Understanding the Food Supply Chain using Social Media Data Analysis

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***Abstract*— This paper proposes a big data analytics based approach, which considers social media (Twitter) data for identifying supply chain management issues in food industries. In particular, the proposed approach includes: (i) capturing of relevant tweets based on keywords; (ii) pre-processing of the raw tweets; and, (iii) text analysis using support vector machine (SVM) and hierarchical clustering with multiscale bootstrap resampling. The result of this approach included cluster of words, which can inform supply chain (SC) decision makers about the customer feedback and issues in the flow/quality of the food products. A case study of the beef supply chain was analysed using the proposed approach where three weeks of data from Twitter was used. The results indicated that the proposed text analytic approach can be helpful to efficiently identify and summarise crucial customer feedback for supply chain management.**

Keywords- Twitter data; social media; data mining; clustering.

I. INTRODUCTION

With the advent of online social media, there is lot of consumer information available on Twitter, which reflects the true opinion of customers [9]. Effective analysis of this information can give interesting insight into consumer sentiments and behaviors with respect to one or more specific issues. Using social media data, a retailer can capture a real-time overview of consumer reactions about an episodic event. Social media data is relatively cheap and can be very effective in gathering opinion of large and diverse audiences. Using different information techniques, business organisations can collect social media data in real time and can use it for developing future strategies. However, social media data is qualitative and unstructured in nature and often large in volume, variety and velocity [6]. At times, it is difficult to handle it using traditional operation and management tools and techniques for business purposes. In the past, social media analytics have been implemented in various supply chain problems predominantly in manufacturing supply chains. The research on application of social media analytics in domain of food supply chain is in its primitive stage. In this article, an attempt has been made to use social media data in domain of food supply chain to make it consumer centric. The results from the analysis have been linked with all the segments of supply chain to improve customer satisfaction.

Firstly, data was extracted from Twitter (via Twitter streaming API) using relevant keywords related to consumer's opinion about different food products. Thereafter, pre-processing and text mining was performed to investigate the positive and negative sentiments of tweets using Support Vector Machine (SVM). Hierarchical clustering of tweets from different geographical locations (World, UK, Australia and USA) using multiscale bootstrap resampling was performed. Further, root causes of issues affecting consumer satisfaction were identified and linked with various segments of supply chain to make it more efficient. Finally, the recommendations for consumer centric supply chain were described.

This paper is organized as follows. Section II, presents the literature review related to food products supply chain and state-of-the-art methods used in the area. In Section III, the proposed methodology is discussed in detail. Section IV presents the results obtained by applying proposed twitter based analytics for beef supply chain. Section V details the managerial implications of the proposed analysis method in food products supply chain. Finally, Section VI concludes this research with some guidelines for future research.

II. LITERATURE REVIEW

Food products supply chain, such as for beef products consists of various stakeholders, which are farmer, abattoir and processor, retailer and consumer. Literature consists of research publications on diverse characteristics of beef supply chain such as waste minimisation, vertical coordination in supply chain, traceability, greenhouse gas emission, meat quality, meat safety. For instance, Francis et al. [4] have applied value chain analysis for examination of beef sector in UK. The opportunities for waste minimisation at producer and processor level have been identified in the UK by comparing them to practices followed in Argentina. Consequently, good management practices have been suggested to mitigate the waste generated in UK beef industry. Wang et al. [16] have utilised the standardized performance analysis data to examine the beef farms in Texas Rolling plants.

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In literature, several types of framework have been proposed to investigate problems and issues associated with supply chain through big data analysis. Chae [1] has developed a Twitter analytics framework for evaluation of Twitter information in the field of supply chain management. An attempt has been made by them to fathom the potential engagement of Twitter in the application of supply chain management and further research and development. Tan et al. [14] have suggested an analytic mechanism for capturing and processing of big data generated in the corporate world. It employed deduction graph technique. Hazen et al. [7] have determined the problems associated with quality of data in the field of supply chain management and a novel procedure for monitoring and managing of data quality was suggested. Vera-Baquero et al. [15] have recommended a cloud-based mechanism utilising big data procedures to efficiently improve the performance analysis of corporations. Frizzo et al. [5] have done a thorough analysis of literature on big data available in reputed business journals. A very limited work is being done to explore the characteristics of food supply chain by utilising social media data.

