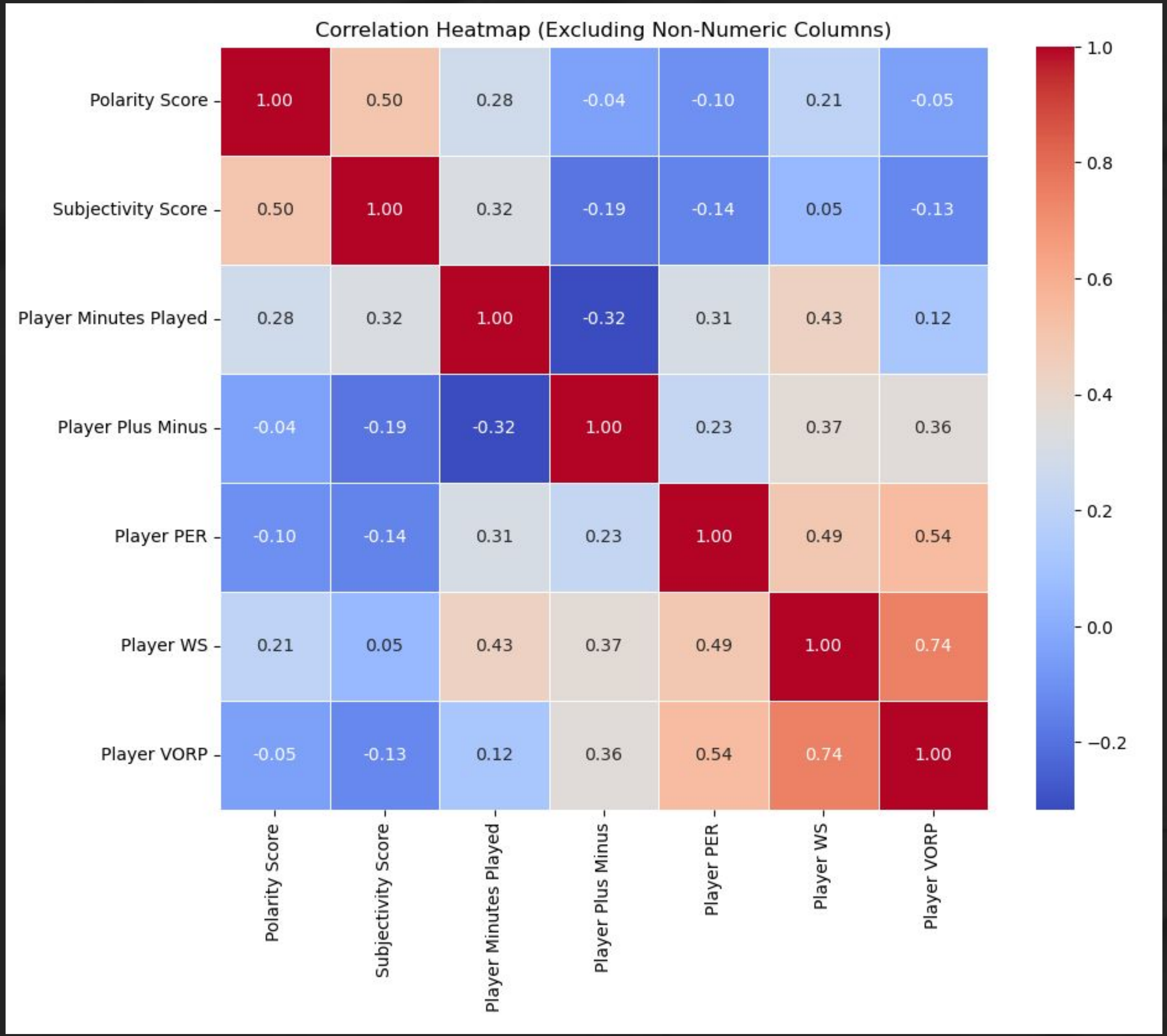
Multi Word Sentiment:

- Textblob utilizes PatternAnalyzer, a tool that can use multi word expressions to adjust the sentiment scores
- VADER relies on single word intensifiers, less effective for longer text

