**Social media data analytics for supply chain management in food industries**

**Abstract**

Application of social media data in food supply chain is in primitive stage. Paper proposes a big data analytics approach for identifying issues in beef supply chain: (i) capturing of relevant tweets based on keywords; (ii) pre-processing of raw tweets; (iii) text analysis using support vector machine, hierarchical clustering with multiscale bootstrap resampling. Findings of cluster analysis will help decision makers to gain insights into customer opinion. Execution process of proposed holistic approach is demonstrated on Twitter data. Results indicated that text analytics approach could be helpful to efficiently identify and summarise crucial customer feedback for consumer centric supply chain.

Keywords – Beef Supply Chain, Twitter Data, Sentiment Analysis

1. **Introduction**

In modern day, food is a crucial commodity for consumers as it has a direct impact on their health (Caplan, 2013; Swaminathan 2015; Tarasuk, et al., 2015). The food supply chain is more complicated than the manufacturing and other conventional supply chains due to the perishable nature of the food products (La Scalia et al., 2015; Handayati et al., 2015). Food retailers aim to make their supply chain consumer centric (A supply chain designed as per the requirements of end consumers by addressing organisational, strategic, technology, process and metrics factors) by taking into account various methods including market survey, market research, interviews and giving opportunity to consumers to give feedback within the retailer store. However, food retailers are not able to attract large audiences by following these procedures and thereby making the data sample small. Any decisions made based on smaller sample of customer feedback are prone to be ineffective. With the advent of online social media, there is lot of consumer information available on Twitter, which reflects the true opinion of customers (Liang and Dai 2013; Katal et al., 2013). Effective analysis of this information can give interesting insight into consumer sentiments and behaviours with respect to 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 (Liang and Dai 2013; Katal et al., 2013). 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 (He et al., 2013; Hashem et al., 2015; Zikopoulos and Eaton, 2011). 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. For instance, the issues faced by consumers of beef products such as discoloration, presence of foreign bodies, extra fat, hard texture etc. has been linked to their root causes in the upstream of the supply chain. 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 has been 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 is performed. Further, root causes of issues affecting consumer satisfaction are identified and linked with various segments of supply chain to make it more efficient. Finally, the recommendations for consumer centric supply chain have been prescribed.

The organisation of the paper is as follows: Section 2, explores the various issues associated with big data applications including Twitter and social media. In Section 3, a new framework of social media data analytics adopted in this paper is described in detail. Section 4, provides an implementation of proposed framework on a case study of beef supply chain. It also details the comparison of several sentiment-mining techniques and their results. Section 5, comprises of identification of issues affecting consumer satisfaction and their corresponding mitigation within the supply chain. Section 6, explains the managerial implications to the supply chain decisions. Finally, the paper is concluded in Section 7.

1. **Related work**

In literature, distinct frameworks have been proposed to investigate big data problems and issues associated with supply chain. Hazen et al., (2014) have determined the problems associated with quality of data in the field of supply chain management. Novel procedures for monitoring and managing of data quality were suggested. The importance of quality of data in the application and further research in the field of supply chain management is mentioned. Vera-Baquero et al. (2016) have recommended a cloud based mechanism utilising big data procedures to efficiently improve the performance analysis of corporations. The competence of the framework was revealed in terms of delivering monitoring of business activity comprising of big data in real time with minimum hardware expenses. Frizzo et al., (2016) have done a thorough analysis of literature on big data available in reputed business journals. 219 peer reviewed research papers published in 152 business journals in the duration of 2009 to 2014 were considered. Both quantitative and qualitative investigation of literature was done by utilising NVivo 10 software. Their investigation revealed that research work done in domain of big data is fragmented and primitive with respect to empirical analysis, variation in methodology and theoretical grounding.

Twitter information has emerged as one of the most widely used data source for research in academia and practical applications. Various examples associated with practical applications of Twitter information are available in literature like brand management (Malhotra et al., 2012), stock forecasting (Arias et al., 2013) and crisis management (Wyatt, 2013). It is anticipated that there will be swift expansion in utilisation of Twitter information for numerous other purposes like market prediction, public safety and humanitarian relief and assistance (Dataminr, 2014). In the past, Twitter data based studies have been conducted in various domains. Most of the research work is being performed in the area of Computer science for various purposes such as sentiment analysis (Schumaker et al., 2016; Mostafa, 2013; Kontopoulos et al., 2013; Rui et al., 2013; Ghiassi et al. 2013; Hodeghatta & Sahney, 2016; Pak and Paroubek, 2010), topic detection (Cigarrán et al., 2016), gathering market intelligence (Li & Li, 2013; Lu et al., 2014; Neethu & Rajasree, 2013), insight of stock market (Bollen et al., 2011), etc. There are few studies conducted in the domain of disaster management like dispatching resources in a natural disaster by monitoring real time tweets (Chen et al., 2016), exploring the application of social media by non-profit organisations and media firms during natural disasters (Muralidharan et al., 2011), etc. Analysis of Twitter data has also been conducted by researchers in the domain of Operation Management such as capturing big data in form of tweets to improve supply chain innovation capabilities (Tan et al., 2015), investigating the state of logistics related customer service provided by e-retailers on Twitter (Bhattacharjya et al., 2016), examining the process of service recovery in the context of operations management (Fan et al., 2016), developing a framework for assimilating social media into supply chain management (Sianipar and Yudoko, 2014; Chae, 2015), determine the ranking of knowledge creation modes by using extended fuzzy analytic hierarchy process (Tyagi et al., 2016), exploring the amalgamation of conventional knowledge management and insights derived from social media (O'leary, 2011), improving efficiency of knowledge creation process by developing set of lean thinking tools (Tyagi et al., 2015a), optimization of configuration of a platform via couple of product generations (Tyagi et al., 2015b).

