INSY 336 Final Project

Premier League Performance and Google Engagement

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Introduction

Our initial thoughts and predictions

Introduction

- Our initial motivations were to explore the link between a Premier League teams' social media engagement on matchdays and their game performance
- Some relationships we wanted to explore were:
 - The correlation between social media engagement and game performance
 - The correlation between the competitiveness of matches and social media engagement
 - The difference between lower performing teams' and higher performing teams social media engagement



What's the relationship between Premier League teams' performance and online engagement?

Data Collection

Our process and difficulties we faced

Data Collection

Scraped tables from 2021/22-2023/24 season from fbref.com

4

Files were automatically renamed to their team names and placed in folders corresponding to season

Created a script that made links with Google trends' standardized link format

5

Each CSV was combined by Season and added with other CSV's for data on match results etc

3

Scraped the daily data from each Premier League teams' data for a season

6

All data was added to a CSV appropriately titled "the_holy_grail.csv"

Data Collection

Online Engagement

Daily Google Trends Data

Daily Google Trends data is standardized and ranges from 0-100. All of the data is relative to the 100th value, the day with the largest internet traffic in the given time period. Weekly Google Search Traffic

Weekly Google Search Traffic shows actual traffic for Google internet searches for a team in a given week, making it suitable for comparing data across teams. Performance

Matchday Performance

Matchday performance data looked at the performance of each individual team on days that they played a Premier League match; this could result in a win, tie or loss.

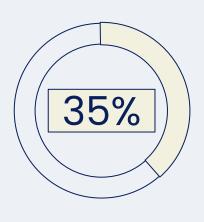
Weekly Ranking

Weekly ranking data involved the team's ranking on the table at the moment of a game in that season.

Results

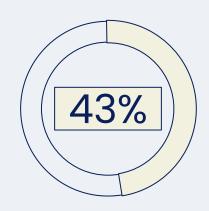
Our findings and analysis

Daily Google Trends Data and Match Outcome



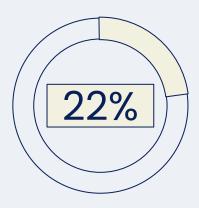
When having a higher normalized daily traffic index than the opponent

Win



Loss

When having a higher normalized daily traffic index than the opponent



Draw

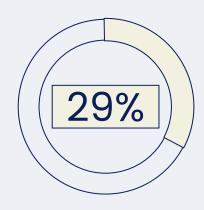
When having a higher normalized daily traffic index than the opponent

Weekly Google Search Traffic and Match Outcome



When average weekly engagement is higher than the opponents

Win



Loss

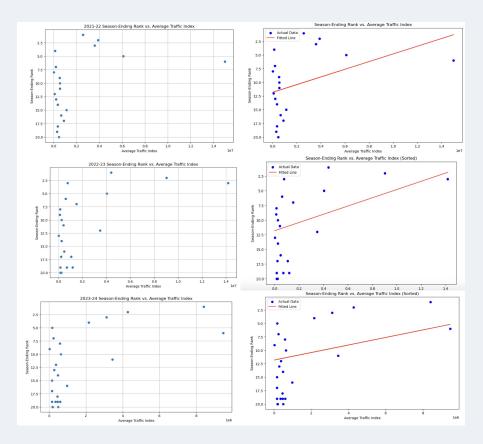
When average weekly engagement is higher than the opponents



Draw

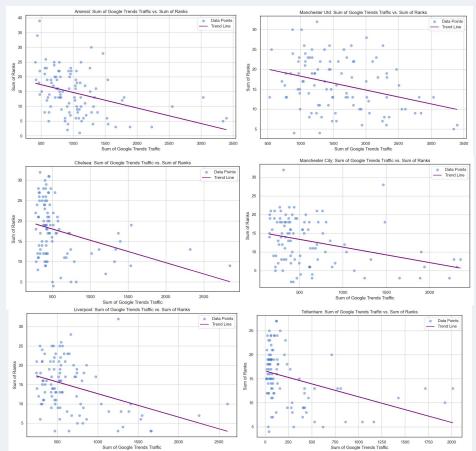
When average weekly engagement is higher than the opponents

End of Season Rank and Weekly Google Search Traffic



- -Positive correlation between positioning and weekly Google Search Traffic for all 3 seasons
- -The teams who are positioned better in the standings tend to have a higher average Google Search Traffic
- -A positive coefficient and a p-value for the 'Average Traffic' coefficient of 0.02, which shows that having high engagement has a high association with being a higher ranked team

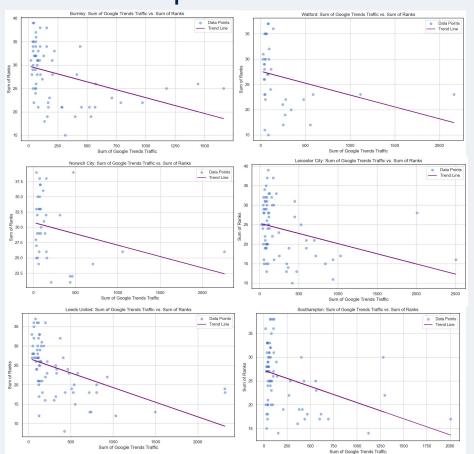
Match Competitiveness and Google Traffic Engagement