Subjectivity Detection:

- Textblob also contains a subjectivity score to distinguish between objective and subjective statements

Analysis



<u>Correlation Tests:</u>

Pearson correlation test:

- Linear relationships between two continuous variables, normally distributed
- ex: sentiment score vs win shares

Spearman correlation test:

- Similar to pearson but also handles non normally distributed variables, can be non linear
- ex: sentiment score vs minutes played

Point-Biserial correlation test:

- Relationship between a continuous variable and a binary variable
- ex: sentiment score vs rookie awards won

Performing Correlations

Correlation for Numeric Values:

	Sentiment vs. Performance Metric	Pearson r	Pearson p	Spearman ρ	Spearman p	Interpretation
0	Polarity Score & Minutes Played	-0.600	0.590	-0.500	0.667	Weak negative correlation, not significant
1	Polarity Score & Plus Minus	0.581	0.605	0.500	0.667	Weak positive correlation, not significant
2	Polarity Score & PER	-0.835	0.371	-0.866	0.333	Moderate negative correlation, not significant
3	Polarity Score & WS	0.169	0.892	0.500	0.667	Very weak positive correlation, not significant
4	Polarity Score & VORP	-0.644	0.554	-0.500	0.667	Weak negative correlation, not significant
5	Subjectivity Score & Minutes Played	0.674	0.529	0.500	0.667	Weak positive correlation, not significant
6	Subjectivity Score & Plus Minus	-0.691	0.514	-0.500	0.667	Weak negative correlation, not significant
7	Subjectivity Score & PER	-0.696	0.510	-0.866	0.333	Moderate negative correlation, not significant
8	Subjectivity Score & WS	-0.937	0.227	-0.500	0.667	Strong negative correlation, not significant
9	Subjectivity Score & VORP	-0.871	0.327	-1.000	0.000	Strong negative correlation, significant!

Correlation for Binary Values:

	Sentiment vs. Awards	Point-Biserial r	p-value	Interpretation
0	Polarity Score & Awards	0.214	0.153	Weak positive correlation, not significant
1	Subjectivity Score & Awards	0.277	0.062	Weak positive correlation, close to significant

Results and Conclusions

Weak to Moderate Correlations- Most correlations between sentiment scores (Polarity Score & Subjectivity Score) and performance metrics were weak to moderate, indicating no strong predictive power.

No Significant Relationship Between Polarity Score and Performance- The positivity or negativity of scouting reports did not strongly correlate with rookie success.

Subjectivity Score & VORP Showed the Strongest (Negative) Correlation- A strong negative Spearman correlation (-1.000, $p = 0.000$) suggests that more subjective reports were linked to lower VORP scores, possibly indicating that highly opinionated scouting reports do not align with actual player impact.

Awards & Sentiment Scores Had Weak Correlations- polarity score and awards had a weak positive correlation ($r = 0.214$, $p = 0.153$). Subjectivity score and awards had a slightly stronger positive correlation ($r = 0.277$, $p = 0.062$, close to significance).
This suggests that players with more subjective scouting reports were slightly more likely to win awards, but the effect is not statistically strong.

** Since we conducted multiple statistical tests, we recognize the increased risk of false positives. A multiple comparison correction would further validate our findings, but we did not apply these due to time constraints **

Limitations and Next Steps

Limitations

Sentiment Model Limitations

VADER and TextBlob primarily capture surface-level sentiment, but they lack sports-specific context.

Potential Bias in Scouting Reports

Writers of scouting reports may have preconceived biases. They may also write less for talents that everyone is already familiar with (Victor Wembanyama).

Small Sample Sizes

External Factors Affecting Performance Metrics

Players performance can be altered by coaching decisions, team dynamics, injuries, and other factors.

Next Steps

Expand the Dataset

Include multiple draft classes of rookies or multiple years per draft class to increase statistical power.

More Advanced Sentiment Models and Statistics

Analyze Social Media Content About Players for Public Narrative

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GitHub: https://github.com/Kianjputnam/DS-4402-M1

Questions?