Researchers have used numerous methods for extracting intelligence from tweets, which is detailed in Table 1. For instance, Ghiassi et al., (2013) have used n-gram analysis and artificial neural network for determining sentiments of brand related tweets. Their methodology gives better precision in classification of sentiment and minimised the complexity of modeling as compared to conventional sentiment lexicons. However, their study was conducted by offsetting the false positives and performed on a single brand. Hence, the efficacy of the framework needs to be verified on other brands. Bollen et al., (2011) have utilised Granger causality analysis and a Self-Organizing Fuzzy Neural Network to analyse tweets to measure the mood of people associated with stock market. Their framework was capable enough to measure the mood of people along six distinct dimensions (such as alert, sure, kind, happy, etc.) by accuracy of 86.7%. Li & Li (2013), have developed a numeric opinion summarization framework for extracting market intelligence. The aggregated scores generated by the framework assists the decision maker to effectively gain the insight of market trends through following the fluctuation in tweet sentiments. However, their study doesn’t take into account the synonym of terms while classifying the tweets into thematic topics as different users might use distinct terms in their tweets. For instance, a dictionary-based approach could be applied to incorporate all possible synonyms. Lu et al., (2014) have proposed a visual analytics toolkit to gather data from Bitly and Twitter to predict the ratings and revenue generated by the movies. The advantages of interactive environment for predictive analysis were demonstrated over statistical modelling methods using results from vast box office challenge, 2013. The proposed framework is flexible to be used in other social media platforms for analysis of advertisement and forecasting of sales. However, the data cleaning and sentiment analysis process employed is very challenging and it gets complicated for the larger data sets. Mostafa, (2013) have applied lexicon based sentiment analysis to explore the consumer opinion towards certain cosmopolitan brands. The text mining techniques utilised were capable to explore the hidden patterns of consumer’s opinions. However, their framework was quite oversimplified and was not designed to perform some of the prevalent analysis such as topic detection. Tan et al., (2015) have developed deduction graph model for extracting big data to improve the capabilities for supply chain innovation. This model extracts and develop inter relations among distinct competence sets thereby generating opportunity for extensive strategic analysis of a firm’s capabilities. The mathematical methodology followed to achieve the optimum results is quite sophisticated and monotonous considering it is not autonomous. Chae, (2015) have 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. This mechanism is composed of three procedures, which are known as descriptive analysis, network analysis and content analysis. The shortcoming of this research is that data collection was performed using ‘#supply chain’ instead of keywords. Therefore, the data collected may not be the true representative of the consumer’s opinion. Bhattacharjya et al., (2016) have implemented inductive coding to examine the efficiency of e-retailer’s logistics specific customer service communications on social media (Twitter). Their approach can depict informative interactions and was precisely able to distinguish the beginning and conclusion of interactions among e-retailers and consumers. However, the data mining mechanism utilised might be overlooking certain kinds of exchanges, which are relatively low in frequency. Kontopoulos et al., (2013) have used Formal Concept Analysis (FCA) to develop an ontology-based model for sentiment analysis. Their framework does efficient sentiment analysis of tweets by differentiating the features of the domain and allocates a respective sentiment grade to it. However, their framework was not robust enough to deal with advertisement tweets. It was either considered as positive tweets or rejected by their mechanism thereby reducing the precision of sentiment analysis. Similarly, Cigarran et al., (2016) have also utilised FCA approach for analysing tweets for topic detection. Although FCA approach is quite efficient, it is not robust enough to deal with tweets having lack of clarity and therefore creates uncertainty on its ability to give precise sentiment grades. Rui et al., (2013) have used an amalgamation of Naive Bayesian classifier and support vector machine to explore the impact of pre-consumer opinion and post-consumer opinion with respect to movie sales data. The algorithms utilised by them for sentiment analysis of tweets was good to classify them into positive, negative and neutral sentiments. The only limitation is that Naive Bayesian classifier is considered to be oversimplified method and their accuracy results are not appreciable as compared to some of the more sophisticated tools available currently for sentiment analysis. Pak and Paroubek, (2010) have developed a Twitter corpus by gathering tweets via Twitter API. It was utilised to create a sentiment classifier derived from multinomial Naïve Bayes classifier (using N-gram and POS-tags as features). This framework leaves room for error as only polarity of emoticons was employed to label the tweet emotions in training data set. Only the tweets with emoticons are available in the training data set, which makes it fairly inefficient. Neethu & Rajasree, (2013) have utilised machine-learning approach to investigate the tweets on electronic products such as laptop, mobile phone, etc. A new feature vector is proposed for sentiment analysis and gathers intelligence from people’s view on these products. During the study, they found that support vector machine classifier gives more accurate results than Naïve Bayes classifier.

Application of social media data in food supply chain is in primitive stage. This study addresses the gap in the literature by analysing social media data to identify issues in food supply chain and how they can be mitigated to achieve consumer centric supply chain. The consumer tweets regarding beef products were analysed using SVM and hierarchal clustering using multiscale bootstrap resampling to explore the major issues faced by consumers. For accumulation of ultimate opinions, the subjectivity and polarity associated with the opinions is identified and merges them in the form of a numeric semantic score (SS). The identified issues from the consumer tweets have been linked to their root causes in different segments of supply chain. For instance, issues like bad flavour, unpleasant smell, discoloration of meat, presence of foreign bodies, etc. have been linked to their root causes in the upstream of the supply chain at beef farms, abattoir, processor and retailer. The corresponding mitigation of these issues is also provided in detail. The next section describes the Twitter data analysis process employed in this article.

Table 1: Studies based on social media analytics in the literature

|  |  |  |
| --- | --- | --- |
| **Area** | **Method** | **References** |
| Sentiment analysis, topic detection and gathering market intelligence | Formal Concept Analysis (FCA), Descriptive statistics, ANOVA and t-tests, *n*-gram analysis and dynamic artificial neural network, numeric opinion summarization framework, Naive Bayesian classifier and support vector machine, lexicon-based Sentiment analysis, Granger causality analysis and a Self-Organizing Fuzzy Neural Network, Crowdsourced sentiment analysis | Schumaker et al., (2016); Mostafa, (2013); Kontopoulos et al., (2013); Rui et al., (2013); Ghiassi et al. (2013); Hodeghatta & Sahney, (2016); Cigarrán et al., 2016; Li & Li, (2013); Bollen et al., (2011), Lu et al., (2014); Neethu & Rajasree, (2013); Pak and Paroubek, (2010) |
| Disaster management | Implementation of a real-time tweet-based geodatabase, Content analysis.  | Chen et al., (2016); Muralidharan et al., (2011). |
| Operation and Supply chain management  | Descriptive analysis, Content analysis, Network analysis, Grounded theory approach, Inductive coding, sentiment analysis, Extended Fuzzy- AHP approach, Lean thinking, knowledge creation, DNA- based framework. | Chae, (2015); Tan et al., 2015; Fan et al. (2016); Tyagi et al., (2016); Bhattacharjya et al., (2016); Sianipar and Yudoko, (2014); O'leary, (2011), Tyagi et al., (2015a), Tyagi et al., (2015b) |

**3. Twitter data analysis process**

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.