The 'Big 6'

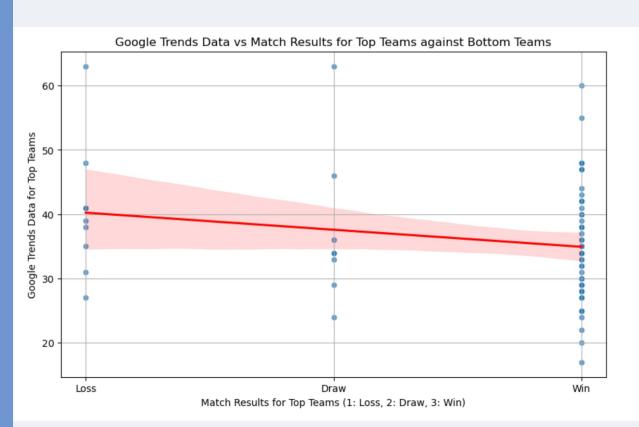
- Across all teams there was positive correlation between 'match competitiveness' and Google search traffic
- 'Match Competitiveness' was defined by the sum of the rank of the two teams at the time of the game: a match between first and second represented a Sum of Ranks of 3, while a match between last and second last represented a sum of 39
- While the relationship was significant across all teams (p-value<0.05), the R² was consistently low, generally ranging around 0.1-0.2
 - The model (Google traffic) did a poor job explaining the variability of the ranks of the teams

Match Competitiveness and Google Traffic Engagement



			sion Results				
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Model:	Sum of Ranks		Adj. R-squared:		0.147		
Method:	Least 9		Adj. K-squared: F-statistic:		17.05		
			Prob (F-statistic):				
Time:	2011, 07 A	1 · 11 · 08	Log-Likelihood:		-338.11		
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Df Residuals:			BIC:		685.5		
Df Model:		1	5101				
Covariance Type:	nor						
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Sum of Google Trends							-0.00
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Prob(Omnibus):					1.629		
Skew:			<pre>Jarque-Bera Prob(JB):</pre>		3.089 0.213		
Kurtosis:			Cond. No.		2.55e+03		
Kurtosis:							
OLS Regression Resu							
			ion Results				
	Sum of Ranks				0.114		
Model:			Adj. R-squared:		0.105		
Method:	Least Squares		F-statistic:		12.77		
Date: Time:	Sun, 07 Apr 2024		Prob (F-statistic):		0.000547		
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No. Observations:			AIC:		649.0 654.2		
Df Residuals:		99 1	BIC:		654	1.2	
Df Model:		-					
Covariance Type:							
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sum of doogle frend							0.002
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Prob(Omnibus):			Jarque-Bera		1.4		
		Prob(JB):		0.483			
Kurtosis: 3.234				1.26e+03			
=======================================							
Notes:							
					one is sonn	octly specif	ind
[1] Standard Errors							
[1] Standard Errors [2] The condition n							ieu.

Traditional top 4 teams against bottom 5



OLS Regression Results											
De	ep. Variable	: Goog	le Trends	Data	R-s	quared:	0.064				
	Model:		: OLS			Adj. R-squared:					
	Method:		: Least Squares			F-statistic:					
	Date:		: Sun, 07 Apr 2024			Prob (F-statistic):					
	Time):	20:3	4:22	Log-Like	elihood:	-310.46				
No. O	servations	i:		86		AIC:	624.9				
D	f Residuals	s :		84		BIC:	629.8				
	Df Mode	l:		1							
Covariance Type: nonrobust											
	coef	std err	t	P> t	[0.025	0.975]					
const	40.6916	3.173	12.825	0.000	34.382	47.001					
Result	-2.9831	1.242	-2.401	0.019	-5.453	-0.513					
	Omnibus:	4.544	Durbin-	Watson	: 1.504						
Prob(0	Omnibus):	0.103	Jarque-B	era (JB)	: 3.871						
	Skew:	0.498	F	Prob(JB)	0.144						
	Kurtosis:	3.299	С	ond. No	9.47						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Conclusion

Conclusions reached and limitations

Conclusion

Winning games and higher rankings have a significant relationship with Google Search Traffic

- 2 Matches with high Google Search Traffic showed a significant correlation with better ranked teams
- There was little to no relationship between online engagement of top performing teams to their performance against low performing teams

Limitations in our approach

Keywords used posed challenges

 For Google search data, many teams had standard names; searches under their name were not necessarily related to the team. Example: Wolverhampton Wanderers and Wolves

Weekly and daily data did not account for external factors

- Teams play matches in other competitions outside the Premier League that drive online engagement
- Club news also drives online engagement.
 Example: Cristiano Ronaldo's move to
 Manchester United in August 2021

Not enough data in general

 While our data frames included thousands of data points, there is high variability within each season. More seasons are needed to account for seasonal differences

Google search traffic and trends may not be the best measure for online engagement

 We believe that other measures of social media engagement, like proactive involvement on social media apps would lead to stronger results

Thanks!

Questions?

