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**Methods in Computational Linguistics II**

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**Introduction**

European Football is the most played sport in the world – it is also the most discussed. Social Media provides ample material to study and analyze. Several platforms allow fans to encourage, cheer, jeer, and outright berate players over the internet. Is online sentiment about a player justified based on their statistics only, or do other factors need to be considered?

This paper analyzes player performances in a given season, 2020/2021, and the sentiment regarding each player respectively online. Sentiment analysis, or opinion mining, is a rapidly developing research area in computer science and computational linguistics (Mäntylä). The usability of opinion mining has grown beyond product design and marketing, enabling researchers to measure sentiment about current events, political campaigns, stock market strategies, etc. (Gupta). Sentiment analysis is a vital tool for elaborative feedback on any topic involving human judgement.

Opinion mining also has the potential to analyze judgements in the political and social realm. Regarding controversial policies and social movements, politicians may benefit from having a firmer grasp of their constituents’ viewpoint. Beyond helping politicians gain political power, however, sentiment analysis enables researchers to measure a population’s approval or indignation of social ideas. This can be used to measure shifts in opinion about tax policies, social justice movements, and even conflicts between differing populations. This paper’s goal is smaller in scope but has implications which outspan the realm of sports into the social sciences.

How can we determine if a population’s sentiment is justified? Which variables should be studied and measured to judge an opinion? Objective based activities provide a simple measure of success to assess judgements. Logically speaking, if a player performs well in achieving the objective, then that player will be judged appropriately. If a player performs poorly, then sentiment should be negatively skewed. The straightforward objective of scoring a goal, ensuring the football - or soccer ball - crosses the goal line, and not allowing the opponent to do the same should provide a suitable standard for success.

Each position should have clear metrics for success: (1) Forwards must score and create goals. Important statistics include goals, assists, chances created, chances missed, and passes. (2) Midfielders must create and score goals but also have defensive duties. Important statistics include goals, assists, tackles, passes, chances created, and clean sheets. (3) Defenders must focus on clearing any threats from the opposing team but can also provide support in attack. Important statistics include clean sheets, tackles, clearances, goals, and assists. (4) goalkeepers must stop any ball from crossing the goal line. Important statistics include clean sheets, goals conceded, and saves. For more information about each statistic’s point value, please read https://fantasy.premierleague.com/help/rules.

Other minor statistics for each position may be considered, but judgements should be based off major stats first. Also, while Defenders may contribute to goals it should have less weight than their primary defensive duties. A team’s last line of defense, *the sweeper,* should be judged negatively if his goals conceded statistic is high regardless of how many goal involvements.

**Method**

The analysis was completed in three steps – gather player performance statistics, gather tweets for sentiment, and run sentiment analysis on the tweets. Data regarding each player was gathered with a combination of web-scraping and API access. Player statistics were scraped from the English Premier League’s website using selenium webdriver, and the tweets were gathered using a python twitter API module called Tweepy. Sentiment analysis was computed by VADER (Valence Aware Dictionary and sEntiment Reasoner) in Python.

First, performance data was gathered using a scraping technique involving Selenium. With Selenium, I was able to simulate normal ‘human’ interactions - such as clicking, waiting, entering text - on a webpage to navigate the web driver to the appropriate pages. From there, I scraped the XML data and stored them as variables for each player’s performance statistics. Relevant statistics were gathered for the player based on their position, but I also scraped the top performer for each statistic per position. Comparing each player to the top performer should give valuable context for twitter sentiment. Typical XML extraction was hindered because of the web-scripting that English Premier League uses. Each player’s page had to load the scripting before loading the correct statistics. Hence, I used the web driver to simulate a user ‘waiting’ for the correct information to display before scraping it.

Once the performance statistics were scraped, I used the Tweepy API to gather tweets. A year’s worth of tweets (2020/2021 season) was gathered for each player. Retweets, duplicate, and irrelevant tweets were removed from the collection before running sentiment analysis. This led to some players having an insignificant number of tweets to analyze. Therefore, only players with acceptable twitter popularity were chosen for analysis.

Sentiment analysis was conducted using the open-source tool, Valence Aware Dictionary and sEntiment Reasoner (VADER). VADER is a rule-based tool which analyses sentiment based on a word’s polarity. VADER consults a lexicon in which each word has a polarity score (positive, negative, neutral) and judges a piece of text’s polarity based on its words.

A word’s polarity can give either +2, +1, -1, or -2. If a tweet’s score is above .0001, it will be judged positive. If a tweet’s score is below -.0001, it will be judged negative. A score of 0 will earn a neutral judgment.