Twitter, Facebook and Youtube denote the swift expansion of Web2.0 and applications on social media lately. Twitter is the most rapidly growing social media platform since its outset in 2006. More than 75% of corporate firms enlisted in Fortune Global 100 have one or more Twitter account for the entire firm and for their distinct brands [10]. This research study will use Twitter data for the identifying issues in supply chain management (SCM) in food industries. The next section describes the research study conducted in this paper.

III. ANALYTICS APPROACH

In case of social media data analysis, three major issues are to be considered, namely, data harvesting/capturing, data storage, and data analysis. Data capturing in case of twitter starts with finding the topic of interest by using appropriate keywords list (including texts and hashtags). This keywords list is used together with the twitter streaming APIs to gather publicly available datasets from the twitter postings. Twitter streaming APIs allows data analysts to collect 1% of available Twitter datasets. There are other third party commercial data providers like Firehose with full historical twitter datasets.

The Twitter streaming API allowed us to store/append twitter data in a text file. The analysis of the gathered Twitter data is generally complex due to the presence of unstructured textual information, which typically requires Natural Language Processing (NLP) algorithms. We proposed two main types of content analysis techniques – sentiment mining and clustering analysis for investigating the extracted Twitter data; see Figure 1. More information about the proposed sentiment mining method and hierarchical clustering method is detailed in the following subsections.

A. *Data Analysis*

The information available on social media is predominantly in the unstructured textual format. Therefore, it is essential to employ Content Analysis (CA) approaches, which includes a wide array of text mining and NLP methods to accumulate knowledge from Web 2.0 [2]. An appropriate cleaning of text and further processing is required for effective knowledge gathering. There is no best way to perform data cleaning and several applications have used their own heuristics to clean the data. A text cleaning exercise, which included removal of extra spaces, punctuation, numbers, symbols, and html links were used. Then, a list of major food retailers in the world (including their names and Twitter handles) was used to filter and select a subset of tweets, which are used for analysis.

1) *Sentiment analysis based on SVM*

Tweets contain sentiments as well as information about the topic. Thus, sophisticated text mining procedures like sentiment analysis are vital for extracting true customer opinion. The objective here is to categorise each tweet with positive and negative sentiment. Sentiment analysis, which is also widely known as opinion mining is defined as the domain of research that evaluates public's sentiments, appraisals, attitudes, emotions, evaluations, opinions towards various commodities like services, corporations, products, problems, situations, subjects and their characteristics.

The identification of polarity mentioned in opinion is a crucial for transforming the format of opinion from text to numeric value. The performance of data mining methods such as SVM is excellent for sentiment classification. SVM model is employed in this approach for the division of polarity of opinions. Initially, a set of features from the data must be chosen. In this case, we have used Unigrams and Bigrams, which are the tokens of one-word and two-word, respectively, identified from the tweets. In this study, we used binary value {0,1} to represent the presence of these features in the microblog.

SVM is a technique for supervised machine learning, which requires a training data set to identify best Maximum Margin Hyperplane (MMH). In the past, researchers have used approach where they have manually analysed and marked data prior to their use as training data set. In this case, we have examined the use of emoticons to identify sentiment of opinions. In this paper, Twitter data was pre-processed based on emoticons to create training dataset for SVM. Microblogs with ":)" were marked as "+1" representing positive polarity, whereas messages with ":(" were marked as "-1" representing negative polarity. It was observed that more than 89% messages were marked precisely by following this procedure. Thus, the training data set was captured using this approach for SVM analysis. Then, a grid search (Hsu et al., 2003) was employed to train SVM. The polarity (Pol_m={+1,-1}) representing positive and negative sentiment respectively of microblog m can be predicted using trained SVM. In real life, when consumers buy beef products, they leave their true opinion (feedback) on Twitter. In this article, the SVM classifier has been utilised to classify these sentiments into positive and negative and consequently gather intelligence from these tweets.

