Enterprise Competitive Analysis and Consumer Sentiments on Social Media
Insights from Telecommunication Companies

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Abstract: The utilization of Social media tools in business enterprises has tremendously increased with an increased number of users and a corresponding upsurge in time spent online. Online social media services such as Facebook and Twitter are used by companies to introduce new products and services, provide various supports and interact with customers on daily basis. This regular interaction of businesses and consumers results in huge amount of customer-generated content which is becoming a source of insight in analysing the often erratic consumer behaviour. For companies to harness the business potential of social media to increase competitive advantage, sentiments behind textual data of both their customers and that of their competitors must be keenly monitored and analysed. This paper demonstrates how companies especially those in the Telecommunication industry can seize the opportunity presented by social media to mine textual data to gain advantage over competitors by cumulatively understanding consumer opinions, frustrations and satisfaction. Using Facebook and Twitter sites of the top three telecommunication companies in Ghana: MTN, Vodafone and Tigo the paper reveals insights from unstructured texts of customers of these three companies. The results show (1) the exponential growth of social media users in Ghana (2) impact and numbers behind active social media participation in the telecommunication industry (3) the power of social media opinion mining for competitive analysis (4) how business value could be extracted from the huge unstructured textual data available on social media and (5) the company that is more responsive to customer concerns.

1 INTRODUCTION

Online social media is now an integral part of our lives. Recent research works by (Wollan and Smith, 2010; Barlow and Thomas, 2011; Qualman, 2009; Safko, 2010) corroborate the exponential growth of social media as a new strategic asset for businesses. In particular, (Barker, 2008; Sinderen and Almeida, 2011; Weber, 2009; Gillin and Schwartzman, 2011) enumerate some of the ways social media can be put to use by businesses. Some of these are (1) identifying new product ideas (2) finding new business opportunities (3) creating brand awareness (4) strengthening customer relationships and (5) establishing contacts with employees, partners and even with competitors. A recent study report by McKinsey (McKinsey, 2013) on how organizations are using social media tools also reveals a range of benefits for business enterprises as shown in table 1. For example 69% of the respondents reported an increase in how effective marketing on social media has been to their companies with 52% reporting an increase in customer satisfaction. Despite these purported benefits, Harvard Business Review (HBR, 2010) posits that though companies are aware of the huge business potential of social media, most of them are only making investments for the future because they still doubt or view the potential as hyped.

Even as the debate on the potential of social media to businesses lingers on with little work from academia to support the discussion according to Jussila et al. (2014), the wealth of textual data from social media continues to pile up on daily basis.

Textual data especially those expressing concerns, frustrations and acceptance from

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Table 1: Business and Web 2.0 - Benefits from customer use to organizations. Source: McKinsey.

Benefits	(%)
Increasing effectiveness of marketing	69
Reducing marketing costs	47
Reducing customer support costs	36
Reducing travel costs	47
Increasing customer satisfaction	52
Increasing revenue	24
Increasing number of successful innovations	22
Reducing time to markets	28

customers are rich in knowledge which needs to be mined for insights. The wealth of knowledge behind customers' comments, posts and tweets on "wall pages" of companies could prove valuable in identifying popular brands and level of customer satisfaction among others (Bradley and McDonald, 2011; Governatori and Iannella, 2011). For example the ''like" feature on Facebook which allows users to approve a post can prove valuable in identifying types of users and their interests in a service or product (Lipsman et al., 2012).

The emergence of online social media now gives consumers a rare but powerful influence for publicly expressing their opinion and thoughts on products and services. This brings revolution in the way customers and companies interact by proffering new ideas about customer relationship and brand management. To process, aggregate and gauge the influence of customers' opinions, sentiment analysis and text mining in general are used. Feldman (2013) explains the role of sentiment analysis in organizations and how it could be employed to monitor the activities of customers in the various social media sites in real time.

In the following sections, we briefly explained the concept of sentiment analysis and its related applications, followed by research questions posed for this paper. Next is the methodology including the samples and procedures used. A case study of the sentiment analysis approach is conducted using the top three telecommunication companies in Ghana. The key findings are discussed followed by how responsive the companies are to customer specific concerns.