Morstatter et al., (2013) presented a good comparison on the data sample collected by Twitter Streaming API and full data stored by Firehose. This was done to test if the data obtained by Streaming API is a good/sufficient representation of user activity on Twitter. Their study suggested that there are various ways of setting up API to increase the representativeness of the data collected. One of the ways was to create more specific parameter sets with bounding boxes and keywords. This approach can be used to extract more data from the API. Another key issue highlighted in their study was – the representation accuracy (in terms of topics) increased when the data collected from streaming API was large. Following these recommendations, we have used set of specific keywords and regions to extract data from streaming API such that data coverage and in turn representation accuracy can be increased.

The Twitter streaming API allowed us to store/append twitter data in a text file. Then, a parsing method was implemented to extract datasets relevant to this study (e.g. tweets, coordinates, hastags, urls, retweet count, follower count, screen name, favorited, location and others). See Figure 1 for details on the overall approach. 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. More information about the proposed sentiment mining method and hierarchical clustering method is detailed in following subsections.



Figure 1: Overall approach for social media data analysis

**3.1 Content 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 (Chau and Xu, 2012). A tweet (with maximum of 140 characters) comprises small set of words, URLs, hashtags, numbers and emoticons. 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.

**3.1.1 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. It denotes a broad arena of issues. Many names exist with marginally distinguished actions like opinion mining, sentiment mining, sentiment analysis, opinion extraction, affect analysis, emotion analysis, subjectivity analysis, review mining. Nonetheless, all these names are covered under the broad domain of opinion mining or sentiment analysis. In literature, both opinion mining and sentiment analysis are intermittently utilised.

In the proposed sentiment mining approach, an opinion is elicited in form of numeric values from a microblog (in text format). This approach identifies the subjectivity and polarity associated with the opinions and merges them in the form of a numeric semantic score (SS) for accumulation of ultimate opinions. Following is the steps involved in this approach:

*Identifying subjectivity from the text:* While posts on microblogging websites are quite short in length, still some post comprises of multiple sentences highlighting numerous subjects or views. The subjectivity of an opinion is investigated by determining the strength of an opinion for a topic. Bai (2005) and Duan and Whinston (2005) have classified the opinion into subjective and objective opinions. Objective opinions reveal the basic information associated with an entity and does not have subjective and emotional perspectives. On the other hand, subjective opinion represents personal viewpoints. As the purpose of this framework is to analyse Twitter user’s perspective on food products, subjective opinion is more crucial. Mostly, people utilise emotional words while describing their opinions rather than objective information. Therefore, the Opinion Subjectivity (OS) of a post is defined as average sentimental and emotional word density in every sentence of microblog *m*, which describes topic *t* (in this study, words related to *beef*/*steak*).

The subjectivity level of opinions could be evaluated by developing a subjective word set, which comprises of sentimental and emotional words by expansion of word set using WordNet. WordNet is a web based semantic lexicon having the database of synonyms and antonyms of words. In this approach, a small set of seeds or sentiment words with defined positive and negative inclination is initially gathered manually. Then, the algorithm expands this set by exploring the online dictionary such as WordNet for their respective synonyms and antonyms. The fresh words found are transferred to the small set. Thereafter, next iteration is started. This iterative procedure is concluded when the search is complete and no fresh words could be found. This approach was followed in Hu and Liu (2004). Following this procedure, a subjective word set $ϕ$ is identified. The opinion subjectivity associated with a post *m* as per the topic *t,* represented as $OS\_{m,t}$, is represented as:

$$OS\_{m,t}=\frac{\left(\sum\_{s\in S\_{t}^{m}}^{}\frac{\left|U\_{s}∩ϕ\right|}{U\_{s}}\right)}{\left|S\_{t}^{m}\right|}$$

where, $U\_{s}$ denotes the set of unigrams contained in sentence and $S\_{t}^{m}$ represents the set of sentences in tweet ‘*m’* which has topic ‘*t*’.

*Sentiment classification module:* 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 support vector machine (SVM) is excellent for sentiment classification (Popescu & Etzioni, 2005). SVM model is employed in this approach for the division of polarity of opinions. The prerequisites for SVM are threefold. Initially, the features of the data must be chosen. Then, data set utilised in training process needs to be marked with its true classes. Finally, the optimum combination of model settings and constraints needs to be calculated. The Unigrams and Bigrams are the tokens of one-word and two-word respectively identified from the microblog. While there is a constraint on the length of the microblogging post, the probability of iterative occurrence of a characteristic in same post is quite low. As such, this study uses binary value {0,1} to represent the presence of these features in the microblog. The appearance of a feature in a message is denoted by “1” whereas the absence of a feature is denoted by “0”.

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. Posts on a microblogging website are short and therefore the number of features associated with them are also limited. 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 identify the optimum combination of variables γ and *c* for carrying out SVM along with a Radial Basis Function kernel. The polarity ($Pol\_{m}\in \{+1,-1\}$) representing positive and negative sentiment respectively of microblog *m* can be predicted using trained SVM. Thus, the semantic score, SS, can be calculated by using resultant subjectivity and opinion polarity on for a topic *t* by following equation:

$$SS\_{m,t}=Pol\_{m}×OS\_{m,t}$$

where, $SS\_{m,t}\in \left[-1,1\right]$

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.

**3.1.2 Word and Hashtag analysis**

Another type of content analysis that is conducted in this paper is word analysis. This type of analysis includes term frequency identification, summarisation of document and word clustering. Term frequency is commonly utilised in text data retrieval and identification of word clusters and word clouds. These analyses can help is identifying various issues being discussed in the tweets and their relevance to the food supply chain management practices. Term frequency can help in extracting popular hashtags and Twitter handles, which can give information about tweet features and its relevance. Other types of analysis include machine learning based clustering and association rules mining. The association rules mining can help to identify associations of different terms, which are frequently occurring in the tweets.

**3.1.3 Hierarchical clustering with *p*-values using multiscale bootstrap resampling**

In this research, we have employed a hierarchical clustering with *p*-values via multiscale bootstrap resampling (Suzuki and Shimodaira, 2006). 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 (Murtagh and Legendre 2014). The pseudocode for the hierarchical clustering algorithm is presented in Fig 2.

