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A sentiment analysis of who participates, how and why, at social media sport websites: How differently men and women write about football

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A sentiment analysis of who participates, how and why, at social media sport websites

How differently men and women write about football

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Abstract

Purpose – Due to an immense rise of social media in recent years, the purpose of this paper is to investigate who, how and why participates in creating content at football websites. Specifically, it provides a sentiment analysis of user comments from gender perspective, i.e. how differently men and women write about football. The analysis is based on user comments published on Facebook pages of the top five 2015-2016 Premier League football clubs during the 1st and the 19th week of the season.

Design/methodology/approach – This analysis uses a data collection via social media website and a sentiment analysis of the collected data.

Findings – Results show certain unexpected similarities in social media activities between male and female football fans. A comparison of the user comments from Facebook pages of the top five 2015-2016 Premier League football clubs revealed that men and women similarly express hard emotions such as anger or fear, while there is a significant difference in expressing soft emotions such as joy or sadness.

Originality/value – This paper provides an original insight into qualitative content analysis of male and female comments published at social media websites of the top five Premier League football clubs during the 1st and the 19th week of the 2015-2016 season.

Keywords Social media, Facebook, Sentiment analysis, Football online consumption, Gender perspectives

Paper type Research paper

Introduction

In recent years, public space of men's football events has enlarged tremendously due to an immense rise of social media, thus allowing fans to go beyond geographical barriers in forming communities that could not otherwise exist (Guschwan, 2016), and to become active contributors of ideas, improvements and extensions to the professional producers of social media content (Ravindran and Garg, 2015).

Although the large majority of football fans are men, the number of female fans is increasing, and there is a positive development in the attention paid to women (Selmer and Sülzle, 2010). However, women fans are still perceived as "inauthentic supporters" (Pope, 2014), and have to cope with a measure of sexism, but they can adopt the men's perspectives in order to be accepted as "authentic fans", and can be as dedicated and loyal as their male fellows (Mintert and Pfister, 2015). Moreover, men's and women's

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pre-viewing (e.g. talking to others about the game, or reading about what might happen in the game) and post-viewing behaviours (e.g. watching the game highlights on a news broadcast) do not differ, nor does their motivation for watching televised sport (Gantz and Wenner, 1995). A recent study of Gencer (2015) shows no differences between female and male football fans in terms of motives and points of attachment, whereas Sveinson and Hoeber (2015) suggest certain different perspectives on fandom from a female viewpoint, e.g. from the feminist standpoint approach, an authentic fan does not need to wear official, branded clothing or attend games in person, but does need to be positive, supportive and enthusiastic.

Sport is a place where gender roles are created (Sparhawk *et al.*, 1989), and gender differences are usually explained by their production at the individual and structural levels through practices, interactions or performative iterations, where masculinities and femininities are "configurations of practice" (Connell, 2005). The dominant and most idealized form of masculinity in any gender regime is "hegemonic masculinity" which reinforces androcentric privilege, subjugating women, and discriminating against gay men (Kian *et al.*, 2011), whereas "emphasized femininity" practices are nurturing, submissive and sexualized (Connell, 1987).

Although mainstream sport media is increasingly policed for homophobia and sexism, the anonymity of the internet still permits hegemonic masculinity to flourish in specific locations, without contestation (Kian *et al.*, 2011). According to Jones (2008), women respond to sexism and homophobia by expressing disgust at abuse, sometimes redefining fandom to exclude abusers, by downplaying sexism, or by embracing gender stereotypes, arguing that femininity was inconsistent with "authentic" fandom and that abuse was a fundamental part of football. In addition, launching a women's fan group can also be interpreted as a means of opposition to the dominance of men (Lenneis and Pfister, 2015). Women have also sought to contest this masculine domain in part by adopting typically masculine linguistic practices of insult (McDowell, 2011), since the sentiments expressed by football fans in the stories that they tell are often intensified by the use of swear words (Byrne and Corney, 2014).

There are apparent phonological and pragmatic differences between male and female language use in speech, informal writing and electronic messaging (Koppel *et al.*, 2003), e.g. when men recall their past experience, they tend to use positive words while women use both positive as well as negative words, however, for both men and women the most salient emotion words present an antonymic pair sadness-happiness (Wang and Hsieh, 2007). Such an approach is rarely used relating to football fandom, except for the analyses of abusive language (Byrne and Corney, 2014; Koppel *et al.*, 2003; McDowell, 2011).

We propose to fill this gap by exploring social media text corpus to model, extract and analyse the space of emotions at the intersection of natural language processing, sentiment analysis and football fandom. In this paper, we present our results about men's football online consumption from gender perspective (actual sexual orientation of individuals is beyond the scope of this study). Utilizing a significant amount of fan-generated content from social media, we argue that in certain aspects men and women feel the same about football. However, both the number of female football fans and the amount of different soft emotional expressions about football still confirm the stereotype that men, in general, enjoy football much more than women.

Our study is based on the idea that humans experience cross-cultural, universal emotions, recognized by universal facial expressions, i.e. anger, disgust, fear, joy, sadness and surprise (Ekman, 1992), which can be combined into soft (associated with expressing vulnerability) and hard (associated with asserting power) emotions

(Sanford, 2007). We use an automatic detection of expressions of emotions in natural language which is the core effort in the area of sentiment analysis and opinion mining, aiming at the classification of a textual document into a subjective category or along a single continuous dimension from negative to positive (Ballatore and Adams, 2015). To identify such classes, affective dictionaries provide terms associated with emotions (Strapparava and Valitutti, 2004; Liu, 2015).

Although there are many challenges facing sentiment analysis, e.g. people can be contradictory or ironic in their statements, its current implementations provide sufficiently good results (Vinodhini and Chandrasekaran, 2012), and within football fandom domain, we join the efforts of applying it to acquire new aspects of gender-based human behaviour.