2 SENTIMENT ANALYSIS

Sentiment Analysis sometimes referred to as opinion mining often combines the study of Natural Language Processing (NLP), Statistics and Machine learning to extract and classify the sentiments of a textual input. There exists two basic sentiment analysis tasks namely subjectivity and polarity detection. In the subjectivity approach, prediction is made on whether an inputted text is subjective or otherwise whiles the polarity technique makes an overall prediction of whether a subjective text is positive, neutral or negative (Buckley and Paltoglou, 2012). The polarity technique learns to classify the polarity (positive or negative) of a statement, comment or post and determine whether the sentiment behind a statement or comment is positive, negative or neutral (Koppel and Schler, 2006; Pang and Lee, 2008; Dave et al., 2003; Pang et al., 2002; Wiebe, 1994). In the process a document is flagged as positive, negative or neutral. A score of zero denotes a neutral sentiment.

Sentiment analysis, unlike classical text mining which focusses on topical words, picks only sentiment signals for real time analysis (Pang and Lee, 2008).

Additionally, two main approaches are used in the task of automatically extracting sentiments from text. These are text classification and the lexicon-based method. In the former approach, a classifier is typically built from labeled instances of texts or sentences in a supervised classification (Turney, 2002). This employs the use of statistical and machine learning techniques. Some of the most popular algorithms and techniques employed in text classification based sentiment analysis include but are not limited to support vector machines, naive Bayes, Ada Boost, k-nearest neighbours, and maximum entropy (Pang et al., 2002; Cao et al., 2013). These techniques are used when appropriate with Natural language processing and statistical techniques.

On the other hand, the lexicon-based approach works by computing the polarity of a document based on the semantic orientation of words or phrases in the document (Toboada et al, 2011; Vaithyanathan, 2002) In practice, the lexicon-based approach depends on dictionaries of words marked with the word's semantic polarity in computing the overall polarity of a document. Some of the widely used dictionaries for lexicon-based approaches are SentiWordNet and Wordnet though a customized dictionary can be created (Tong, 2001) using seed words to expand the list of existing words as demonstrated by Taboada et al (2011). In this paper, we use the lexicon-based approach with the SentiWordNet (Esuli and Sebastiani, 2006) dictionary to generate the sentiment scores.

Sentiment analysis has been applied to a wide range of domains and disciplines. Notable among these are in the area of consumer product and services reviews (Feldman, 2013) and in voter sentiments in politics (Pang and Lee, 2008). For example (Zhang and Wan, 2013) used sentiment analysis to find possible weaknesses of products from customers' feedback. Kang and Park (2014) designed a new framework that uses sentiment analysis and VIKOR method to measure customer satisfaction in a mobile service. Ghiassi, Skinner and Zimbra (2013) also combined neural network with n-ngram for twitter sentiment analysis and to show that their proposed Twitter-specific lexicon is significantly more effective in classification recall and accuracy metrics than some of the traditional twitter lexicons. A sentiment analysis based on unsupervised and domain-independent model was designed by (Bagheri et al., 2013) to detect explicit and implicit aspects in reviews whiles (Bai, 2011) proposed a heuristic search-enhanced Markov blanket model to predict consumer sentiments from online text.

The interest in sentiment analysis has brought about a wide range of tools both commercial and open source. Dyer (2013) lists some of the top 50 sentiment analysis tools. These tools help find insights and patterns from unstructured textual data (Sashi, 2011; Zeng et al., 2012b).

This paper used a python programming language module called *pattern* together with SentiWordNet to generate the sentiment scores of user comments for the research. In the following sections we explain the sentiment analysis architecture adopted, the methodology guiding the research and subsequently use a case study of consumer comments of the top 3 Telecommunication companies in Ghana. The resulting sentiment scores are then used for a competitive analysis.

3.1 Research Questions

Studies have shown a gradual interest in user-generated content on social media (Feldman, 2013; Akehurst, 2009; Aggarwal et al., 2011). This paper employed opinion mining to do a competitive analysis using unstructured textual information on Facebook and Twitter sites of the top 3 telecommunications company. The data was collected from 02-02-2014 to 07-03-2014. The following research questions guided the study.