$d\_{i,j}$: distance between cluster $i$ and $j$

$C$: set of all clusters

***D****:* set of all $d\_{i,j}$

$n\_{i}$: number of data points in cluster $i$

**Step 1:** Find smallest element $d\_{i,j}$ in ***D***

**Step 2:** Create new cluster $k$ by merging cluster $i$ and $j$ (where $i,j\in C$*)*

**Step 3:** Compute new distances $d\_{k,l}$(where $l\in C$and$l\ne k$)as

$$d\_{k,l}=α\_{i}d\_{i,l}+α\_{j}d\_{j,l}+βd\_{i,j}$$

Computenumber of data points in cluster $k$ as $n\_{k}$as

$$n\_{k}=n\_{i}+n\_{j}$$

 where, $α\_{i}=\frac{n\_{i}+n\_{l}}{n\_{k}+n\_{l}}$, $α\_{j}=\frac{n\_{j}+n\_{l}}{n\_{k}+n\_{l}}$, $β=\frac{-n\_{l}}{n\_{k}+n\_{l}}$ (Ward’s minimum variance method)

**Step 4:** Repeat steps 1 to 3 until ***D*** contains a single group made of all data points.

Figure 2: Hierarchical Clustering Algorithm

Fig. 2 illustrates how hierarchical clustering generates a dendrogram, which contains clusters. However, the support of the data for these clusters is not determined using the method detailed in Fig 2. One of the ways of determining the support of data for these clusters is 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 (see Fig. 2). 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 AU (approximately unbiased)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 (as presented in Fig. 2). 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 (approximately unbiased) *p*-values (left), BP (bootstrap probability) values (right), and cluster labels (bottom). Clusters with AU >= 95% are usually shown by the red rectangles, which represents significant clusters (as depicted in Figure 4).

1. **Case study and Twitter data analysis**

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 3 illustrates the location of tweets, which has the geolocation data, on the world map. Then, keywords were selected to capture the tweets relevant to this study. In order to select the keywords, site visit was made to various main and convenience retail stores in the UK to find out the different negative and positive feedback left by the consumers with respect to beef products. The interviews of staff members of retail store dealing with consumer complaints was performed, who provided access to database of consumer complaints regarding beef products. Interviews of some consumers were also conducted to explore the type of keywords used by them to express their view. The research team involved in this article also investigated the various complaints made by consumers in the store worldwide. Different keywords employed on Twitter for beef products were captured and discussed with retailers and consumers. Consequently, a comprehensive list of the keywords (as shown in Table 2) was made to explore issues related to beef products highlighted by consumers on Twitter. 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 3. Top twitter handles (users who are mentioned very frequently) are identified among the extracted tweets. Those Twitter users who have been mentioned more than 2000 times are considered as top Twitter handles and they are presented in Table 4.

|  |
| --- |
| Table 2. Keywords used for extracting consumer tweets |
| Beef#disappointment | Beef#rotten  | Beef# rancid | Beef#was very chewy |
| Beef#taste awful | Beef#unhappy | Beef#packaging blown | Beef#was very fatty |
| Beef#odd colour beef | Beef#discoloured | Beef#plastic in beef | Beef#gristle in beef |
| Beef#complaint | Beef#grey colour | Beef#oxidised beef | Beef#taste |
| Beef#flavour | Beef#smell | Beef#rotten | Beef#funny colour |
| Beef#horsemeat | Beef#customer support | Beef#bone | Beef#inedible |
| Beef#mushy | Beef#skimpy | Beef#use by date | Beef#stingy |
| Beef#grey colour | Beef#packaging | Beef#oxidised | Beef#odd colour |
| Beef#gristle | Beef#fatty | Beef#green colour | Beef#lack of meat |
| Beef#rubbery | Beef#suet | Beef#receipt | Beef#stop selling |
| Beef#deal | Beef#bargain | Beef#discoloured | Beef#dish |
| Beef#stink | Beef#bin | Beef#goes off | Beef#rubbish |
| Beef#delivery | Beef#scrummy | Beef#advertisement | Beef#promotion |
| Beef#traceability | Beef#carbon footprint | Beef#nutrition | Beef#labelling |
| Beef#price | Beef#organic/ inorganic | Beef#MAP packaging | Beef#tenderness |



Figure 3: Visualisation of tweets with geolocation data

Table 3: Top hashtags used

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Hashtag** | **Freq (>1000)** | **Freq (%)** |  | **Hashtag** | **Freq (>1000)** | **Freq (%)** |  | **Hashtag** | **Freq (>1000)** | **Freq (%)** |
| #beef | 17708 | 16.24% | #aodafail | 1908 | 1.75% | #bmg | 1255 | 1.15% |
| #steak | 14496 | 13.29% | #earls | 1859 | 1.70% | #delicious | 1243 | 1.14% |
| #food | 7418 | 6.80% | #votemainefpp | 1795 | 1.65% | #soundcloud | 1169 | 1.07% |
| #foodporn | 5028 | 4.61% | #win | 1761 | 1.62% | #vegan | 1131 | 1.04% |
| #whcd | 5001 | 4.59% | #ad | 1754 | 1.61% | #rt | 1128 | 1.03% |
| #foodie | 4219 | 3.87% | #cooking | 1688 | 1.55% | #mrpoints | 1116 | 1.02% |
| #recipe | 4106 | 3.77% | #mplusplaces | 1686 | 1.55% | #staydc | 1116 | 1.02% |
| #boycottearls | 3356 | 3.08% | #meat | 1607 | 1.47% | #wine | 1072 | 0.98% |
| #gbbw | 3354 | 3.08% | #lunch | 1577 | 1.45% | #np | 1069 | 0.98% |
| #kca | 2898 | 2.66% | #bbq | 1557 | 1.43% | #yelp | 1052 | 0.96% |
| #dinner | 2724 | 2.50% | #yum | 1424 | 1.31% | #ufc196 | 1048 | 0.96% |
| #recipes | 2159 | 1.98% | #yummy | 1257 | 1.15% | #britishbeefweek | 1045 | 0.96% |
| #accessibility | 1999 | 1.83% | #bdg | 1255 | 1.15% |  |  |  |

As described in subsection 3.1.1, 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 microblogs/tweets consisting of “:)” was marked as “+1” whereas messages comprising of “:(” were marked as a “-1.” The tweets consisting both “:)” and “:(” were removed. 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 implement 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. Then, numeric values in messages were replaced with a unique token “NUMBER”. A prefix “NOT\_” was added to the words followed by negative word (such as “never”, “not” and words ending with “n’t”) in each sentence. In the end, Porter Stemming algorithm was utilised to stem the rest of the words (Rijsbergen et al., 1980).