Research questions

This study seeks to find more about how football matches affect user commenting activity on social networking websites from gender perspective utilizing sentiment analysis of user comments from Facebook. More specifically, it aims to answer the following subset of questions:

- *RQ1.* How football matches affect the amount and quality of male and female comments?
- *RQ2.* What kind of emotions males and females express at these websites? Is there a difference between male and female emotional expressions in polarity and emotion range?
- *RQ3.* What kind of language is used for expressing male and female emotions?

Methods

Based on the research questions identified, it was decided that the investigation would be carried out in two main parts: data collection; and sentiment analysis of data items.

Data collection

Facebook is the largest social network in the world with over a billion and a half monthly active users (Smith, 2016), and therefore, in this study, we use it as a resource for our data set and a representative of social media in general. On the other hand, English Premier League is the most-watched football league in the world (Byrne and Corney, 2014), and its lucrative television deals mean that all 20 teams in the English division make the top 40 richest globally (*Economist*, 2015). Therefore, it serves us as a representative of football in general. We have limited our data set to the top five 2015-2016 Premier League clubs (Arsenal, Leicester City, Manchester City, Manchester United and Tottenham Hotspurs) because they represent relatively large economic stakeholders with substantial portion of their value coming from their brands (*Forbes*, 2016).

We have taken Facebook data published during the 1st and 19th week of the 2015-2016 season, as the 1st week represents the beginning of the season, and is the expected time for the increase of social media activities. The 19th week represents the end of the first half of the season, which gives us a representative sample of data from the "middle of the season".

An excerpt from the fan statistics fetched on 30th January 2016 at 10 a.m. from Facebook page of each club (Facebook, 2016) is given in the Table I.

The "Talking about" column is an estimate of the number of people talking about the subject at the moment of presence at Facebook, the "Fans" column is a total number of fans (who liked the particular football club official Facebook page) and the "Last week fans" column is an increase of a total number of fans during the last week. The numbers show that Manchester United is the most popular football club and the Leicester City is the least popular club among these. However, trends for increasing the number of fans shown by "Last week fans" column indicate an increase of 4,434 per cent total number of fans by one week for Leicester City while for Manchester United it is 0,253 per cent. The growing interest in Leicester City is explainable by its current standing in the Premier League table. While Leicester City was not among most successful clubs over the last few seasons, it is the biggest positive surprise of the 2015-2016 season and the mid-season leader. On the other hand, Manchester United is the most successful Premier League club of the last decade.

Utilizing Facebook's Graph API Explorer, a programme was written which retrieved posts and their comments published online from 8 to 10 August 2015 (Season 2015-2016: week 1) and from 28 to 30 December 2015 (Season 2015-2016: week 19) for each club. The size of our data set, measured in total number of posts and user comments, is given in the Table II.

It can be observed that although having the smallest number of fans, Leicester City exhibits an outstanding posting activity on its Facebook website. However, the number of user comments is still modest compared to the number of user comments at other club's websites. Manchester United has expectedly the largest size of user-generated data although its website publishes a moderate number of posts compared to others.

Our final data set upon which a sentiment analysis is conducted is available at: https://goo.gl/qXKn9r. It is a collection of ten files, each containing posts and comments of one club per one week with the assigned values of "message", "likes_count" and "gender" variables for each user comment.

Sentiment analysis

A sentiment is a view or attitude towards a person, place or thing, whereas a sentiment analysis (also called opinion mining) is a field of study that analyses people's opinions,

Football club	Talking about	Fans	Last week fans
Arsenal	794.054	34,926,672	140.345
Leicester City	*234.971*	*1,371,050*	60.806
Manchester City	249.092	20,274,497	74.986
Manchester United	**998.084**	**67,853,880**	**171.943**
Tottenham Hotspur	255.229	7,253,768	*40.971*

Note: Maximum value in the column is bold, and the minimum is italic

Table I. Facebook pages' statistics for the top five 2015-2016 Premier League football clubs (snapshot on 30 January 2016)

	Week 1		Week 19	
Football club	Posts	Users' comments	Posts	Users' comments
Arsenal	16	22.733	20	19.184
Leicester City	**43**	1.578	**40**	3.513
Manchester City	*10*	*1.434*	*11*	*2.254*
Manchester United	20	**36.210**	15	**28.086**
Tottenham Hotspur	25	3.086	34	3.941

Note: Maximum value in the column is bold, and the minimum is italic

Table II. Data set statistics for the top five 2015-2016 Premier League football clubs (Season 2015-2016: week 1 and week 19) sentiments, evaluations, appraisals, attitudes and emotions towards entities such as products, services, organizations, individuals, issues, events, topics and their attributes (Liu, 2015), based on textual records such as customer reviews, newspaper headlines, novels, e-mails, blogs, and tweets (Mohammad, 2016). Much research exists on sentiment analysis of user opinion data, which mainly judges the polarities of user reviews (Vinodhini and Chandrasekaran, 2012).

Sentiment analysis fits under the umbrella of data mining, which provides the necessary tools for discovering patterns in data (Zafarani *et al.*, 2014). Compared to traditional analytical tools which rely on the fact that small differences between two pieces of text do not change the meaning very much, sentiment analysis is much more sensitive to small textual differences (Adedoyin-Olowe *et al.*, 2014). Similar tools are available for opinion analysis/formation, product ratings/reviews, topic detection/tracking, or for information extraction from non-textual, sentiment-bearing sources such as speech, or video.

Data items in our data set are user comments from Facebook, and we use sentiment analysis system implemented by Jurka (2012) to obtain two outputs: content attributes polarity and emotion. Given our data set as an input; for each user comment the polarity attribute shows the presence or manifestation of opposite or contrasting principles or tendencies (Ballatore and Adams, 2015), and the emotion attribute indicates one of six Ekman's emotions (Ekman, 1992). The domain of each content attribute is predefined as follows (Jurka, 2012):

- polarity: an item carries a positive, negative, or neutral emotion; and
- emotion: an item carries one of the following set of emotions: anger, disgust, fear, joy, sadness and surprise.