1. What patterns can be found from their Facebook and twitter sites respectively?
2. How do customers feel about their products or brand?
3. Which Telecom company is most competitive as far as issues of customers are concerned?

3.2 Methodology

The study was carried out in phases to help answer the research questions. First, descriptive quantitative data was collected from the respective individual social media sites. In particular, we collected the number of *tweets, followers and following* from Twitter and the *likes*, *talking about this* and *notes* features from Facebook. Relevant for the research were also the demographics and geographical location of users, number of postings from the companies, comments made by users, time of the day when most posts are made and the frequency of postings between 02-2014 and 02-03-2014 as shown in figures 2-6 respectively. Next, we applied sentiment analysis techniques to analyse and flag each user comment as negative, positive or neutral. This helped in discovering the sentiments behind each user comment, the manner and pace each company responds to user concerns and the general pattern of how the three companies have been active on social media in relation to their customers.

The sentiment analysis of user comments on social media adopted for the competitive analysis of telecom companies follows the architecture shown in figure 1. The methodology adopted is basically broken into three steps below.

Step1: Text pre-processing:
In the pre-processing stage, we first used Repustate - an online analytical tool to 'scrape' user comments from the social media sites (Facebook and Twitter) of the 3 top telecommunication companies. Each user comment, post or review extracted was treated as a document. The collection of documents-the corpus was saved in comma separated value format (CSV). Then the documents in the corpus were each converted to text and pre-processed using linguistic tools basically of tokenization and stemming in python pattern module. The pre-processed corpus was loaded together with the SentiWordNet dictionary into python for subsequent processing.

Step2: Text processing
The sentiment analysis approach adopted for this research is the lexicon-based approach. First, each document (e.g., post, tweet, review etc.) collected is tokenized into a word list. Next each token's log probability is identified in the word list. The log probabilities of each token are then added together to determine the probability of each sentiment for the entire document. To determine a binary 'positive' or 'negative' label with scores for each document in the corpus (user comment), the SentiWordNet scores are

accumulated with the more subjective comment having a higher score.

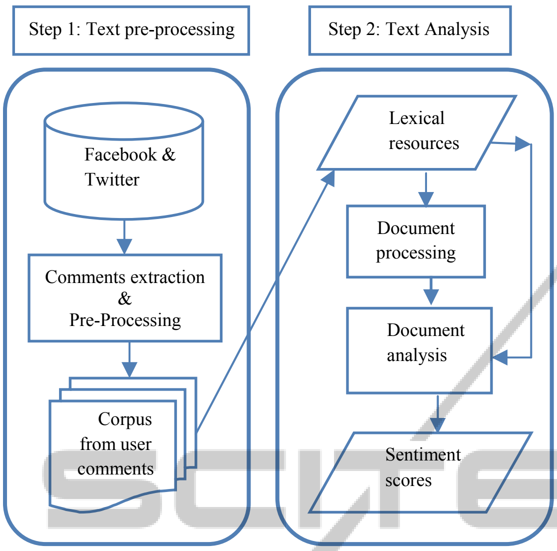

Figure 1: Lexicon-based sentiment analysis architecture for social media.

Step3: Python pattern vrs other software tools
To ascertain the effectiveness of the sentiment analysis techniques we adopted and subsequently the polarity scores for each user comment, comparison was made with other sentiment analysis tools notably *RapidMiner* and *Python NLTK 2.0.4 text classification*. The RapidMiner sentiment analysis tool detected the polarity of a document without sentiment scores. However the results turned out to be consistent with our results in terms of the polarity (negative, positive or neutral) assigned to each of our user comments. In the case of Python NLTK text classification, whiles almost all the polarity labels of 'positive', 'negative' or 'neutral' label for each of our documents were consistent, the scores assigned to each user comment turned out to be slightly different. For instance in Table 5 row 3, the comment "*MTN not good at all*" though a negative polarity in both Python pattern and NLTK text classification, was assigned a score of -0.6 in NLTK compared to a -1 in Python pattern module.

