SOCIALIZING BUSINESS PROCESS USING ENTERPRISE SOCIAL NETWORK SENTIMENT ANALYSIS: ESAF

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ABSTRACT

Sentiment analysis has become a rich research area due to the growth of social networks applications in the enterprise market. The influence of sentiment analysis has entered the business process domain through enterprise social networks. Sentiment analysis collected from public applications such as Twitter helps organizations to improve their business processes in order to provide good service or better products. However, the amount of research in this field is limited. Existing studies and researches focus only on the results of sentiment analysis without considering impact of these results on the organization business process and how it effects the improvement of products or services. In this context, this research identifies the process of reusing the analysis of sentiment analysis in the organization business application and proposes a framework, eSAF (Enterprise Sentiment Analysis Framework) to enhance organization business processes using Twitter sentiment analysis. The framework crawlers Twitter API from ESN, filter gathered data and apply sentiment analysis techniques based on Naïve Bayes algorithm. Finally, it exposes the result into a SOA environment in the form of web services to be used in other business applications. The framework shows promising results in term of users' opinions and satisfaction, which provides organizations with accurate statistics about their products or services allowing for future improvements.

Keywords: *Sentiment Analysis, Web Service, Business Process, SOA*

1. INTRODUCTION

Sentiment analysis has changed the enterprise market. It provides enterprises with customers' opinions and reviews about their products or services so they can reengineer their business processes to align with market changes. It also defines the attitude of customers towards different topics by classifying their expression either happy, sad or neutral.

In the Internet world, customers are content producers using public tools such as Twitter, Facebook or Instagram. By participating and using these tools, customers can give their opinions about certain product or services and these can be categorized, processed and analyzed to produce a meaningful result and valuable information for any enterprise. However, there is no direct way to perform this type of analysis and reuse it in other business applications inside organizations.

The reuse of sentiment analysis results by other business applications like Customer Relationship Management (CRM) or Enterprise Resource Management (ERP) can impact organizations business process positively. For example, the availability of these sentiment analysis results in the form of web services can facilitate many tasks for developers and decision makers. Developers can invoke web services regardless of the application they are using to design business process or workflows. Furthermore, decision makers can access these results in their business application using the regular workflow to take appropriate action toward services or products.

In this research, therefore, the main purpose is to present a framework proposed for business processes enhancement based on Twitter data to enable IT developers to reuse it as a web service, and assist decision makers to improve organizations products and service. The framework uses sentiment analysis techniques based on Naïve Bayes to prepare, process and analysis tweets through Twitter API in ESN. The results of this analysis are stored in a database for future use by web services. These web services retrieve the results and make them available in

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form of RESTful web service into a SOA environment so they can be invoked by other business applications. The framework has been validated by a case study and it shows promising results of the sentiment analysis part.

The rest of this research is organized as follows. Section 2 gives details about related works in the literature. Section 3 introduces the sentiments analysis techniques. Section 4 illustrates the proposed framework followed by an experiment and validation a real case study in section 5. Section 6 presents the conclusion and future work.

2. RELATED WORK

Due to the rapid growth of social networks, users' opinions have become very important and they influence decision making in any business activities. This is not only true for business owners, but also for governments and organizations that are seeking to improve their services or products, based on customer reviews and opinions.

Several studies have investigated and presented different methods of sentiments analysis and the use of microblogs information in different fields. Romanowski and Skuza (2017) proposed a sentiment analysis based system to predict future stock prices. The authors collected Twitter data for 3 months and applied machine learning for sentiment classification to estimate future stock prices [1]. Moreover, García (2016), used twitter sentiment analysis and Random Matrix Theory to study the correlation matrix structure of public tweets and global financial indices. The study concludes that both public tweets and financial information effect the global correlation structure which might be preserved [2].

Other research conducted by Neppalli , Caragea and Stehle (2017) shows the importance of sentiments during disaster events. In their work, the authors executed a sentiments analysis during Hurricane Sandy and found that users' sentiments vary according to their distance from the disaster and their location. This result helps decision makers to treat disaster zones by developing stronger situational awareness programs [3].

In order to visualize and analyze the steams of social media messages, Lipizzi et al (2016) in [4] presented a methodology to build visual devices based on Twitter concept maps and a mix of sentiment and topological metrics. Their finding shows that the proposed methodology can capture and quantify many back channeling interactions. Furthermore, the authors in [5] proposed a method to measure the reputation of a given company based on an N-gram learning approach and sentiment analysis of the company and its' products. The evaluation of the proposed method shows it has better efficiency and performance in terms of recall and precision when compared to Bayesian and Neural Network method.