The basis for the polarity and emotion inter-coding procedure is an affective dictionary of nearly 6,800 English words (Jurka, 2012; Liu, 2015; Strapparava and Valitutti, 2004; Wilson *et al.*, 2005), where each word has a priori assigned polarity and emotional value. Consequently, the overall polarity/emotion result of a textual item depends on the initial reliability of these dictionaries. Here are several examples of existing words in the affective dictionary of Liu (2015):

- positive: beautifully, free, fun, love, sexy, smile, trust;
- negative: dizzy, messy, miss, nervous, noise, sucks, pain;
- joy: good, friend, heart, love, preference, respect, satisfy; and
- sadness: bore, broken hearted, distress, loneliness, miserably.

Given a user comment as an input to a sentiment analysis system, an algorithm calculates a score based on the number of times a positive/negative/neutral, or an anger/disgust/fear/joy/sadness/surprise word occurred (Ravindran and Garg, 2015). Based on these scores, the system decides on the polarity and emotion of the given user comment.

Furthermore, each of these emotions can be rated according to its hardness/softness, where hard emotion is associated with power assertion, pursuit of self-centred goals and negative communication, and soft emotion is associated with expressions of vulnerability, pursuit of pro-social goals and positive communication (Sanford, 2007). For instance, if a person perceives the other as angry, they will recognize a threat so they will respond with a hard emotion like anger or blame. Or, if a person is perceived to be sad or vulnerable, they will recognize a negligence and will respond softly.

Likewise, anger, frustration and disappointment are hard emotions, and behind these are often soft emotions like grief, sadness, loneliness and fear (Christensen, 2000). Hard emotions are selfish and associated with exerting power and control, while soft emotions are pro-social. Therefore, if one only expresses hard feelings this might lead to the escalation of conflicts. To speak about and convey soft emotions might instead create greater intimacy and warmth and reduce conflicts (Reevy *et al.*, 2010).

Following these foundations, we put joy and sadness into the class of soft emotions, and anger, disgust, fear and surprise into the class of hard emotions.

Results

From the theoretical framework and our sample of football fan comments from Facebook, we formulate the following hypothesis with its sub-hypotheses about football fans at social media;

H1. Male and female football fans express different emotions at social media.

H1a. Male and female football fans express different emotional polarity (negative/neutral/positive) at social media.

H1b. Male and female football fans express different soft emotions (joy/sadness) at social media.

H1c. Male and female football fans express different hard emotions (anger/disgust/fear/surprise) at social media.

For the purpose of testing these sub-hypotheses, we mix qualitative (sentiment) analysis with quantitative statistical analysis in order to obtain qualitative results under a data set whose size is beyond the scope of manual processing, yet to generalize our results beyond Facebook and Premier League.

According to our research questions, we first report on certain quantitative aspects of our data set; the distribution of the lengths of user comments and the correlation between these lengths and the number of Facebook likes of each comment.

The Figure 1 shows a bar-chart with a length distribution of user comments per sex (red bars for females and blue bars for males) regardless of club (Figure 1(a)) and per club and sex (Figure 1(b)). It is obvious from y-axis scaling that females in general comment less than males, which is due to their smaller number in total fan population. However, although the quantity of male comments is significantly larger than female's, it can observed from the following listing of the length summary statistics of user comments that the means (or medians) do not differ much in absolute value between males and females (Table III). Furthermore, it should be noted that x-axes are scaled up to 500 characters, so outliers are removed from the figure for better visualization of more frequent length items.

An interesting observation from Figure 1 is the shape resemblance of male and female bar-charts at the Figure 1(a), and the shape resemblance of the respective male and female bar-charts within a club at the Figure 1(b). Without mathematical proofs, it is safe to conclude that for both men and women most of the comments are concentrated in the left-side of the distribution indicating that short comments notably exceed the amount of long ones. The "long tail" in the right-side of the distribution indicates rare presence of very long comments in total amount of comments. This implies that female and male fans are almost equally likely to write a comment of any size, i.e. female and male fans exhibit similar fandom behaviour given a comment length as a fandom measure parameter.

(a)