3.3 Case Study

The Telecommunications Industry in Africa continues to grow at an unprecedented rate (McKinsey, 2010; Chavula, 2013; Mahmoud and Hinson, 2012). In Ghana, there are currently six (6) major operators providing wide range of services such as cell phone telephony, broadband internet, and mobile financial services among others. These are as at 2013, *Expresso, Millicom Ghana known in the market as Tigo SCANCOM known as MTN, Vodafone Mobile, Airtel, and Glo Mobile*. According to the National Communications Authority (NCA); a body mandated by the Government of Ghana to among other things, grant licenses, monitor telecom service quality and protect consumers; Ghana's total mobile subscribership currently stands at 28,026482, a growth of 7.4% from 2012 (NCA-Ghana, 2013). In spite of the apparent growth, service quality continues to be a challenge for consumers prompting the NCA-GH to slam five (5) of the operators a total fine of USD 464,413.50 in 2011. The advent of social media has therefore provided consumers in Ghana, a platform to interact with telecom providers in real-time; venting frustrations, reviewing products and generally receiving customer supports.

It is on this premise that we use sentiment analysis to find how telecom companies in Ghana competitively respond to issues of customer concerns and also generally delve into what consumers think of these companies. We use the top three telecom companies (by subscriber base) in Ghana according to (NCA-Ghana, 2013). These are *MTN*, *Vodafone* and *Tigo* respectively in the order of customer size. As at December 2013, MTN had a subscriber base of 12,929,528 users with Vodafone and Tigo recording 6,048,792 and 4,021,225 respectively.

The selection of the three (3) telecommunication companies for this research is necessitated by their strong presence on social media compared to the other operators. *MTN*, *Vodafone* and *Tigo* interact with their customers almost on daily basis The time period of Feb 2 –March 7 was also chosen because of two important events within this period. These events are Valentine's and Independence Day celebrations. During these events, a lot of telephony activity is recorded because of the large numbers of people both youth and elderly who access telecommunication services. Our initial findings in this research reveal that MTN made an average of 1 and 9 posts on their Facebook and Twitter pages respectively between 02-02-2014 to 07-03-2014. Vodafone made an average of 4 and 2 posts on Facebook and Twitter respectively whiles Tigo posted an average of 2 and 1 message respectively as shown in table 2 and 3.

In figures 2 and 3, the daily trend of user comments posted on Twitter and Facebook is shown. The trend shows that within the period of the research, MTN users interacted more with their telecom operator on Facebook than Vodafone and TiGo users. On Twitter, TiGo users exchanged more

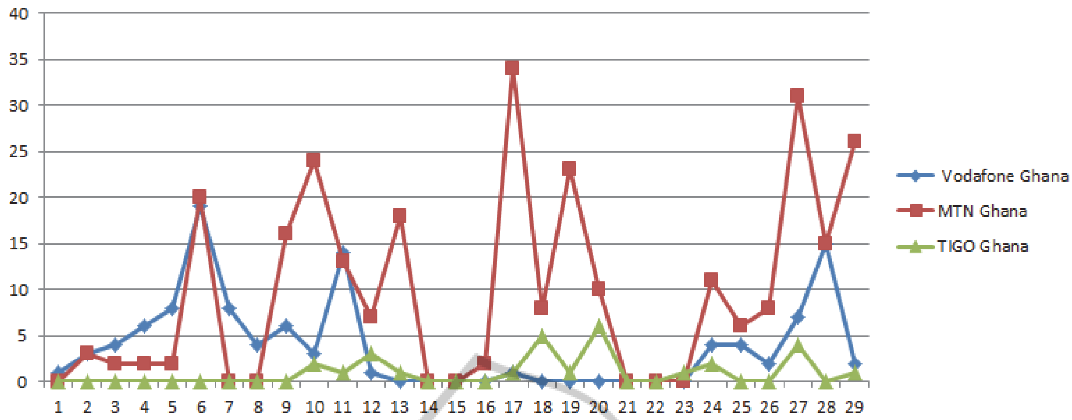

Figure 2: Trend of Tweets from Feb 2 - March 7, 2014 for the 3 companies.