Various feature sets were collected and their accuracy level was examined. Unigrams and bigrams representing one-word and two-word tokens were extracted from the microblog posts. 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. We have also implemented a Naïve Bayes classifier to compare the performance of the SVM classifier.

Table 5 reports the performance of Naïve Bayes (NB) and SVM based classifiers on the collected microblogs. The best performance is provided when using unigram feature set in both SVM and Naïve Bayes classifiers. It can be seen that the performance of SVM is always superior to the Naïve Bayes classifier in terms of sentiment classification. 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.

The sentiment analysis based on SVM was performed on the country wise classification of tweets. Table 6 shows the example tweets and their sentiment scores.

Table 4: Top Twitter users

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Twitter Handle** | **Freq (>2k)** | **Freq (%)** |   | **Twitter Handle** | **Freq (>2k)** | **Freq (%)** |   | **Twitter Handle** | **Freq (>2k)** | **Freq (%)** |
| @historyflick | 10903 | 9.16% | @chipotletweets | 3701 | 3.11% | @shukzldn | 2203 | 1.85% |
| @metrroboomin | 10725 | 9.01% | @globalgrind | 3626 | 3.05% | @zacefron | 2201 | 1.85% |
| @jackgilinsky | 8814 | 7.40% | @trapicalgod | 3499 | 2.94% | @foodpornsx | 2190 | 1.84% |
| @itsfoodporn | 8691 | 7.30% | @viralbuzznewss | 2964 | 2.49% | @redtractorfood | 2166 | 1.82% |
| @kanyewset | 7452 | 6.26% | @crazyfightz | 2798 | 2.35% | @sza | 2155 | 1.81% |
| @youtube | 6593 | 5.54% | @soioucity | 2795 | 2.35% | @therock | 2131 | 1.79% |
| @earlsrestaurant | 5822 | 4.89% | @kardashianreact | 2765 | 2.32% | @tmzupdates | 2093 | 1.76% |
| @hotfreestyle | 3794 | 3.19% | @sexualgif | 2564 | 2.15% | @ayookd | 2031 | 1.71% |
| @audiesamuels | 3775 | 3.17% | @cnn | 2504 | 2.10% | @mcjuggernuggets | 2015 | 1.69% |
| @freddyamazin | 3758 | 3.16% | @euphonik | 2335 | 1.96% |  |  |  |

Table 5: Performance of SVM and Naïve Bayes based classifier on selected feature sets; CV – 5-fold cross validation, NB – Naïve Bayes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Representation scheme** | **Feature Type** | **Number of Features** | **SVM** | **NB** |
| CV (%) | Test data (%) | Test data (%) |
| Binary | Unigram | 12,257 | 91.75 | 90.80 | 70.68 |
| Bigram | 44,485 | 76.80 | 74.46 | 63.60 |
| Unigram + bigram | 56,438 | 87.12 | 83.28 | 63.48 |
| Subjective word set($ϕ$) | 6,789 | 66.58 | 65.52 | 41.10 |
| Term Frequency | Unigram | 12,257 | 88.78 | 86.27 | 72.35 |
| Bigram | 44,485 | 77.49 | 71.68 | 65.90 |
| Unigram + bigram | 56,438 | 84.81 | 80.97 | 59.24 |
| Subjective word set ($ϕ$) | 6,789 | 68.21 | 62.25 | 39.71 |

Table 6: Raw Tweets with Sentiment Polarity

|  |  |
| --- | --- |
| Sentiment Polarity | Raw Tweets |
| Negative | *@Tesco just got this from your D'ham Mkt store. It's supposed to be Men's Health Beef Jerky...The smell is revolting https://t.co/vTKVRIARW5* |
| 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* |
| Positive | *@AldiUK beef chilli con carne! always a fav that goes down well in our house! of course with lots of added cheese on top! #WIN* |

To identify meaningful topics and their content in the collected tweets, initially, we performed sentiment analysis to identify sentiments of each of the tweets. To gain more insight, the sentiment scores and country type was then used to perform content analysis. The next section explains the results by sub-setting the captured data based on sentiment scores and country type.

**4.1 Content analysis based on country type**

* + 1. ***Analysis of all the tweets from the world***

The collected tweets were examined to identify the most frequently used words by consumers to express their views. Beef and steak are most frequently used words followed by fresh, taste, smell. Then, the association rule mining of these tweets is performed to find out which words are mostly used in conjunction with ‘beef’ and ‘steak’. It was found out that the words ‘celebrate’, ‘redtractorfood’ are most widely used and words like ‘smell’, ‘roast’ are scarcely used with ‘beef’. For instance, tweets like “*Celebrate St. Patrick's Day with dinner at the Brickstone! Irish Corned Beef and Cabbage tops the menu! https://t.co/vRnewdKZYd*” have very high frequency compared to the tweets similar to “*@Tesco just got this from your D'ham Mkt store. It's supposed to be Men's Health Beef Jerky...The smell is revolting https://t.co/vTKVRIARW5.*”

Further, cluster analysis is applied to classify them into some groups (or clusters) as per the similarities between tweets. The proposed clustering approach involves hierarchical cluster analysis (HCA) with uncertainty assessment. For each cluster in hierarchical clustering, *p*-values are calculated using multiscale bootstrap resampling. *P*-value of a cluster indicates its strength (*i.e.* how well it is supported by data). A parallel computing based HCA with *p*-values is implemented to quickly analyse the large number of tweets. The cluster, which has high *p*-values (approximate unbiased) are strongly supported by the capture tweets. These clusters can help us to explain user’s opinion on beef and steak across the globe. The two predominant clusters identified (with significance >0.95 level) is represented in Figure 4 as red coloured rectangles. The first cluster consists of some closely related words like *gbbw, win, celebrate, and hamper, redtractorfood and dish*. It primarily highlights an event called *Great British Beef Week* in UK, where an organisation associated with farm assurance schemes called red tractor has asked customers to share their dish to win a beef hamper to celebrate this event. The second cluster consists of words like *bone*, which highlights presence of bone fragments in the beef and steak of the customers. The *taste, smell, freshness* and various *recipes* of the beef products are both appreciated and complained in the customer tweets. The details of the deals and promotions associated with food products primarily beef have been described.