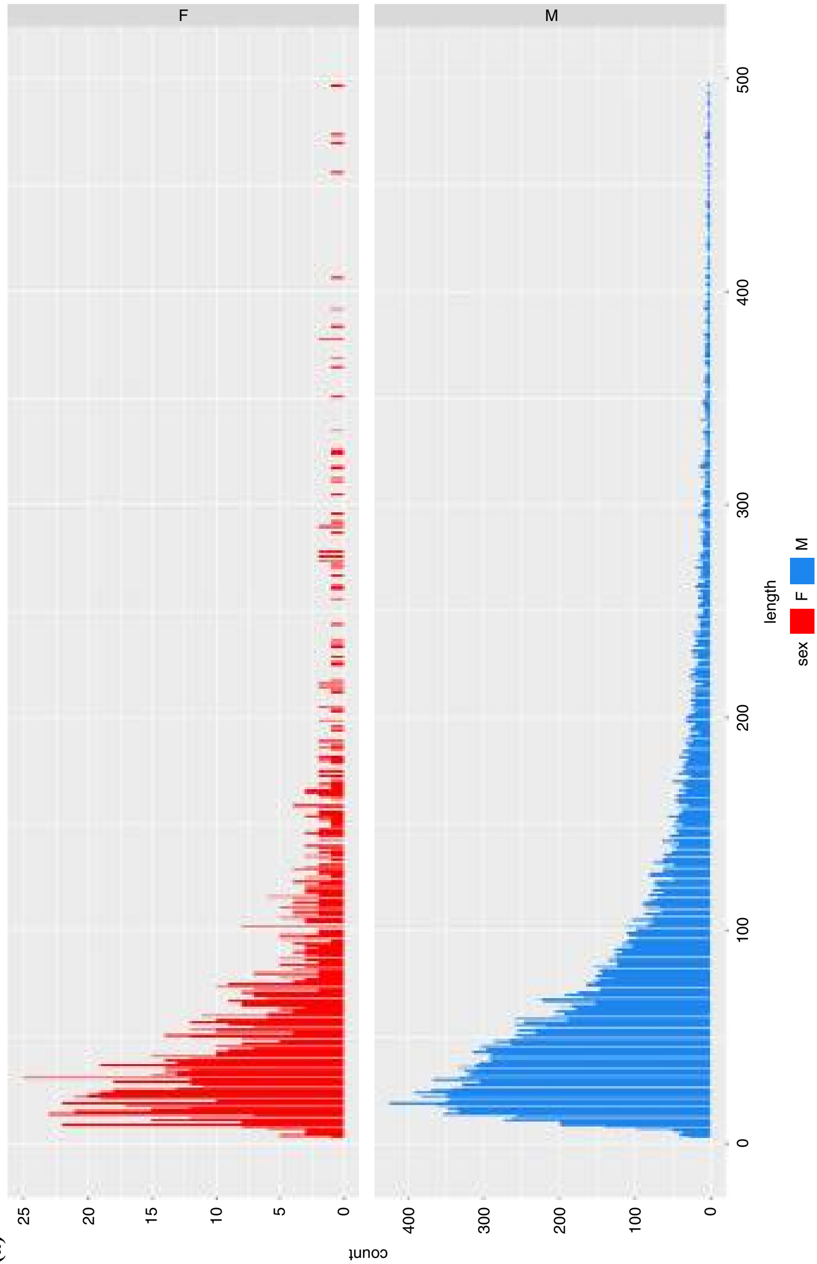

Figure 1.
Length distribution of user comments (a) per sex and (b) per club and sex

(*continued*)

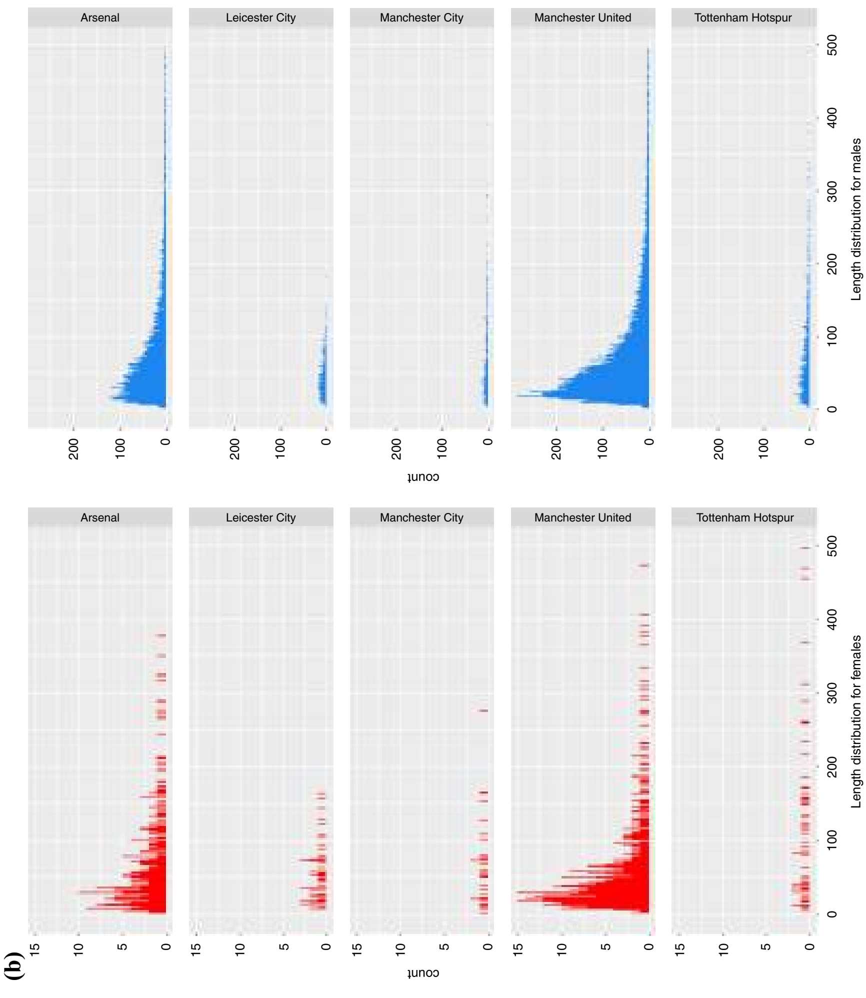
(b)
Arsenal
Leicester City
Manchester City
Manchester United
Tottenham Hotspur
count
Length distribution for males
Length distribution for females

Figure 1.

The correlation between the length (in the number of characters) and number of likes for each user comment can be summarized by the following regression models:

(1) females (regardless of club):
   - intercept = 0.977491, $t = 3.887$, $se = 0.251507$, $p = 0.000103$
   - slope = 0.007189, $t = 7.124$, $sd = 0.001009$, $p = 1.25e{-}12$

(2) males (regardless of club):
   - intercept = 1.7160460, $t = 20.221$, $se = 0.084866$, $p = 2e{-}16$
   - slope = 0.0008596, $t = 2.771$, $se = 0.0003102$, $p = 0.00559$

Here, estimates for the model's coefficients (intercepts and slopes) are provided along with their standard error (se), a t value and probability for a null hypothesis that the coefficients have values of zero (p value). In both cases, we see that there is strong evidence ($p < 0.05$) that both intercepts and slopes are significantly different than zero. The positive slope of our linear regression models indicate the positive correlation between the number of likes and comment lengths, i.e. to get one new like, it takes 139 characters for males, and 3,223 characters for females. This implies that both male and female fans on Facebook like longer comments from other fans, i.e. they enjoy and appreciate extensive elaborations with many arguments regarding a football match. However, the stronger requirement in number of characters for women indicates that women get likes harder, which can be explained by the traditional marginalization of women's participation as referees in professional football (Forbes *et al.*, 2015), or by the perception of female fans as "new consumers", or "inauthentic fans" (Pope, 2014).

Summary statistics for the number of likes is given in the Table IV. It should be noted that this refers only to liking user comments and not the posts published by clubs which usually have much more likes than comments do.