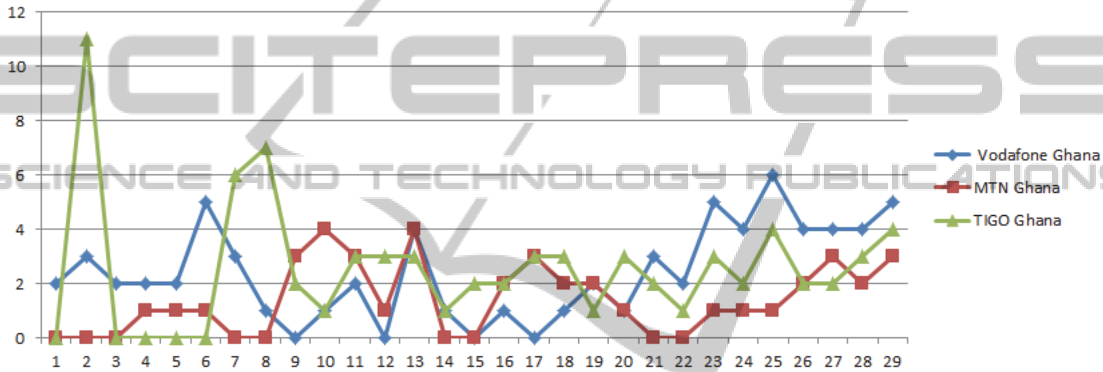

Figure 3: Trend of Facebook posts from Feb 2 - March 7, 2014 for the 3 companies.

comments and posts between them and their operators than as it happened on Vodafone and MTN.

3.4 Preliminary Findings

The web scraping for textual data (posts, comments, tweets etc.) returned valuable information about the social media activity of the three telecom companies. This included the number of posts made in a day, number of likes/followers, and other features specific to one social media such as notes, talking about this on Facebook and following on Twitter as shown in tables 2 and 3 respectively.

The number of tweets and posts on Twitter and Facebook respectively were generated within the month dedicated to the research.

The study shows that the three companies seem to have a strong presence on Facebook than on Twitter. MTN for example posted 289 messages on their Facebook wall compared to only 46 on Twitter in the same period as shown in table 2 and 3. Vodafone recorded 127 posts on Facebook with 89 on twitter whiles Tigo managed 67 posts on Facebook and 74 on Twitter as indicated in tables 2 and 3. The trend showed MTN as the most active telecom company in Ghana on Facebook as far as posts emanating from the company was concerned whiles Tigo appeared slightly the most active on Twitter in the period as shown in figures 2 and 3.

Table 2: Stats on Facebook Feb. 2 – Mar. 7, 2014.

	Likes	No. of Posts	Talking about this	Notes
Tigo	313,287	67	6,011	13
MTN	211,649	289	3,179	19
Vodafone	274,863	127	1,600	143

Table 3: Stats on Twitter from Feb 2 - Mar 2, 2014.

	Tweets	Followers	Following
Tigo	74	9,834	6,084
MTN	46	30,170	3,147
Vodafone	89	21,911	1,743

Table 4: Classification of sentiments on Facebook.

	Negative	Positive	Neutral	Total
Tigo	161	381	462	1004
MTN	101	297	291	689
Vodafone	301	966	1721	2988

It can be seen in figures 2 and 3 above that the peak time of *posts* and *tweets* on Facebook and Twitter respectively did not occur at the same time period. A content analysis of the entire posts and tweets revealed that the reason for the discrepancies was because the three telecom companies embarked on different events, deals, special monthly offers such as discounts and incentives at different days. MTN for example had an SMS scam alert message to their fans/customers on Facebook which generated responses and *re-posts* within the period. The disparity in the *postings* and *tweets* was again evident in the times of the day that customers/fans interacted with their telecom providers on social media. In figures 4-6, an interesting pattern emerges on the time of the day that customers/fans were most active on the pages of these three companies. The action intelligence to be extracted from this would be the ideal time for the companies to target their customers/ fans with new products, special offers and important messages such as alert on scams as was done by MTN.