Figure 4: Hierarchical cluster analysis of the all tweets originating in the World; approximately unbiased p-value (AU, in red), bootstrap probability value (BP, in green)

During the analysis, it was found that Twitter data can be broadly classified in two clusters: tweets associated with episodic event and tweets associated with opinion of consumers on beef products. The intelligence gathered from episodic event cluster can help retailers in pursuing effective marketing campaigns of their new products. Retailers can also identify the factors having high influence within the network and their association with other related products. They can also use these medium to address consumer concerns. The second cluster will provide insight into likes and dislikes of consumers. Some tweets in this cluster were positive and others were negative, which are explained in next subsections.

***4.1.2 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) is represented in Figure 5 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 5 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 opportunity to mitigate these problems and raise customer satisfaction and their consequent revenue.



Figure 5: Hierarchical cluster analysis of the negative tweets originating in the World

***4.1.3 Analysis of positive tweets from the world***

The positive tweets from the world are analysed and most frequently used words after ‘beef’ and ‘steak’ were ‘fresh’, ‘dish’ and ‘taste’.

The association rule mining evaluation of the positive tweets from around the world is performed. It is found that ‘beef’ was closely associated with words like ‘celebrate’, ‘redtractorfood’ and was rarely used with words like ‘months’ and ‘ways’. The word ‘steak’ was frequently used with words like ‘awards’, ‘kca’ and was sparsely used with ‘chew’, ‘night’.

The positive tweets from the world are classified into two clusters based on the similarity in their tweets. They are divided into two clusters as shown in Figure 6. The first cluster is composed of words like ‘*dish, win, gbbw, celebrate, redrtractorfood, share, hamper*’. These tweets are associated with the celebration of Great British beef week in the UK. A British farm assurance firm known as red tractor has asked customers to share their dish to win a beef hamper. The findings from this cluster does not contribute to the objective of this study to develop consumer centric supply chain. However, retailers can utilise it to develop a strategy to introduce appropriate promotional deals to capture larger market share than their rivals during events like great British beef week. The second cluster is composed of words like *love, taste, best roast, delicious food* where customers have praised the taste and overall quality (like smell, tenderness) of the beef products. The words like ‘*deal, great*’ highlight the promotions, which were very popular among customers while purchasing beef products.

This cluster analysis will help global supermarkets to show their best performing beef products and their strength like taste, promotions. It will help them in the introduction of new products and promotions.



 Figure 6: Hierarchical cluster analysis of the positive tweets originating in the World

***4.1.4 Analysis of positive tweets from UK***

The positive tweets from UK were analysed and most widely used words after ‘beef’ and ‘steak’ were ‘adliuk, ‘morrisons’, ‘waitrose’ ‘tesco’. The association rule mining of tweets from UK with positive sentiment was conducted and the word ‘beef’ was most closely associated with terms like ‘roast britishbeef’, ‘Sunday’. and least used with words like ‘type’, ‘tell’. The term ‘steak’ was most frequently used with words like ‘days’, ‘date’, ‘free’. and was rarely used with terms like ‘supper’, ‘quick’, ‘happy’.

The positive tweets from the UK are classified into three clusters based on the similarity among their tweets. The first cluster consists of words like ‘*leeds* and *nfunortheast’*, which highlights an event took place in Leeds, UK where Asda has joined NFU Northeast in selling red tractor (farm assurance) approved beef products. The second cluster consists of words like ‘*delicious, roast, lunch, Sunday*’, where customers are talking about cooking roast beef products on Sunday, which turn out to be delicious. Third cluster is composed of words like ‘*thanks, love, made, meal*’, where customers are grateful for the good quality of beef products after cooking them.

The cluster analysis will help UK supermarkets to find out the preference of customers. For instance, they prefer the beef originating from the farms approved by farm assurance schemes (Red Tractor). They can also monitor their best performing beef products, which will assist them in launching their new products. It will help retailers to develop a strategy to align their products with the preference of the consumers.

***4.1.5 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 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.

***4.1.6 Analysis of negative tweets from Australia***

The tweets with negative sentiment from Australia were analysed and the most frequently used words after ‘beef’ and ‘steak’ were ‘*aldi’* and ‘*safeway’*. The association analysis show that the term ‘beef’ was most closely associated with words like ‘*safeway’*, and ‘*corned’* and was least associated with ‘*grass, ‘gross’, packaged*’. The word ‘*steak’* was mostly used in conjunction with terms like ‘*woolworths’, ‘breast’, ‘complain*’ and was rarely used with terms like ‘*waste’, ‘wine’, ‘tough*’.

Cluster analysis has been performed on the negative tweets from Australia and they have been classified into two clusters based on similarity in their tweets. The first cluster consists of words like ‘*feel, eat, complain*’, which reflects to customers complaining the quality of beef products especially tenderness and flavour. The second cluster comprises of words like ‘*disappointed, cuts, cook, sold, dinner*’, which shows the annoyance of customers with beef products cooked for dinner especially in terms of smell, cooking time and overall quality.

This analysis will assist the Australian supermarkets to explore the issues faced by customers. It will help them to backtrack their supply chain and mitigate them in order to improve customer satisfaction and consequent revenue.

***4.1.7 Analysis of positive tweets from Australia***

The tweets from Australia having positive sentiment is analysed and the most frequently used words after ‘beef’ and ‘steak’ were ‘aldi’, ‘woolworths’, ‘flemings’, ‘roast’. The association analysis indicated that the word ‘beef’ was most closely associated with terms like ‘roast’, ‘safeway’, ‘sandwich’ and was least used with terms like ‘see’, ‘slow’, ‘far’. The word steak was commonly used with terms like ‘flemings’, ‘plate’ and is rarely used with words like ‘spent’, ‘prime’, house’.

Cluster analysis has been performed on the positive tweets from Australia. Two significant clusters were identified. The first cluster consists of words like ‘*new, sandwich, best, try*’, where customers are praising the new beef sandwich they tried in different supermarkets. The second cluster includes words such as ‘*delicious, Sunday, well, roast, best*’, in which customers are appreciating the flavour of roast beef cooked on Sunday, bought form different supermarkets.