Small mean values and zero median indicate small amount of likes in general. The explanation of the difference between maximum number of likes for males and females depends on whether the likers are mostly males or females. Here is the most *liked* female comment:

> Get out there and win the game against Bournemouth! The Southampton game was embarrassing to watch, so please have your heads in today's game and get the job done. Drawing is not an option; Arsenal needs a significant, comfortable win to boost the goal difference that was lost at Southampton. Get out there and do it for the team, the Club and the supporters!

Table III. Summary statistics for user comments' length

			Length summary			
Sex	Min.	1st quartile	Median	Mean	3rd quartile	Max.
Females	0.00	15.00	28.00	56.61	57.00	13,810.00
Males	0.00	16.00	33.00	72.07	73.00	18,520.00

Table IV. Summary statistics for number of likes

			Likes summary			
Sex	Min.	1st quartile	Median	Mean	3rd quartile	Max.
Females	0.00	0.00	0.00	1.38	0.00	549.00
Males	0.00	0.00	0.00	1.78	0.00	2,880.00

It is written by a female fan of Arsenal and has a length of 359 characters. And, here is the most liked male comment:

> […] this is the last game of Van Gaal at Utd. like if u agree

It is written by a male fan of Manchester United and has a length of 57 characters. The female comment confirms the above findings, but the male comment is obviously more of an exception than a rule for getting more likes we have inferred. However, both comments are actually very typical male and female writings. The female one is an emotional appeal for winning, and the male one is just a rational statement. Men and women are considered to be naturally different in certain aspects and women are defined as being more expressive and emotional than men (Koppel *et al.*, 2003), which our example confirms. Women are more emotional than men so they have better conceptual knowledge in emotional terms; however, with the description of their experiences, women tend to use detailed and specific terms which are not as abundant as the basic emotional terms (Wang and Hsieh, 2007).

For qualitative analysis of our data set, we first use sentiment analysis system by Jurka (2012) as a means to identify positive, negative or neutral emotions.

The dashboard in Figure 2 shows our results obtained for the polarity distribution for males and females per football club. An interpretation of obtained results should be

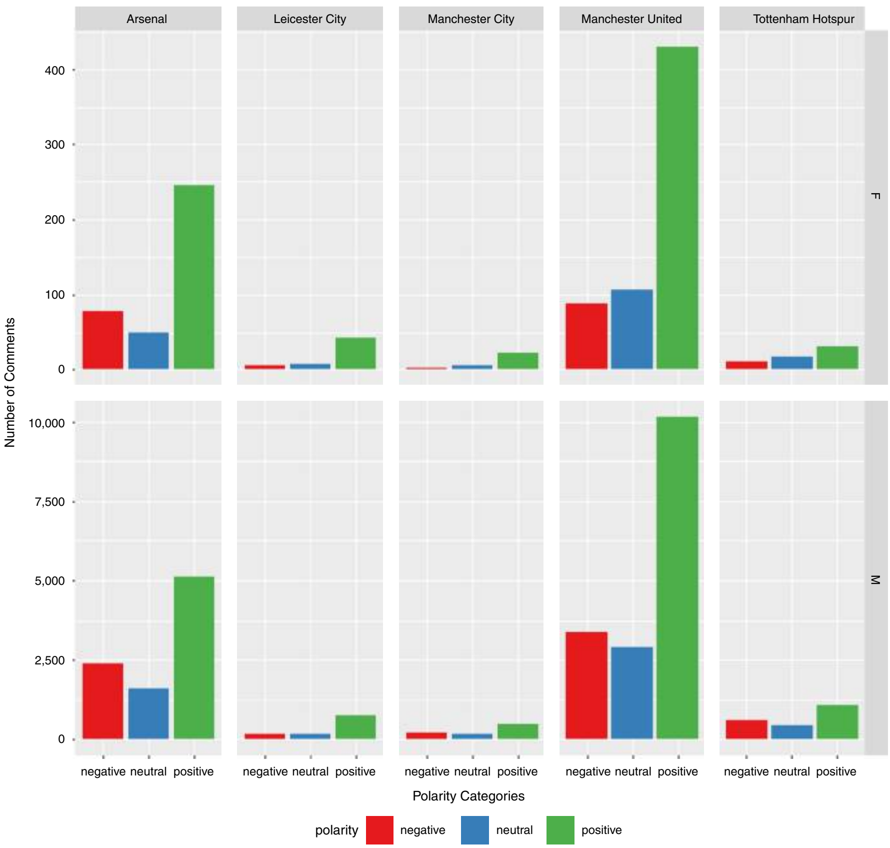

Figure 2.
Frequency distribution of users' comments by polarity categories

placed into an affective context of football matches that were played during the 1st and the 19th week (Table V), as it must have affected fans' emotions and posting activities on Facebook (e.g. a lost match is a potential cause of negative comments and criticism, while a won match attracts more joy and positive emotions, and perhaps increases a total number of comments).

To interpret our results shown in Figure 2, we focus on relative ratios of positive, negative and neutral emotions given at the top of Table VI. Considering the numbers in a "Positive" column for both males and females, it can be noted that the minimum amount of positive emotion is provided by Arsenal and Tottenham fans, and at the same time, the maximum amount of negative emotions. It is quite unexpected that males and females have the same perception of these played matches.

The most positive male and female comments are those of Leicester fans, which can be correlated to its standing in the Premier League table, i.e. its outstanding success during the 24th season of the Premier League. A slight difference between Leicester's male and female fans is in the relative ratio of neutral to negative emotions, which indicates that females are more neutral and less negative than males. This finding can be interpreted that males were more critical than females about the match when Leicester draw with Manchester City.

Similar conclusion about the relative ratio of neutral to negative emotions is valid for Manchester City, Manchester United and Tottenham, because for all three, males are more negative than neutral, and females are more neutral than negative. The interpretation is that males feel "stronger" emotions about loss or draw outcome of a match, while females are more tolerant about loss and draw, or just cannot feel the same empathy the males do.