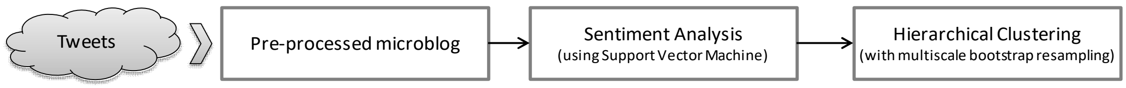

Figure 1. Overall approach for social media data analysis

2) Hierarchical clustering with p-values using multiscale bootstrap resampling

In this research, we also employed a hierarchical clustering with *p*-values via multiscale bootstrap resampling method to analyse the content of tweets with positive and negative sentiments [13]. The clustering method creates hierarchical clusters of words and also computes their significance using *p*-values (obtained after multiscale bootstrap resampling). This helps in easily identifying significant clusters in the datasets and their hierarchy. The agglomerative method used is ward.D2 [11]

In a typical data clustering approach, data support for the identified clusters is not present. The support of data for these clusters can be obtained by adopting multiscale bootstrap resampling. In this approach, the dataset is replicated by resampling for large number of times and the hierarchical clustering is applied. During resampling, replicating sample sizes was changed to multiple values including smaller, larger and equal to the original sample size. Then, bootstrap probabilities are determined by counting the number of dendrograms, which contained a particular cluster and dividing it by the number of bootstrap samples. This is done for all the clusters and sample sizes. Then, these bootstrap probabilities are used to estimate *p*-value, which is also known as Approximately Unbiased (AU) value.

The result of hierarchical clustering with multiscale bootstrap resampling is a cluster dendrogram. At every stage, the two clusters, which have the highest resemblance are combined to form one new cluster. The distance or dissimilarity between the clusters is denoted by the vertical axis of dendrogram. The various items and clusters are represented on horizontal axis. It also illustrates several values at branches, such as AU *p*-values (left), Bootstrap Probability (BP) values (right), and cluster labels (bottom). Clusters with AU >= 95% are usually shown by the red rectangles, which represents significant clusters.

IV. RESULTS AND DISCUSSION

The proposed Twitter data analysis approach is used to understand issues related to the beef/steak supply chain based on consumer feedback on Twitter. This analysis can help to analyse reasons for positive and negative sentiments, identify communication patterns, prevalent topics and content, and characteristics of Twitter users discussing about beef and steak. Based on the result of the proposed analysis, a set of recommendations have been prescribed for developing customer centric supply chain. The total number of tweets extracted for this research was 1,338,638 (as per the procedure discussed in Section 3). They were captured from 23/03/2016 to 13/04/2016 using the keywords beef and steak. Only tweets in English language were considered with no geographic constraint. Figure 2 shows the geo-located tweets in the collected dataset. Then, keywords were selected to capture the tweets relevant to this study. The overall tweets were then filtered using this list of keywords so that only the relevant tweets (26,269) are retrieved. Then, country wise classification of tweets was performed by using the name of supermarket corresponding to each country. It was observed that tweets from USA, UK and Australia and World were 1605, 822, 338 and 15214 respectively. There were many hashtags observed in the collected tweets. The most frequently used hashtags (more than 1000) were highlighted in Table 1.

As described in the previous subsection, the collection of training data for SVM was done automatically based on emoticons. The training data was developed by collecting 10,664 messages from the Twitter data captured with emoticons ":)" and ":(". The automatic marking process concluded by generating 8560 positive, 2104 negative and 143 discarded messages. Positive and negative messages were then randomly classified into five categories. The 8531 messages in first four categories were utilised as training data set and the rest of the 2133 messages were utilised as the test data set.