From the above studies, it is very obvious that sentiment analysis can be used in many fields to improve service or products, based on customer opinions. However, very little research investigates the improvement of business processes using sentiment analysis. This gap in the research encourages us to propose a framework to interface sentiment analysis within running business processes.

3. SENTIMENT ANALYSIS

Sentiment analysis have become a rich research area due to the growth of social networks applications in the enterprise market. In the Internet world anyone can be a content producer and participate with opinions about products or services and markets and services are effected either positively or negatively by these opinions. Today, many platforms, such as Twitter, allow customers to practice this type of business interaction.

3.1. Twitter

Twitter is one of the most popular platforms for conversation between users. It allows users to write (tweet) daily events or activities, express professional business discussion, or even broadcast malicious content. Twitter lets users express themselves with only 140 characters in each post. These characters restrict users to be very straightforward in expressing their feeling such as agreement, happiness, anger or neutrality.

Although Twitter is a public social network, it still can be used with other enterprise solutions like Enterprise Social Network. It provides public streams and REST API to read and write Twitter data. Moreover, Twitter posts can be integrated easily in ESN by creating a public widget from the Twitter account to generate a script which can be used in ESN web parts, as shown in figure 1. With

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this type of integration, business owners can detect important information about an organization, products or services, which may impact the future development of the organization from different perspectives. However, it is not that easy to understand all types of opinions unless a careful sentiment analysis is applied to filter these posts.

With sentiment analysis, Tweets can be classified as positive, negative or neutral. These classifications can enhance organizations' business process by taking into consideration the quality of the service or products provided and they allows decision makers to reengineer some BP according to the result of the sentiments analysis. Furthermore, organizations can perform analysis of other competitors or predict and measure the gap of market sales with other competitors.

```
<a class="twitter-timeline"
href="https://twitter.com/eOman_ITA">Tweets by
eOman_ITA</a> <script async
src="//platform.twitter.com/widgets.js"
charset="utf-8"></script>
```

Figure 1: Twitter Widget Script

The study conducted by Kim, Zhang and Jeong (2016) in [6] compared two smartphone companies' opinion mining and found that the sales performance gap was similar to social opinion gap. Similarly, a study reported by Chamlertwat et al (2012), who used sentiment analysis in their proposed MSAS system, successfully provides supportive information for next generation products [7].

3.2. Sentiment analysis methods:

Several approaches have been proposed and used for sentiment analysis. These can be mainly categorized into machine learning approach (supervised and unsupervised learning) and Lexicons-based approach (Dictionary-based approach and Corpus-based approach) [8].

3.2.1. machine learning approach

The supervised method is a machine learning operation which classifies documents into positive, negative or neutral sentiments. It is based on training classifications such as the Support Vector Machine (SVM) , Naïve Bayes, and Maximum Entropy [9]. The SVM can determine the liner separators and separate different classes. Because of the sparse nature of text in Twitter, the SVM organizes it into linear separable categories and separates classes linearly with a hyperplane [8]. On other hand, the Naïve Bayes classifier is considered as the most widely used classifier [10]. It simply calculates the distribution of words in the document based on the posterior probability of a class. The probabilistic of this method is based on the Bayesian theorem as follows:

$$P(x/Y)= (P(Y/x) . P(x)) / P(Y)$$

where $P(x/Y)$ = probability of x, given Y ; $P(Y/x)$ = probability of Y, given x; $P(Y)$:prior probability of training data Y; $P(x)$ = prior probability of hypothesis x.

Another supervised classifier is the Maximum Entropy approach which is basically a model for probability distribution that should be as uniform as possible [9]. This approach presents unbiased model as possible by satisfying any given constraints. Moreover, with this feature based model approach, distribution over different classes can be found using logistic regression. In other words, this approach provides the probabilities to determine if certain document belongs to a particular class.

The unsupervised methods rely on documents' statistical properties, lexicons and Natural language Processing (NLP) processes [11]. The unsupervised method is based on clustering where similar groups of data are organized. Clustering has been used in many files including medicine, sociology, library science and marketing. Major techniques of unsupervised methods are k-means, hierarchical clustering and density based clustering.

3.2.2. Lexicons-based approach

Opinions can be expressed positively or negatively depending on the desired and undesired states of the users. Moreover, opinion phrases and idioms are called the opinion lexicon. In sentiment analysis the Lexicons-based approach is defined by the Dictionary-based approach and the Corpus-based approach [12]. The Dictionary-based approach is simply collecting opinion words with a known orientation manually and then seeding them with an online dictionary such as WordNet to find synonyms and antonyms [13]. This process continues by adding new opinion words to the list until no new words are found. The last step is a manual inspection to remove or correct error.