The mean and standard deviation of polarity categories for males and females regardless of club are given at the bottom of Table VI. An interesting observation of the mean is that both males and females show large amount of positive emotions, while the relative ratio of negative to neutral is larger for males than females. The result

Football match	Week 1	Football match	Week 19
Arsenal – West Ham	0:2	Arsenal – Bournemouth	2:0
Leicester – Sunderland	4:2	Leicester – Manchester City	0:0
Manchester City – WBA	3:0	Manchester United – Chelsea	0:0
Manchester United – Tottenham	1:0	Tottenham – Watford	2:1

Table V. Summary statistics for number of likes

	Male (%)			Female (%)		
Football club	Positive	Neutral	Negative	Positive	Neutral	Negative
Arsenal	56,325	17,339	26,141	65,951	13,137	**20,912**
Leicester City	**70,930**	*14,351*	*14,719*	**76,786**	*12,500*	10,714
Manchester City	58,796	17,355	23,848	74,193	16,129	*9,677*
Manchester United	61,816	17,718	20,466	69,021	17,014	13,965
Tottenham Hotspur	*51,441*	**20,831**	**27,728**	*51,667*	**30,000**	18,333
	Mean			SD		
Sex	Positive	Neutral	Negative	Positive	Neutral	Negative
Male	59,862	17,519	22.580	7,261	2,297	5,173
Female	67,524	17,756	14.720	9,829	7,108	4,833

Note: Maximum value in the column is bold, and the minimum is italic

Table VI. Polarity classification and statistics coincides with the above findings for Manchester City, Manchester United and Tottenham because their total data set size exceeds that of Leicester and Arsenal. However, the similarity of these statistical values for males and females has motivated us to explore in more depth if there are any statistically significant similarities in the obtained results.

The second step of our sentiment analysis is to classify user comments in different types of emotion, namely, anger, disgust, fear, joy, sadness and surprise.

Table VII presents an excerpt from our randomly chosen sample results showing an example for every emotion detected in our data set. These examples are not the original writings from Facebook, but rather a "cleaned" data obtained after removing punctuation, numbers, URLs, and stopwords.

The following dashboard shows the emotion distribution for the five studied clubs (Figure 3).

The interpretation of the results should also be placed into the affective context of played matches during the observed period, as for the polarities above. Figure 3 is complemented with Table VIII which shows the same data as the figure, but in terms of relative ratios; each row sums up to 100 per cent.

It can be noted that the only positive emotion (joy) has similar distribution (among clubs for both sexes) to the distribution of positive polarity in Figure 2 and Table VII. The least joyous male fans are those of Manchester City, Arsenal and Tottenham and the least joyous female fans are those of Arsenal and Tottenham. Accordingly, the saddest are both female and male fans of Arsenal and Tottenham. These findings give more evidence for our previous explanation of possible influence of match outcomes to user comments. Then, Manchester City's male fans wrote the smallest amount of joyous comments, and a significant amount of sad, angry and disgusted comments. This is not the case for their female fans who wrote the most joyous comments of all female fans. This, however, is a strong evidence for differences in football perception by males and females.

The mean and standard deviation of emotion categories for males and females regardless of club are given at the bottom of Table VIII. These statistics and shape

User comment	Emotion	Polarity	Sex
so frustrating we need points now just so lethargic	Anger	Negative	M
gotta score more goals not jut hitting the posts attack attack attack	Anger	Negative	M
so you are showing your beautiful ground to hide your horrible performances nowdays	Disgust	Negative	M
please remove rooney s picture its disgusting to see him these days	Disgust	Neutral	M
i fear we may get slaughtered	Fear	Negative	M
too slow premier league is a cruel place to be if your can t think or move quickly enough	Fear	Negative	M
manchester united i love you	Joy	Positive	F
well done mahrez great goals today	Joy	Positive	F
top sorry no way sloppy sloppy spurs	Sadness	Negative	M
wenger buy a striker that can deliver not relying on that your french striver giroud who always would put sadness on our faces	Sadness	Negative	M
blind always make stupid mistake that can cause super counter attack how long you want to put hopes in young and de gea to save ball	Surprise	Negative	M
go back to october st we had a draw bore against sunderland but arsenal beat manchester utd to send leicester city to the top of the premiership today feels special	Surprise	Positive	F