4 KEY FINDINGS

This section briefly explains some of the key findings from the social media sites of the three telecom companies as far as business competitive and sentiment analysis were concerned. In table 4, a summary of the classification of all the textual information extracted from the social media sites of the three companies into *negative*, *neutral* and *positive* comments is presented.

On Facebook, Vodafone had the largest number of interactions than MTN and Tigo within the period of the research. A total of 2,988 textual information were extracted from Vodafone's Facebook wall. This number includes both posts originating from the company and the responses/comments generated as a result of the posts. The implication is that, with 127 posts on Vodafone's Facebook's wall as seen in table 2, it elicited 2,861 responses from fans/customers. Competitively, it means a far positive customer-company interaction occurred for Vodafone than MTN which posted 289 posts (see table 2) but generated a paltry 654 user comments and responses within the period. It is also worthy to note that even with Tigo's 67 posts on their wall within the month of February to March, customer generated comments/responses and posts (1004) was more than that of MTN.

4.1 Sentiment Analysis on Facebook

The sentiment analysis architecture adopted generated sentiment scores of -1 to +1 indicating most negative to most positive comments to classify the sentiments behind the textual data on the three companies. As shown in table 4, Vodafone had 301 negative comments representing 10.07%, 966 positives (32.33%) and 1,721 (57.60%) neutral comments out of the total of 2,988 texts generated. The classification generated 161 negative comments on Tigo representing (16.03%), 381 (37.95%) positives and 462 (46.02%) neutral comments. MTN on the other hand had 101 negative comments representing 14.66%, 297 positives (43.10%) and 291 (42.20%) neutral comments.

Whereas a cursory analysis of table 4 does not reveal any disturbing trend for any of the three companies as far as the numbers recorded for the total negative comments is concerned, content analysis of the actual individual comments and their relative sentiment scores shown in tables 5-7 is telling on the performance of the companies and their brands in Ghana.

The individual sentiments from the three companies in tables 5-7 reveal gravely dissatisfied customers with strong statements of dissatisfaction. For instance comments like "*Airtime s**kers. Can't even browse for 30mins with 2gh airtime*" for MTN, "*tigo is the most useless network in Ghana. bought the ghc39.99 bundle its too slow. I can't even open common google. you have just lost a customer and I will never*" for Tigo and "*a disappointing network, in Takoradi but yet barely able to connect. would not recommend*" for Vodafone signify discontent. To gain competitive advantage, the companies must respond positively and quickly to these comments to have an edge over their competitors. In-depth content analyses of the positive comments on Facebook reveal interesting responses by the three companies to specific customer queries or enquiries. Tables 8-10 are some specific responses to enquiries by their customers.

Customers feel more relaxed and cared for if they are being identified by name on specific and direct responses to their concerns (Mittal and Lassar, 1996; Peppers and Rogers, 1995). From our content analysis and as can be seen in table 8, MTN

Table 5: Some selected MTN negative comments.

	Comment	Score
1	*Airtime s**kers. Can't even browse for 30mins with 2gh airtime.*	-1
2	*Its annoying if as at now you call yourselves best network in Ghana and still we can't get good network to make calls for browsing, don't wanna talk, I know what to do. :(*	-1
3	*MTN not good at all*	-1
4	*MTN, Like seriously, u r the most useless and disgraceful network I've ever experienced in my life... I regret the day I bought ur chip. I'm porting straight to vodafone and I*	-1
5	*so..when..would..u..stop..stealing..my..airtime.?*	-1

Table 6: Some selected Tigo negative comments.