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The Corpus-based approach is performed by either a statistical approach or semantic approach. The statistical approach uses statistical techniques to find co-occurrence opinion words in a corpus. It depends on the polarity of word (positive, negative or natural). It measures the occurrence frequency of words in a large corpus and identifies positive, negative or natural polarity based on the occurrence of words [14]. However, the semantic approach depends on different principles for measuring the similarity between words by assigning similar sentiment values to semantically close words [8].

Table 1 shows the strengths and weaknesses of the above approaches [15].

Table 1: Strengths and Weakness of Sentiment Analysis Methods

Approach	Strengths	Weaknesses
Supervised method	Can adopt new cases	Time consuming to build the model
Unsupervised method	Annotated training data not required	Show low performance in individual cases
Lexicons-based approach	Easily understood and modified by human.[16] Easily transformable into different language.	Shows low performance comparing to machine learning approaches.

4. THE PROPOSED SENTIMENT ANALYSIS FRAMEWORK

In this section, we will present our proposed framework, eSAF, that uses the technologies described in above sections. The eSAF is a software architecture that contains set of components, connections, storage and interface. Figure2 illustrates the eSAF subsystems and these are discussed in the following subsections.

4.1 Enterprise Social Network

Enterprise Social Network (ESN) is a social collaboration system for internal business purposes. It enables organizations to perform social formal business activities, tasks and processes that they are not available in BPM applications. Such business processes are sets of activities performed by knowledgeable actors such as employees, partners or customers. Baghdadi (2013) described these business processes as “a set of dynamically interconnected knowledgeable actors through Enterprise Social Interactions” [17]. ESN provides various benefits to an enterprise. For instance, with ESN, managers can approve project progress report documents through the workflow process, improve collaboration with employees across other site or remote locations or accept a meeting with customers.

According to an industry survey conducted by Gartner in [18], there are three enterprise social networking standards: ActivityStea.ms, OpenSocial and Open Graph Protocol. Table2 summaries these standards with current products details.

Apart from the famous ESN described in Table2, there are also open source ESN solutions available for the same purposes such as eXo, Elgg and EurekaStreams Platforms.

4.2 ESN Crawler

The main functionality of the ESN crawler is to retrieve and classify information from ESN and its API such as Twitter API, Email API or news API. The output results of this crawler are preprocessed in the “data preprocessing” engine. Researchers refer to the web crawler as a web spider or web robot [19]. This tool searches online data sources through Uniform Resource Locator (URL), and its hyperlinks.

In this study, the eSAF crawler retrieves ESN unstructured data through intranet URL or an API that are available in the internet URL such as Twitter API.

4.3 Data Preprocessing

The source of ESN unstructured data came from different APIs like Twitter and e-mail APIs.

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This data consists of acronyms, emotions and unnecessary data like stop words (a, the, at, which). Therefore, ESN unstructured data is preprocessed to present the right emotions when it come to the sentiment analysis. The eSAF presents three preprocessing stages as illustrated in Figure3:

1) *Tokenization:* This process identifies the most meaningful words in the document by "breaking a stream of text up into phrases, words, symbols, or other meaningful elements called tokens" as Verma et al explain in [20].
2) *Removing Stop Words:* After splitting ESN unstructured data, words like *a, the, at, which,* etc are removed from the dataset. This will accelerate the eSAF processes by minimizing number of words in the document. However, special attention should be made to domain specific stop words. In the information system domain, for example, general words such as "IT" or "PC" are not useful words when are we seeking a specific qualification, but they may reflect very important terminology in other domains. Therefore, for each domain these words should be excluded in this step to end up with an accurate results of words.
3) *Stemming*: This is the process of returning words to their root by reducing the inflectional forms. It removes prefixes, suffixes and infixes of words which increases the accuracy of words and reduces variant of words [21].

4.4 Sentiment Analysis Engine

Sentiment analysis techniques are used in this component of the eSAF. It depends on Naïve Bayes algorithm which is frequently used by researchers due its performance, effectiveness and simplicity. Table 3 shows the summary of sentiment classification studies which investigate the use of Naïve Bayes. The algorithm uses probability theory to classify texts into class of positive, negative or neutral.