Table VII. Examples of emotions detected in the data set

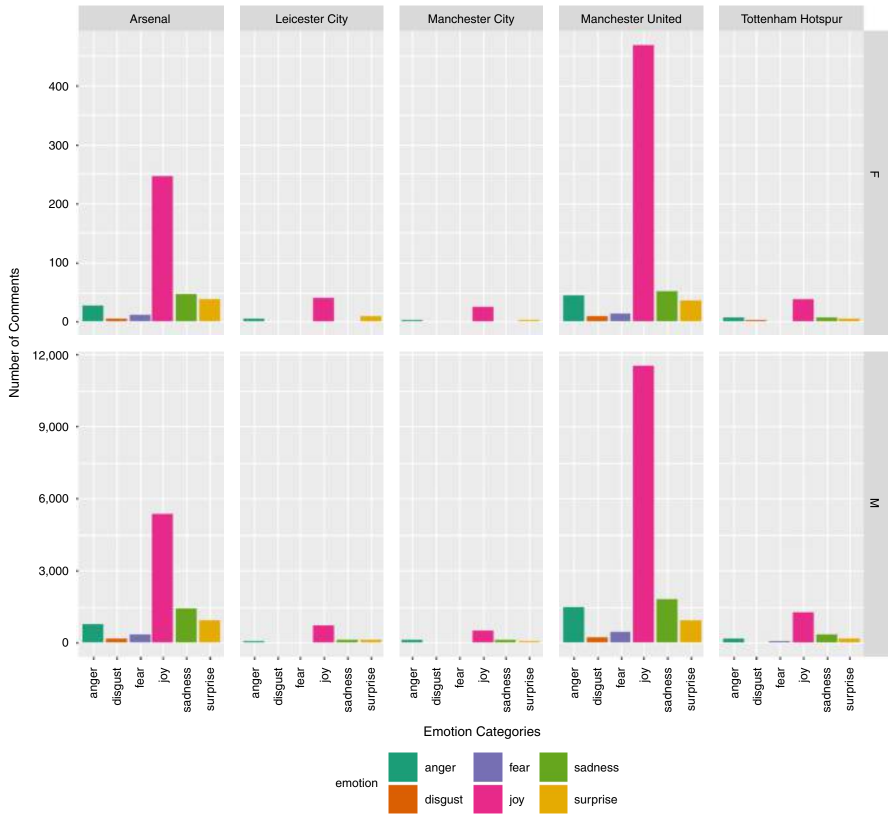

Figure 3.
Frequency distribution of users' comments by emotion categories

Table VIII.
Emotion classification and statistics

	Male (%)					
Football Club	Anger	Disgust	Fear	Joy	Sadness	Surprise
Arsenal	8,784	1,823	3,679	59,264	15,887	10,562
Leicester City	*6,532*	*0,552*	*1,748*	67,893	*10,396*	**12,879**
Manchester City	**16,647**	**2,007**	3,306	*57,025*	12,987	8,028
Manchester United	8,989	1,392	2,832	**70,040**	10,953	5,793
Tottenham Hotspur	9,353	1,181	**4,298**	60,557	**16,533**	8,077
	Female (%)					
Football club	Anger	Disgust	Fear	Joy	Sadness	Surprise
Arsenal	7,238	1,072	**2,949**	65,952	**12,600**	10,188
Leicester City	7,143	*0*	*0*	73,214	*1,786*	**17,857**
Manchester City	9,677	*0*	*0*	**80,645**	3,226	6,452
Manchester United	*7,062*	1,445	2,247	75,281	8,347	*5,618*
Tottenham Hotspur	**11,667**	**5,000**	1,667	*63,333*	11,667	6,667
	Mean					
Sex	Anger	Disgust	Fear	Joy	Sadness	Surprise
Male	10,061	1,391	3,173	62,956	13,351	9,069
Female	8,557	1,503	1,373	71,685	7,525	9,356
	SD					
Sex	Anger	Disgust	Fear	Joy	Sadness	Surprise
Male	3,844	0,573	0,959	5,682	2,792	2,718
Female	2,055	2,058	1,332	7,039	4,873	5,064

Note: Maximum value in the column is bold, and the minimum is italic resemblance between male and female distributions for emotions have motivated us to apply statistical tests to get better insight into differences between male and female football perceptions.

In order to test our hypothesis, together with its sub-hypotheses *H1a*-*H1c*, we have used a statistical test for testing groups for equal proportions, i.e. an implementation of a two-sample test for equality of proportions with continuity correction (R Development Core Team, 2015). We compare the number of comments in each polarity/emotion category for males and females as they are our testing groups regardless of the club. This amounts to labelling "being in a specific polarity/emotion category" as "success". We take the numbers who belongs to which category in each group and the total number of females/males in each group to obtain the results.

Tests show that there is a significant difference in expressing positive and negative emotional polarity ($p < 0.05$) between males and females, as expected. However, an interesting finding is that there is no significant difference in expressing neutral emotions ($p > 0.05$) between males and females.

Furthermore, there is a significant difference in expressing "soft" emotions between males and females ($p < 0.05$), as expected. However, contrary to our expectations, there is no significant difference in expressing "hard" emotions between them ($p > 0.05$) between males and females.

Precisely, the list of polarity test outcomes, i.e. the 95 per cent confidence interval estimate of the difference between the female and male proportion of polarity is provided along with χ^2 and p-value in Table IX.

Then, the list of test outcomes, i.e. the 95 per cent confidence interval estimate of the difference between the female and male proportion of emotion, is presented with Table X.

Various methods have been used to measure the accuracy of sentiment analysis, which was used as a main method in our research. From the performance achieved it is difficult to judge the best choice of underlying sentiment analysis method, since each method uses a variety of resources and different collections of documents for testing, various feature selection methods and different text granularity; however, a range of approximately 60-90 per cent of accuracy is usually achieved (Vinodhini and Chandrasekaran, 2012). For the improvement of accuracy, the main challenges exist in dealing with negation expressions, complexity of sentences, handling of implicit

Polarity	Proportion difference interval	χ^2	p
Positive	(5.174, 10.804)	28.918	7.551*e*−08
Negative	(−8.657, −4.191)	25.782	3.823*e*−07
Neutral	(−3.789, 0.659)	1.7451	0.1865

Table IX.
Polarity test results

Emotion	Proportion difference interval	χ^2	p
Joy	(3.331, 8.759)	17.609	2.713*e*−05
Sadness	(−5,237, −1,669)	11.468	0.0007079
Anger	(−3.2461, −0.044)	3.4313	0.06397
Disgust	(−0.836, 0.645)	0.018948	0.8905
Fear	(−1.828, 0.0368)	2.6184	0.1056
Surprise	(−1.583, 1.673)	1.7414e−28	1

Table X.
Emotion test results

language features, etc. The size of our data set makes it impossible to validate the results manually, however, the accuracy is dependent on the affective dictionary and the algorithm implemented by Jurka, (2012), as well as on the actual textual corpus of our data set.

Finally, to elaborate our hypothesis and findings in a less mathematical form (yet with a strong mathematical background), we show wordclouds for females and males built from the corpora of words they used in their comments in Figure 4 (the top is females' cloud, and the bottom is males'). Each wordcloud is arranged in a non-random order, with the higher-frequency words placed closer to the centre. We have used the same colour palette as in the previous figure to distinguish between the words based on their emotion category (e.g. pink for joy).