	Comment	Score
1	*tigo is the most useless network in Ghana. bought the ghc39.99 bundle its too slow. I can't even open common google. you have just lost a customer and I will never*	-1
2	*In fact ur internet network is the poorest in Ghana, what network be this?. What it pains me koraa is....I persuaded my galfriend to port her favorite MTN to Tigo, further on to*	-1
3	*masa if u think we re goin to encounter netwrk problems den dont let us activate internet bundles and later on we cnt use dem.#Poorservice "#Frown uv got tigo"*	-1
4	*Tigo Ghana your internet service is really killing me guys, I have a deadline today and I can't even get anything done. Your Internet is soo slow I can't even open a single page.*	-1
5	*hw3 all u pple do is brag. ur service is v.slow. on and off lyk ecg. 0278686875. i will b leaving soon if u guys dnt gt serious*	-1

Table 7: Some selected Vodafone negative comments.

	Comment	Score
1	*too bad network.. my interent isnt workn again! bomb! im even usin difrnt ntwrk*	-1
2	*stupid network Vodafone for how long will it take your stupid company to fixed my problem my broadband problem . what the f**k is wrong you with you guys you sick, see*	-1
3	*And ur internet service has been down for 3 months now.. unbelievable*	-1
4	*a disappointing network, in Takoradi but yet barely able to connect. would not recommend*	-1
5	*And as a company what do you do?when there is a problem.6days of no browsing and nothing has been.Tweaaaaaaaaaaaaaa what an incompetent data provider*	-0.4883

Table 8: Some selected MTN positive comments.

	Comment	Score
1	*Y'ello Emmanuel, As per our discussion,kindly visit any MTN office with an ID and relevant documents to prove ownership of the number. Thank you.*	0.5421
2	*Y'ello Vida, Sorry for your experience. Kindly provide your number to enable us investigate your complaint. Thank you*	1
3	*Y'ello Bridget, Thank you for your suggestion,Kindly be informed that it is well noted. Thank you*	1

Table 9: Some selected Tigo positive comments.

	Comment	Score
1	*We sincerely apologize for any inconvenience caused.*	1
2	*Kindly confirm your number and current location for assistance.*	0.56801
3	*Kindly elaborate on your issue to enable us assist you.*	0.68644

Table 10: Some selected Vodafone positive comments.

	Comment	Score
1	*Dial 255 for expert medical advice between 4:00pm and 10:00pm daily.*	0.38518
2	*In the spirit of love, telecom operator, Vodafone Ghana, has settled the medical bills of over 180 patients who were struggling to raise funds to pay their medical bills through*	0.35094
3	*Music doesn't lie. If there is something to be changed in this world, then it can only happen through music.*	0.30982

addresses specific customer concerns and directly mentions the name of each customer in the response. It was also realized in one response that MTN takes on suggestions of customers and acknowledges the customer for the input. Tigo also addresses customers per their concerns. Scanning through the content, there was some deficiency in Vodafone's responses to customer specific queries/enquiries. The company provided Omnibus statements that were meant to address general customer issues. To gain competitive advantage, companies must be seen to be more responsive to customers concerns. Companies who personalize customers concerns turn to retain such customers and increase its competitive urge over rivals. It can be inferred that MTN has an urge in terms of responses to customer concerns per extracted comments on Facebook under the period of study.

4.2 Sentiment Analysis on Twitter

Adopting the same sentiment analysis score of -1 to +1 representing most negative to most positive comments respectively, content analysis of the actual individual comments and their relative sentiment score on twitter for the three companies for randomly selected customers are shown in tables 11-13. Negative comments on twitter for the three companies are similar to that of Facebook. The choice of words indicates that these customers are disgruntled and desire specific response to their concerns. Content analysis of the positive responses on twitter was similar to that of Facebook. However, there were more omnibus statements from the three companies on twitter as compared to Facebook.

5 LIMITATION

Since the word list in SentiWordNet is not comprehensive and does not contain vernacular words some sentiments would not be classified in the analysis. This affects the accuracy of the classification. We will therefore develop a wordlist in future to embody local Ghanaian vernacular words for a comprehensive analysis.

6 CONCLUSIONS

The explosion of data on social media leaves no business enterprise with a focus on customer satisfaction and expansion to be complacent. The emergence of social media presents businesses with a rare chance of analysing publicly available data of their customers/fans and even more importantly that of their competitors for business advantages. Such data driven analysis could help businesses to identify their weaknesses and exploit the weaknesses of their competitors as far as customer retention and brand management is concerned It would also help to.