The cluster analysis of positive tweets will help Australian supermarkets to see the best performing beef products among their brands and their rival brands. It will help them to identify the most popular beef products among customers. It will help them in launching the new beef products and strengthen their position in the market against their rivals.

***4.1.8 Analysis of negative tweets from USA***

The tweets from USA having negative sentiment is being analysed and the most frequently used words were ‘beef’, ‘carnival’, ‘steak’, ‘walmart’, ‘sum’, ‘yall’. The association rule mining was performed and the results indicated that the term ‘beef’ was most closely associated with words like ‘*carnival’, ‘yall’, dietz*’ and is least associated with terms like ‘*cake’, ‘sum’, ‘ride’, ‘grow’*. The word ‘steak’ was most frequently used with terms like *‘shake’, ‘walmart’, ‘stolen’* and is least frequently used with words like *‘show’, ‘minutes’, ‘fries’*.

Cluster analysis is being performed on the negative tweets from the USA and they have been classified into two clusters based on the similarity in their tweets. The first cluster includes words like ‘*mars, corned, beef, cream, really, eggs, trending, bars, personally*’. There was a tweet which was retweeted many times, which has expressed the annoyance of customer for the price of corned beef and has compared it to Mars bars and Cream eggs. The second cluster is composed of terms like *‘jerky, eat, went*’, where customers have gone to supermarket to buy steak or joint but they could only find beef jerky on the shelves.

The negative cluster analysis will help the US supermarket to understand the problem faced by customer. For instance, the high price of corned beef and unavailability of steak and joint were the major issues highlighted. The supermarkets can liaise with their supplier and develop appropriate strategy to satisfy their customers and thereby generate more revenue.

***4.1.9 Analysis of positive tweets from USA***

The positive tweets from USA were analysed and the most frequently used words were ‘beef’, ‘lamb’, ‘lbs’, ‘steak’, ‘tops’, ‘walmart.’ The association rule mining of tweets from USA were performed and the results indicated that term ‘beef’ was most closely associated with words like *‘lamb’, ‘pork’, ‘lbs’, ‘generate*’ and was least associated with terms like ‘*tops’, ‘cheese’, ‘equivalents’*. The word ‘steak’ was most frequently used with terms like ‘butter’, ‘affordable’. and is rarely used with terms like ‘*truffles’, ‘sea’, ‘honey’.*

Two significant clusters were identified. The first cluster consists of words like ‘*tops, equivalents, cheese, greenhouse, gases, generate, pork, every, list, lamb, lbs*’. Customers have compared the greenhouse gases generated by production of beef to that of lamb and cheese. They have suggested that beef has lower emission than lamb. The second cluster comprises of terms such as ‘*top, new, publix, better, best*’ where customers have appreciated the beef products sold by Publix to that of other supermarkets in terms of quality and price.

The cluster analysis of positive tweets will help US supermarkets to find out the qualities preferred by consumers. For instance, they were conscious of the carbon footprint generated in the production of beef, lamb and cheese. They were also looking for high quality beef products at reasonable price. It will help the US supermarket to develop their strategy for introduction of new products.

In the next section, it has been described how content analysis of Twitter data could help retailer in waste minimisation, quality control and efficiency improvement by linking them to upstream of the supply chain.

1. **Identification of issues affecting consumer satisfaction and their mitigation within the supply chain**

During the analysis of consumer tweets, it was revealed that there were numerous issues affecting customer satisfaction such as bad flavour, hard texture, extra fat, discoloration of beef products, presence of horsemeat in beef products, etc. as shown in Table 7. The root causes of these issues are located within various segments of the supply chain as depicted in figure 7 and often they are interrelated. Usually, retailers struggle to establish the relationship between customer dissatisfaction and their root causes. The major issues faced by consumers, their root cause and corresponding mitigation are described below:

1. Bad flavour and unpleasant smell- One of the major reason for bad flavour and unpleasant smell is oxidisation of beef products, which refers to the oxidisation of their proteins and lipids when exposed to air (Brooks, 2007). The beef products associated with issues of bad flavour and unpleasant smell leads to consumer disappointment and often gets discarded. Inefficient packaging methods employed by abattoir and processor and mishandling of beef products in logistics and other stages of beef products leads to their oxidisation (Barbosa-Pereira et al., 2014). Regular maintenance of packaging machines, random sampling of beef products could assist in addressing this issue (Cunningham, 2008). Appropriate training should be provided to the staff of logistics and all segments of supply chains to avoid product mishandling. Inefficiency of cold chain also leads to unpleasant smell and bad flavour (Raab et al., 2011). Maintenance of chilled temperature at the premises of abattoir and processor, retailer and in the logistics vehicle is vital to mitigate this problem (Kim et al., 2012). Periodic maintenance of refrigeration equipment and regular temperature checks is necessary to improve efficiency of cold chain management.

1. Traceability issues in beef products – The analysis of consumer’s tweets reveal their concern about the traceability of beef products especially, horsemeat scandal happened in European market in 2013. It has undermined the consumer confidence in the quality of beef products and on the audits performed by retailers on their suppliers (Barnett et al., 2016). These kinds of issues could be avoided in future by following a strict traceability regime in the beef supply chain mapping all the stakeholders viz. farms, abattoir and processor and retailer (Sarpong, 2014). It should be robust enough so that each beef cut present on retailer shelf could be traced back to the animal from which it has been derived and its associated farm, breed, diet and gender. All the stakeholders of beef supply chain should store the product flow information locally and share it with other stakeholders in the supply chain. It will improve consumer confidence and assist audit authorities to identify any potential adulteration.
2. Extra fat – Presence of extra fat on beef products leads to customer dissatisfaction (Brunsø et al., 2005). The yield of cattle who are not raised as per the weight and conformation specifications of retailer is often associated with excess of fat (Borgogno et al., 2016). Similarly, inefficient trimming procedures at abattoir and processor affect the leanness of beef products (Mena et al., 2014). This issue could be mitigated by implementing appropriate guidelines of animal welfare in beef farms so that cattle are raised as per weight and conformation specifications of the retailer and adopting appropriate trimming procedures at abattoir and processor.
3. Discoloration of beef products – The phenomenon of discoloration of beef products prior to the expiry of their shelf life was reported by some consumers on Twitter. It adds up to the annoyance of consumers as they perceive them as inedible. Deficiency of vitamin E in diet of cattle is its primary root cause, which indicates that cattle is not being raised on fresh grass (Houben et al, 2000). Failure of cold chain also results in beef products losing their fresh red colour. The discoloration of beef products could be avoided by raising the cattle on fresh grass and maintaining efficient cold chain throughout the supply chain.
4. Hard texture – Consumers gets disappointed if it is inconvenient to chew beef products due to lack of tenderness (Huffman et al., 1996). The insufficient maturation of carcass of beef products lead to beef products with low tenderness (Vitale et al., 2014). Carcass is preserved in chilled temperatures for a duration of seven to twenty-one days depending on their age, gender and breed (Riley et al., 2005). Appropriate maturation of carcass could improve the tenderness of beef products.
5. Presence of foreign body – In certain instances, foreign bodies such as insect, piece of plastic, metal were found in beef products. Consumers perceive them as inedible and it adds up to their discontent. This issue is generated by the errors caused by packaging machines of abattoir and processor, deficiency of food safety management procedures such as Hazard Analysis and Critical Control Point (HACCP), lack of safety checks such as metal detection, damage of packaging due to mishandling of beef products (Goodwin, 2014; Lund et al., 2007; Goodwin, 2014). Regular maintenance of packaging machines, performing systematic safety checks like random sampling, physical inspection, metal detection, implementing appropriate food safety process management technique such as Good Manufacturing Practices (GMP), HACCP and providing training to the workforce of all stakeholders of beef supply chain could assist in addressing these issues.