Naïve Bayes classifies data in two phases (training phase and analysis or testing phase). In the training phase, training samples are used to estimate the parameters of probability distribution. The analysis or testing phase computes the posterior probability of the testing samples that belong to each class and then classifies these samples according to the largest posterior probability [27].

The Naïve Bayes classifier calculates the probability of the text that belong to categories that are being tested. Given certain text, the classifier returns the category with the highest probability as follows:

classify(W1,W2,…Wn)=argmaxcatP(cat)∗∏i=1 nP(Wi|cat).

In our study the we focus on the dataset generated by Tweets which is represented as an API in the ESN, and the training set is classified manually into three types of class labels (satisfied, neutral and not satisfied). These classes are going to train the classifier as shown in Figure4.

The following Tweets example shows the class labels:

- Satisfied: " thanks for your service"
- Neutral: " not bad service"
- Not satisfied: " your e-service taking a long time"

We use the most popular evaluation metrics in sentiment analysis which are precision, recall and f-measure to evaluate the effectiveness of this classifier. The Confusion Matrix is also used to figure out the classifier positive or negative prediction from one hand, and true or false prediction correspondence from the other hand to external decision [28]. Table5 shows the Confusion Matrix where True Positive (TP) represents the number of correct positive predictions, and False Positive (FP) is the number incorrectly predicted as positive. The same meaning is applied to the negative class with False negative (FN) and True negative (TN).

Based on the above matrix, precision, recall and f-measure are defined follows:

- Precision (P) is the ratio of the positive predicted records that are really positive to the total number of records that were predicted as positive. It is calculated as: Precision= True Positive / (True Positive+ False Positive)
- Recall (R) is the ration of the positive predicted records that are really positive to the total number of relevant records. That is: Recall= True positive / (True positive+ False negative)
- F-measure is the combination metric of precision and recall which evaluates the

performance of the method and is expressed as:
F-measure = 2* (Precision* Recall) / (Precision+ Recall)

The value of f-measure must be high for good classification. It lies between 0 and 1, and can be obtained as a higher value when precision and recall values are close.

At this level, the results of sentiment analysis are stored in a database to be retrieved by web services inside the organization.

4.5 Web Service and SOA

In this phase, a web service is built to retrieve desirable information from the SA database. There are two possible ways to achieve this task, either by using a Simple Object Access Protocol (SOAP) web service or Representational State Transfer (RESTful) web service. SOAP is a XML protocol that exchanges information between the traditional web services and social web services that are extracted using this framework. However, RESTful is an architectural style which provides an easy interface to build software for clients to invoke services [29]. Both SOAP and RESTful facilitate communication between the services that are described by Web Service Description Language (WSDL). This language defines the functionality of the web service, the specific address of the URL protocol and how to access the service [30]. Each service is published in the form of web services by the Universal Description, Discovery and Integration (UDDI) registry.

There are some advantages of using RESTful web service in the eSAF framework compared to other types of web service. First, the RESTful web service uses basic XML which makes it more flexible. Next, its throughput and response time are much better compared to SOAP, and finally, it depends on HTTP and is reusable across different platforms, such as .NET, PHP, and Java [31]. Furthermore, the REST model has been widely accepted in the industry sectors as an alternative to SOAP-based Web services in service provisioning [32]. Global companies like Google, Amazon, Twitter and Facebook are increasingly exposing their services as RESTful web services for their customers. Therefore, a number of development frameworks have been developed and have appeared to the market (Windows Communication Foundation (WCF)[1], RESTAgent[2], apache2rest[3] and RESTIFYDB[4].

4.6 Business Process

The final component in eSAF framework is the business process, where activities are defined in the form of workflow. These activities invoke internal or external services to map service tasks with web services that exist in the Service Oriented Architecture (SOA) environment. These types of web service are considered as social web services since they hold human interaction outcomes or analyzed data. With these services, stakeholders' voices, concerns or opinions are involved in the running business processes of the organization in order to improve provided services.

5. VALIDATION

In this research, we conducted our experiment on Oman Air (the flagship and national carrier of Oman) to measure customers' satisfaction and the quality of provided service. Oman Air operates international and domestic flights. The airline aims to provide quality and comfortable services to passengers. Customer satisfaction impacts the quality of services and defines new ways to reengineer some processes. This framework helps Oman Air to analyze what customers say about it services and allows top management to take the right decisions, whether to improve the service or maintain the current level of service.