Numerous pre-processing steps were employed to minimise the number of features prior to implementing SVM training. Initially, the target query and terms related to topic (beef/steak related words) were deleted to prevent the classifier from categorising sentiment based on certain queries or topics. Various feature sets were collected and their accuracy level was examined. In terms of performance of the classifier, we have used two types of indicators: (i) 5-fold cross validation (CV) accuracy, and (ii) the accuracy level obtained when trained SVM is used to predict sentiment of test data set.

Table 2 reports the performance of SVM based classifiers on the collected microblogs. The best performance is provided when using unigram feature set in both SVM and Naïve Bayes classifiers. The unigram feature set gives better result than the other feature sets. This is due to the fact that additional casual and new terms are utilised to express the emotions. It negatively affects the precision of subjective word set characteristic as it is based on a dictionary. Also, the binary representation scheme produced comparable results, except for unigrams, with those produced by term frequency (TF) based representation schemes. As the length of micro blogging posts are quite short, binary representation scheme and TF representation scheme are similar and have almost matching performance levels. Therefore, the SVM based classifier with unigrams as feature set represented in binary scheme is used for estimating the sentiment score of the microblog.

Figure 2. Visualisation of tweets with geolocation data

TABLE 1. TOP HASHTAGS USED

Hashtag	Freq (>1000)	Freq (%)
#beef	17708	16.24%
#steak	14496	13.29%
#food	7418	6.80%
#foodporn	5028	4.61%
#whcd	5001	4.59%
#foodie	4219	3.87%
#recipe	4106	3.77%
#boycottearls	3356	3.08%
#gbbw	3354	3.08%
#kca	2898	2.66%
#dinner	2724	2.50%
#recipes	2159	1.98%
#accessibility	1999	1.83%

Hashtag	Freq (>1000)	Freq (%)
#aodafail	1908	1.75%
#earls	1859	1.70%
#votemainefpp	1795	1.65%
#win	1761	1.62%
#ad	1754	1.61%
#cooking	1688	1.55%
#mplusplaces	1686	1.55%
#meat	1607	1.47%
#lunch	1577	1.45%
#bbq	1557	1.43%
#yum	1424	1.31%
#yummy	1257	1.15%
#bdg	1255	1.15%

TABLE 2. PERFORMANCE OF SVM BASED CLASSIFIER ON SELECTED FEATURE SETS

Representation scheme	Feature Type	Number of Features	SVM	
			CV (%)	Test data (%)
Binary	Unigram	12,257	91.75	90.80
	Bigram	44,485	76.80	74.46
	Unigram + bigram	56,438	87.12	83.28
Term Frequency	Unigram	12,257	88.78	86.27
	Bigram	44,485	77.49	71.68
	Unigram + bigram	56,438	84.81	80.97

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To identify meaningful content in the collected tweets, initially, we performed sentiment analysis to identify sentiments of each of the tweets followed by HCA. Following section provides the results of the analysis performed on the tweets (by sentiment) collected worldwide and UK.

a) Analysis of negative tweets from the world

The collected tweets were divided into positive and negative sentiment tweets. In negative sentiment tweets, the most frequently used words associated with 'beef' and 'steak', were 'smell', 'recipe', 'deal', 'colour', 'spicy', 'taste' and 'bone.' Cluster analysis is performed on the negative tweets from the world to divide them into clusters in terms of resemblance among their tweets. The three predominant clusters identified (with significance >0.95 level) are represented in Figure 3 as red coloured rectangles. The first cluster consists of bone and broth, which highlights the excess of bone fragments in broth. The second cluster is composed of jerky and smell. The customers have expressed their annoyance with the bad smell associated with jerky. The third cluster consists of tweets comprising of taste and deal. Customers have often complained to the supermarket about the bad flavour of the beef products bought within the promotion (deal). The rest of the words highlighted in Figure 3 does not lead to any conclusive remarks.