Logistics

Logistics

Abattoir & Processor

Retailer

Beef farms

Extra fat

Discoloration of beef products

Traceability issues in beef products

Bad flavor and unpleasant smell

Hard texture

Presence of foreign body

Figure 7. Highlighting the location of root causes of issues faced by consumers in beef supply chain

Table 7 Summary of issues identified from consumer tweets and their mitigation

|  |  |  |
| --- | --- | --- |
| **S. No.** | **Issues identified from consumer tweets** | **Mitigation of issues** |
| 1 | Bad flavour and unpleasant smell | Periodic maintenance of packaging machines at abattoir and processor, efficient cold chain management, appropriate training of workforce in logistics and throughout the supply chain so that mishandling of beef products is avoided.  |
| 2 | Traceability issues in beef products | Supply chain mapping, strong vertical and horizontal coordination, use of ICT.  |
| 3 | Extra fat | Raising of cattle as per the weight and conformation specifications of retailer and appropriate trimming of primals at abattoir and processor.  |
| 4 | Discoloration of beef products | Raising cattle on fresh grass at beef farms and maintaining efficient cold chain management throughout the supply chain.  |
| 5 | Hard texture | Appropriate maturation of carcass after slaughtering.  |
| 6 | Presence of foreign body | Following renowned food safety process management techniques like GMP, HACCP. Appropriate safety checks such as physical inspection, metal detection, random sampling. Periodic maintenance of machines at abattoir and processor.  |

**6. Managerial Implications**

The finding of this study will 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 tonnes of meat waste occurred because of customer dissatisfaction. The majority of food waste is because of discolouration, bad flavour, smell, packaging issues, and presence of foreign body. Discolouration can be solved by using new packaging technologies and by utilising natural antioxidants in diet of cattle. If the cattle consume 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 colour and lipids. The issues related to bad smell and flavour 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, colour, 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. 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 has different patterns of demand in the market, which leads to carcass imbalance (Simons et al., 2003; Cox & Chicksand 2005). It leads to huge loss to retailers and contribute to food waste. Sometimes, consumers think that meat derived from different cuts like forequarter and hindquarter have different attributes like flavour, tenderness, and cooking time as well as price. The hindquarter products like steak and joint are tenderer, take 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 behaviour. In study, it was found that slow cooking methods like casseroling, stewing, pot- roasting and braising can improve the flavour and tenderness of forequarter products (Guide to Shopping for Rare Breed Beef). By the help of proper marketing, advertisement, retailers can raise awareness between the consumers and can increase the demand of less favourable beef products, which will further assist in waste minimisation and make the supply chain more customer-centric.

The analysis of consumer tweets reveals 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 win the consumer confidence by following the strict traceability regime within the supply chain.

The analysis of positive sentiments of tweets revealed that good promotional deals usually motivate consumers to buy the product from a particular retailer store. As food products have direct impact on the health, consumers give more importance to the quality, food safety and brand image than the price of the beef products. There were lots of positive tweets associated to Red Tractor farm assurance scheme. By proper labelling, retailers will be able to capture maximum market share compared to their competitor. There were numerous discussions on consumers appreciating the combination of roast beef products along with different kinds of wine. They will assist retailers to develop marketing and promotional strategy.

**7 Conclusions**

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 their product offerings. Social media data is one of the cheapest and fastest methods to capture the view of the larger audiences about a particular topic. Food is one of the most significant necessities of human life, which has an impact on their health. In today’s competitive market, consumers are looking for high quality safe products in minimum cost. Both positive and negative sentiments related to a particular product are crucial component to generate customer centric supply chain. 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. Sentiment mining based on SVM and HCA with multiscale bootstrap sampling techniques were proposed to investigate positive and negative sentiments of the consumers; as well as, to identify their issues/concerns about the food products. The collected tweets have analysed to identify the main issues affecting consumer satisfaction. The root causes of these identified issues have been linked to their root causes in different segments of supply chain. As the focus of the paper was to illustrate the use of text mining approach for social media analysis, therefore, it is assumed that the data from Twitter would be representative of the real opinion. During the analysis of the tweets collected, it was found that the main concern related to beef products among consumers were colour, food safety, smell, flavour and presence of foreign particles in beef products. These issues generate huge disappointment among consumers. There were lot of tweets related to positive sentiments where consumers had discovered and share their experience about promotions, deals and a particular combination of food and drinks with beef products. Based on these findings, a set of recommendations have been prescribed to develop consumer centric supply chain. There are some limitations of the proposed approach in this study. During the hierarchical clustering analysis, it was found that some of the results were not linked to the beef supply chain. These findings don’t contribute towards the objective of the study to develop consumer centric supply chain and therefore are not being described in detail. However, these results could be used for different purposes and is a topic for future research. Also, other algorithms such as Latent Dirichlet Algorithm can be used for better understanding of consumer behaviours. A larger volume of tweets could be captured using Twitter firehose instead of streaming API, which have better representativeness of the data. In future, the proposed analysis could be also performed on other food supply chains such as lamb or pork.

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