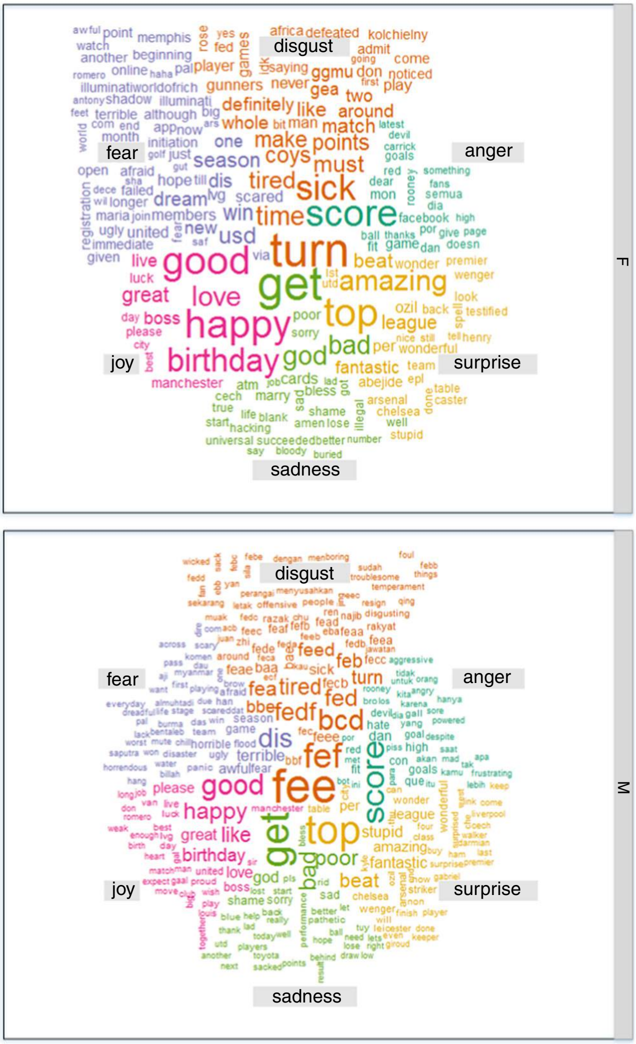

Figure 4.
Sentiment-based wordclouds (female vs male)

The drawback of the overall method for emotion categorization is observed in the wordclouds; there are certain "undefined" words without clear meaning and they appear due to: many abbreviations from colloquial language, non-English text from a lot of foreign fans who write in they own language (our data set is not cleaned of non-English words and the algorithm treats all words as English, yet not all data items are classified in case of insufficient certainty), and lots of typos inherent to real-time writing by both males and females.

Both the size and collection of words in each category indicate certain differences in male and female texts which were the basis for the recognized differences in polarity and emotion expression between the two. In addition, from these words, we have determined that women and men are mostly involved with the following categories of commenting at social media: expression of support and celebration, result prediction (1:0, etc.), best/favourite player, use of symbols without text, but with strong emotional meaning (< 3, :-), ???, etc.) and personal congratulations to players (e.g. happy birthdays).

Discussion

Given social media as our data set resource, this study contributes to rising use of social media as a golden mine of information published by citizens and thus providing us with opportunities to understand individuals at scale and to mine human behavioural patterns otherwise impossible (Zafarani *et al.*, 2014).

While most scholars use fully or partially manual research methods to obtain a data set – an interview, questionnaire, social media content analysis, reader and user data of mass media, or results of surveys – all of which are time consuming, our results are based upon automated data collection method, which is another research benefit from the social media approach. What is even more important is that such an obtained data set is not influenced by the research itself.

Furthermore, as there is nothing like word of mouth marketing, social media platforms (Podobnik *et al.*, 2013) can help affect the growth of any business via the words of real customer. By gathering information on the opinions of consumers, businesses can understand current and potential customers' outlook, and such informative data can guide business decisions, in the long run, influencing the fate of any business (Gencer, 2015). We argue that our results should influence football marketing (Podobnik, 2013) and organizations to develop new strategies in targeting women as growing consumers of football-related products. In addition, as our results indicated certain gender-based differences and similarities in football fan behaviours, these should also be reused and correlated to other domain-specific human behaviour studies.

Built upon psychological, computational-linguistic and computer science research, sentiment analysis methods can play a crucial role in understanding the customer sentiment. Based on our study, further research on sentiment analysis could be extended by gender perspectives, since the state-of-the-art starting point of the analysis is an affective dictionary with unisex approach to semantics of words, i.e. no difference in emotions is given a word from gender perspective. Although sentiment words and phrases are important for sentiment analysis, only using them is far from sufficient, so gender approach might provide one way to go forward.

It is worth mentioning here that not all the user comments in our data set represent emotions, i.e. a few user comments can be just information or a fact, and ideally, they should not be used to assess the sentiment about a particular comment, so there is a need to automate recognition of such text for general purposes.

Another limitation of sentiment analysis is that people can be contradictory in their statements, or, for example, sarcastic. However, this remains the challenge at interdisciplinary level.

Conclusion

Our analysis is merely a first step into investigating the potential of sentiment analysis of user comments from social media websites, however, it shows the power of social media mining to explore and reason upon social phenomena. This paper not only provides information about the gender-based football fandom behaviour at social media websites, but also presents new theoretical perspective that contributes to an understanding of backgrounds and reasons for the gender differences in terms of emotions and their expressions.

As our study implied, outcomes from social media mining bring new insights into human behaviour patterns not otherwise visible, and consequently, these findings should motivate further investigation and verification of such social phenomena. However, without a comprehensive knowledge base that encompasses human knowledge, it is not easy for a sentiment-mining system to grasp the semantics associated with natural language or human behaviour (Cambria, 2016). There are several challenges, e.g. an opinion word that is considered to be positive in one situation may be considered negative in another situation, or that people do not always express opinions in a same way (Vinodhini and Chandrasekaran, 2012). These bring us to the future avenues of research that should include:

- research into whether there are differences in online behaviour from gender perspectives in other domains, i.e. verification of our findings about basic emotions beyond football fandom;
- refinement and extension of content attributes relating to opinions, attitudes, suggestions, ideas, and innovations in different areas of application;
- research of the influence of social media mining findings to the society;
- automated recognition of whether an author of a user comment is male or female based on emotion, opinion or attitude expressed toward a specific topic; and
- extension of sentiment analysis implementation from gender perspective.

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