**Results**

Gylfi Sigurdsson – Center Attacking Midfielder

**Twitter Sentimen**t **and Performance**

Total Points: 122

Negative percent: 0.16 | Neutral percent: 0.66 | Positive percent: 0.18

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**Gylfi Sigurdsson Twitter Sentiment**

James Rodríguez – Central Attacking Midfielder

**Twitter Sentiment and Performance**

Total Points: 101

Negative percent: .19 | Neutral percent: .6 | Positive percent: .21

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Ben Godfrey – Defender

**Twitter Sentiment and Performance**

Total Points: 100

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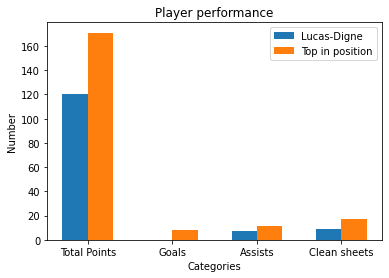
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**Ben Godfrey Twitter Sentiment**

Lucas Digne – Defender

**Twitter Sentiment and Performance**

Total Points: 120

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Description automatically generatedNegative percent: .02 | Neutral percent: .74 | Positive percent: .24

**Lucas Digne Twitter Sentiment**

Seamus Coleman – Defender

**Twitter Sentiment and Performance**

Total Points: 81

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Description automatically generatedNegative percent: .04 | Neutral percent: .76 | Positive percent: .2

Abdoulaye Doucouré – Midfielder

**Twitter Sentiment and Performance**

Total Points: 80

Negative percent: .01 | Neutral percent: .79 | Positive: .2

Chart

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Richarlison – Forward

**Twitter Sentiment and Performance**

Total Points: 123

Negative percent: .09 | Neutral percent: .73 | Positive percent: .18Chart, bar chart

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Dominic Calvert-Lewin – Forward

**Twitter Sentiment and Performance**

Total Points: 165

Negative percent: .04 | Neutral percent: .73 | Positive percent: .23Chart, bar chart

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**Discussion**

VADER provides a basis in which we can analyze how fans/media regard players. With a player’s performance statistics parallel to online sentiment, we can see who might be judged based on factors outside of their point acquisition and performance. Discussion about some key players and their relevant statistics follow.

Seamus Coleman: Seamus accumulated less than half of the points the top player in his position did. He conceded 19 goals and had only 5 clean sheets to his name in 25 appearances. Despite this poor defensive display, 20% of Seamus’ tweets were positive with only 4% being negative.

Abdoulaye Doucouré: With almost 1/3rd of the top performer’s points, his public rating seems overblown. Twitter sentiment is 20% positive with 1% negative. His offensive output seems very low for a midfielder. Not only are his goals/assists low, but his creation (big chances created) statistic is low. A saving grace might be his defensive contributions, but even those don’t stick out at first glance.

Richarlison: 123 total points for the season registers under half of the total points by the top performer for the forward position. 9% negative sentiment with 18% positive might seem acceptable immediately, but his performance stats show a different story. Richarlison missed a total of 10 big chances, had a shooting accuracy of only 40%, and only created 4 big chances for a teammate. A forward’s main duty is to score or create goals - This cannot be overlooked.

These three players’ sentiment don’t quite match their performance in the season. It’s probable that fans don’t consider a player’s point acquisition as the determining factor for positive play. One thing these players have in common is *spirit*. As a fan of the sport, it’s difficult to quantify or describe spirit. It could be anything from a lung-busting offensive run to provide support in attack or dropping back into defense to snuff out a counterattack. A famous example of a spirited run is Andy Robertson of Liverpool Football Club pressing 5 consecutive opponents. After 75 minutes of running, Robertson decides to pursue the ball recklessly. This play was strategically poor and only resulted in Robertson fouling an opponent in conclusion, relieving any pressure the opponent was under – but the fans ate it up (*“The Moment Andrew Robertson Became a Liverpool's Favourite.”).* Examples like this clearly show a spirited moment but don’t give clear indications as to what statistics determine spirit.

In recent years professional leagues have started tracking distance traveled by a player (*“A Real Game Changer: The Use of GPS Tracking Devices in English Football.”*). It’s possible now to track a player’s distance traveled as well as a heatmap of their positioning on the pitch. This development will allow scouters to search for players based on positional play on the pitch, their average distance traveled, and even how quickly they move from position to position. As data science become more important in scouting techniques, it may be able to quantify moments which show spirit alongside more traditional statistics.

**Conclusion**

VADER sentiment analysis provided valuable insight into what twitter consider important in their judgments of soccer players. This analysis gives context to seemingly unjustified positive sentiment surrounding negatively performing players. Traditional statistics such as goals, assists, passes, etc. appear to not be the only litmus test for praise. Data science in sports may soon allow for a greater understanding of performance and value in players by tracking their movement in matches. *Spirit*, something one might consider intangible today, could potentially be jotted down as a combination of numbers on a statistician’s scratch sheet of paper in the coming years.

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For explanation on Premier League Points: https://fantasy.premierleague.com/help/rules