Oman Air uses Customer Relationship Management (CRM) which is a customer-focused strategy instead of product-focused. It helps organizations to understand customer needs and requirements in order to provide value-added services and create business opportunities to the organization [33]. With CRM, Oman Air aims to collect users' opinions about their services in general from their ESN which has a twitter API. This API is collecting tweets from twitter.com and displays them on ESN web-part. Figure5 shows the business process in the CRM.

[1] https://msdn.microsoft.com/en-us/library/dd456779(v=vs.110).aspx

[2] https://github.com/inadarei/restagent

[3] https://github.com/jeteve/Apache2--REST

[4] http://restifydb.com/

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The business process starts checking customers' opinions by calling the eSAF framework. The framework collects the dataset from Twitter.com by using a text mining application (Rapid miner). The start point is to remove retweets by (-rt) to avoid data reappearance in the dataset and training data. Furthermore, any link that starts with http was removed using (-http), since these types of links do not provide any opinions. The final query was (omanair-r –http) and it retrieves English tweets only.

The result of this query was about 300 tweets in English language. We excluded some meaningless tweets such as (this is for testing), in order to manually classify these tweets into class labels (satisfied, neutral and not satisfied). These class labels are going to train the classifier and based on this learning, the classifier can predict the customer tweets sentiment meaning. Table6 shows a real tweet with its class label.

Preprocessing the collected tweets enables the eSAF framework to obtain the right sentiment before applying the naïve Bayes algorithm. Table 7 shows the result of the performance factor accuracy based on percentage of dataset and training data.

Table 2: Performance Factor Accuracy

Training - Data	0.50-0.50	0.79-0.21	0.93-0.07
Naïve Bayes Accuracy	53.12%	64.29%	80%

Splitting the validation using a training set ration improves the accuracy of Naïve Bayes as the number goes close to 1, as shown is Figure 6.

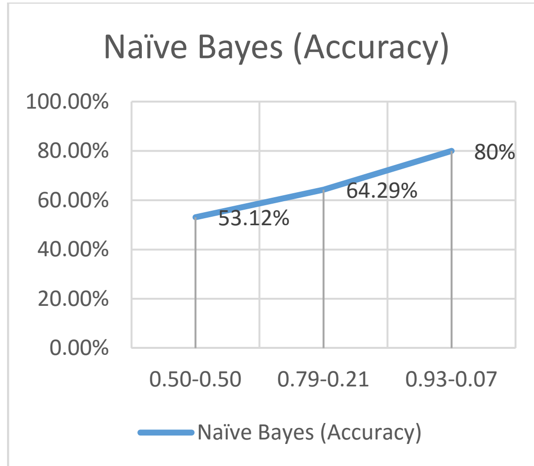

Figure 6: Accuracy Result of Different Training Set

Table7 shows the top 10 final tweets classification and the sentiment prediction. The result of this sentiment analysis is stored as XML format for different reasons. According to W3C, XML is the best carrier for data as it stores data in plain text [29]. As well, XML is more flexible when it comes to software or operating system upgrade. Moreover, it is a self-descriptive language and can be read by computers and humans [34]. Besides, XML integrates with different tools in order to standardize (get, add, change and delete) operations. In this study, the result of sentiment analysis is generated in XML format as depicted in Figure7 below.

The operation in Figure8 counts the number of satisfied, not satisfied and neutral

```
<?xml version="1.0" encoding="UTF-8" ?>
<root>
<0>
                <Text>@omanair Do you have
through checkin with Singapore Airlines?</Text>
                <confidence(neutral
)>0.97149124027205</confidence(neutral )>

        <confidence(satisfy)>0.01436229326968
8</confidence(satisfy)>
                <confidence(not
satisfy)>0.014146466458259</confidence(not
satisfy)>
                <prediction(Sentiment)>neutral
</prediction(Sentiment)>
        </0>
</root>
```

Figure 7: Sentiment Analysis Result in XML

```
for (int i=0; i<Polarity.size();i++){
```

```
if(Polarity.get(i).equals("positive"))
                                        countPos++;
                        else
if(Polarity.get(i).equals("negative"))
                                        countNeg++;
                        else
if(Polarity.get(i).equals("neutral"))
                                        countNet++;
                }
                if(countPos>(countNeg+countNet))
                        status="POS";
                else
                        status="NEG";
                result="The count of POSITIVE
polarity is "+ countPos+"\t"
                                        +"The count of
NEGATIVE polarity is "+ countNeg+"\t"
                                        +"The count of
NEUTRAL polarity is "+ countNet+"\t"
                                        +" and the polarity
status is "+status;
return result;
```

Figure 8: Sentiment Analysis Operation

responses accordingly. It returns the result of for the decision maker to either review the provided service or make no change.