Table 11: Some selected MTN negative comments.

	Comment	Score
1	*Some stupid networks we have in our country @MTNGhana fire burn u all*	-1
2	*u dont care about the plight of Ghanians at all...and also why does it keep sooo long for attendants to pic calls of customers?*	-1
3	*u people y?? U pple dey take ma credit small small. I haven't subscribed for any service aside internet bundles wai. Will port oo*	-0.8334

Table 12: Some selected Tigo negative comments.

	Comment	Score
1	*Everyday for the last 2months "@Wiredu_: Thou sucketh today @TigoGhana"" << it's becoming too much. Fix it tiGo*	-0.4674
2	*massa, ur internet service dey bore.wk on it den shon dey talk trash.*	-0.8820
3	*bt i tot u said 24hrs unlimited. rather 14hrs, such a shame*	

Table 13: Some selected Vodafone negative comments.

	Comment	Score
1	*too bad network.. my interent isnt workn again! bomb! im even usin difrnt ntwrk*	-1
2	*stupid network Vodafone for how long will it take your stupid company to fixed my problem my broadband problem . what the fuck is wrong you with you guys you sick, see*	-1
3	*And ur internet service has been down for 3 months now.. unbelievable*	-0.7765

consolidate strengths and identify new opportunities and threats in the competitive market. In Ghana and Africa as a whole, social media competitive analysis may be a new thing but as our research shows, the numbers of social media users in Africa keep growing at exponential rates (Deloitte and Touche, 2012; United Nations (UN), 2010).

This study demonstrated how businesses could take advantage of social media data to improve upon customer relationship and maintain a competitive urge over rivals. Using a case study of the top three Ghanaian Telecom companies, we demonstrated with sentiment analysis, the general feeling of telecom users in Ghana. The use of sentiment analysis is one of the potent ways in attempting to understand customer behaviour.

The results show how active the three telecom companies are on social media and how they engage with their customers/fans on daily basis. Content analysis of the textual information we extracted reveal a number insights about how customers perceive the services of the three companies. Some of the key patterns and trends we identified are the following:

(1) Response to User Comments

The study revealed that to stay in touch with their customers, the three Telecom companies have specific staff assigned to addressing daily customer complaints. They use the social media platform to launch new products and listen to their feedback on services and products. In responding to customer concerns, two of the companies were seen to be giving omnibus answers to complaints. MTN was innovative in the way they addressed customers by name and proffered real-time solutions to concerns.

(2) Unusual Posts and Tweets

It was also realized in the content analysis that not every posts or tweets by the company was related to their service, products or meant to address a customer complaint. Some of the companies, TiGo in particular made several casual postings about topical issues on their pages to engage their fans in the day. Most of the topics centered on relationships, security tips and upcoming entertainment events in the cities and towns in the country. Though most of these casual posts yielded lots of responses, we could not determine their impact on brand awareness and therefore the competitive urge it gives to such companies over their competitors.

(3) Service Quality

Though some of the posts and comments from customers were not business related, majority (60%) of them were about criticizing or hailing one company or the other about their service or product as shown in Tables 5-13. With mobile number portability service in place in Ghana where users can port their telephone numbers from one company to the other for free, competition has become keen among the various operators about maintaining their core customer base and capitalizing on the number portability service to snatch users from their competitors. In spite of this, some service complaints were not satisfactorily addressed prompting others to threaten to port their numbers to other companies as shown for example by one comment in Table 11 row 3.

(4) Freebies

We also realized that almost all the Telecom companies engage in giving out free phone credits to their customers on social media. Some of these freebies came in the form of answering simple questions about their products and services. Some also came in the form of purchasing tickets to major entertainments programs for customers who got some questions rightly answered.

In all MTN seemed to have a slight competitive urge over their rivals in terms of how the company engages with customers on social media. A company's relative responsiveness to customer concerns such as MTN makes consumers advocate of their brand and therefore increase brand referrals culminating in increased profits and market visibility.

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