This cluster analysis will help global supermarkets to identify the major issues faced by customers. It will provide them the opportunity to mitigate these problems and raise customer satisfaction and their consequent revenue.

TABLE 3. RAW TWEETS WITH SENTIMENT POLARITY

Sentiment	Raw Tweets
Negative	*@Morrisons so you have no comment about the lack of meat in your Family Steak Pie? #morrisons*
Negative	*@AsdaServiceTeam why does my rump steak from asda Kingswood taste distinctly of bleach please?*
Positive	*Wonderful @marksandspencer are now selling #glutenfree steak pies and they are delicious and perfect! Superb stuff.*
Positive	*Ive got one of your tesco finest* beef Chianti's in the microwave oven right now and im pretty pleased about it if im honest*

b) Analysis of negative tweets from UK

The most widely used words after 'beef' and 'steak' were 'tesco', 'coffee', 'asda', 'aldi'. The association rule mining indicated that the word 'beef' was most closely associated with terms like 'brisket', 'rosemary', and 'cooker', etc. It was least used with terms like 'tesco', 'stock', 'bit'. The word 'steak' was highly associated with 'absolute', 'back', 'flat'. and rarely associated with words like 'stealing', 'locked', 'drug'.

The four predominant clusters are identified (with significance >0.95 level). The first cluster contains the words – man, coffee, dunfermline, stealing, locked, addict, drug. When this cluster was analysed together with raw tweets, it was found that this cluster represents an event where a man was caught stealing coffee and steak from a major food store in 'Dunfermline'. The finding from this cluster is not linked to our study. However, it could assist retailers for various purposes such as developing strategy for an efficient security system in stores to address shoplifting. Cluster 2 is related to the tweets discussing high prices of steak meal deals. Cluster 3 represents the concerns of users on the use of horsemeat in many beef products offered by major superstores. It reveals that consumer are concerned about the traceability of beef products. Cluster 4 groups tweets, which discuss the lack of locally produced British sliced beef in the major stores (with #BackBritishFarming). It reflects that consumers prefer the beef derived from British cattle instead of imported beef. Rest of the clusters, when analysed together with raw tweets, did not highlight any conclusive remarks and users were discussing mainly one-off problems with cooking and cutting slices of beef.

The proposed HCA can help to identify (in an automated manner) root causes of the issues with the currently sold beef and steak products. This can help major superstores to monitor and respond quickly to the customer issues raised in the social media platforms.

V. MANAGERIAL IMPLICATIONS

The finding of this study can assist the beef retailers to develop a consumer centric supply chain. During the analysis, it was found that sometimes, consumers were unhappy because of high price of steak products, lack of local meat, bad smell, presence of bone fragments, lack of tenderness, cooking time and overall quality. In a study, Wrap (2008) estimated that 161,000 tones of meat waste occurred because of customer dissatisfaction. The majority of food waste is because of discoloration, bad flavor, smell, packaging issues, and presence of foreign body. Discoloration can be solved by using new packaging technologies and by utilising natural antioxidants in the diet of cattle. If the cattle consumes fresh grass before slaughtering, it can help to increase the Vitamin E in the meat and have a huge impact on delaying the oxidation of color and lipid. The issues related to bad smell and flavor can be caused due to temperature abuse of beef products. The efficient cold chain management throughout the supply chain, raising awareness and proper coordination among different stakeholders can assist retailers to overcome this issue. The packaging of beef products can be affected by mishandling during the product flow in the supply chain or by following inefficient packaging techniques by abattoir and processor, which can also lead to presence of foreign body within beef products. Inefficient packaging affects the quality, color, taste and smell. Periodic maintenance of packaging machines and using more advanced packaging techniques like modified atmosphere packaging and vacuum skin packaging will assist retailers in addressing above mentioned issues.

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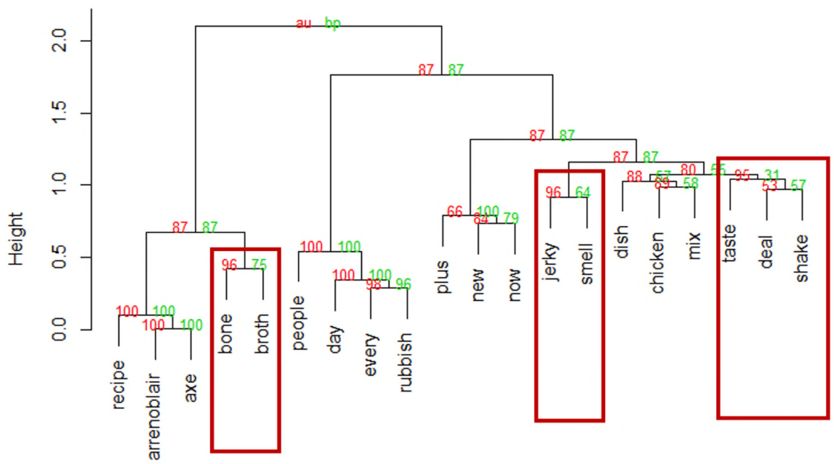

Figure 3. Hierarchical cluster analysis of the negative tweets originating in the World

The high price of beef products can be mitigated by improving the vertical coordination within the beef supply chain. The lack of coordination in the supply chain leads to waste, which results in high price of beef products. Therefore, a strategic planning and its implementation can assist the food retailers to reduce price of their beef products more efficiently than their rivals.

During the analysis, it was found that products made from forequarter and hindquarter of cattle have different patterns of demand in the market, which leads to carcass imbalance [3][12]. It leads to huge loss to retailers and contribute to food waste. Sometimes, consumers think that meat derived from different cuts such as forequarter and hindquarter have different attributes like flavor, tenderness, and cooking time as well as price. The hindquarter products like steak and joint are tenderer, takes less time for cooking and are more expensive whereas forequarter products like mince and burger have less tenderness, takes more time for cooking and are relatively cheaper. Consumers think that beef products derived from the forequarter and hindquarter have different taste and it affects their buying behavior. In this study, it was found that slow cooking methods like casseroling, stewing, pot- roasting and braising can improve the flavor and tenderness of forequarter products. With the help of proper marketing, advertisement, retailers can raise awareness between the consumers and can increase the demand of less favorable beef products, which will further assist in waste minimization and making the supply chain more customer centric.

The analysis of consumer tweets reveal that consumers especially from the UK, were interested in consuming local beef products. Their main concern was quality and food safety. Specially, after horsemeat scandal, customers are prone towards traceability information, i.e., information related to animal breed, slaughtering method, animal welfare, use of pesticides, hormones and other veterinary drugs in beef farms. Retailers can gain the consumer confidence by following the strict traceability regime within the supply chain.

VI. Conclusions and Future Work

Consumers have started to express their views on social media. Using social media data, a company can know the perception of their existing or potential consumers about them and their business rivals. In this study, Twitter data has been used to investigate the consumer sentiments. More than one million tweets related to beef products has been collected using different keywords. Text mining has been performed to investigate positive and negative sentiments of the consumers. During the analysis, it was found that the main concern related to beef products among consumers were color, food safety, smell, flavor and presence of foreign body in beef products. These issues generate huge disappointment among consumers. There were a lot of tweets related to positive sentiments where consumers had discovered and share their experience about promotion, deal and a particular combination of food and drinks with beef products. Based on the findings, some recommendations has been prescribed to develop consumer centric supply chain. In future, extensive list of keywords can be used for further analysis. Future work may include standardizing the data preprocessing steps for better model training and prediction. For instance, positive and negative words can be included in the analysis for better sentiment prediction. Network analysis tools can be also employed to understand the social network communities and identifying marketing opportunities.

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