The web service retrieves XML results and prepare them for publication in an SOA environment as shown in Figure9.

To summarize, the main advantage of this framework is the volume and timeless of discovered customers' opinions information. Specifically, the framework collects and analysis large amount of opinions at low cost. It leverages the benefits of sentiment analysis and text mining by crawling and analyzing Tweets to provide a meaningful web service. This web service is going to change the organization business process by providing an accurate sentiment analysis results which will enhance and improve some part of the business process, to offer better and quality services.

However, this work has some limitation in term of understanding other languages and slangs in local words. It deals only with English text. Adding the Arabic language sentiment analysis will improve the result and the outcome of the framework.

6. CONCLUSION

Organizations improve their services and products by changing their business processes according to customers' feedback and opinions. These days such feedbacks and opinions are taken from social networks as unstructured data. Sentiment analysis techniques are used to analyze these data to understand the implication of customers' opinions. However, sentiment analysis processes do not change the business process of organizations in a direct way. Therefore, in this research we have proposed a framework to enhance organization business processes using a Twitter sentiment analysis. The framework applies the Naïve Bayes algorithm after collecting customers' opinions using Twitter API of organization ESN. The framework offers the result of sentiment analysis in the form of a web service to other business application in a SOA environment.

The framework is evaluated using a descriptive evaluation method. A real case study is taken from the industry and the sentiment analysis is applied. After that, the result is stored as XML format and retrieved as RESTful web service.

As future work, this web service will be tested by other business application like ERP or CRM application by invoking this web service into a real business process. In addition, adding Arabic text to sentiment analysis and validate the results against other algorithms that are used for Arabic language.

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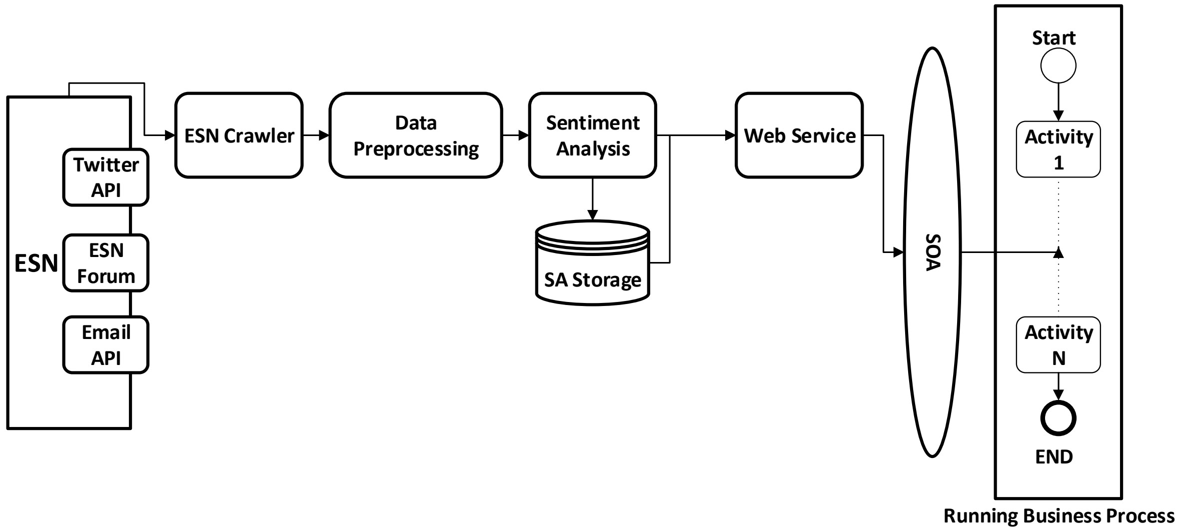

Figure 2: eSAF Framework

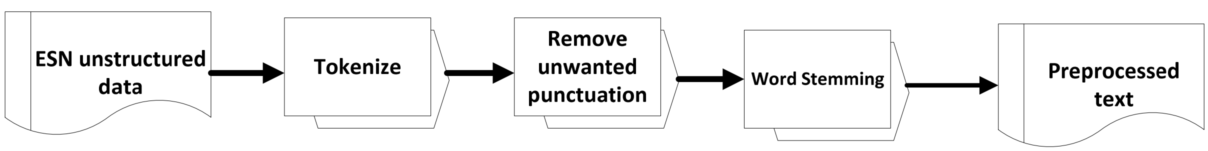

Figure 3: The Preprocessing Steps

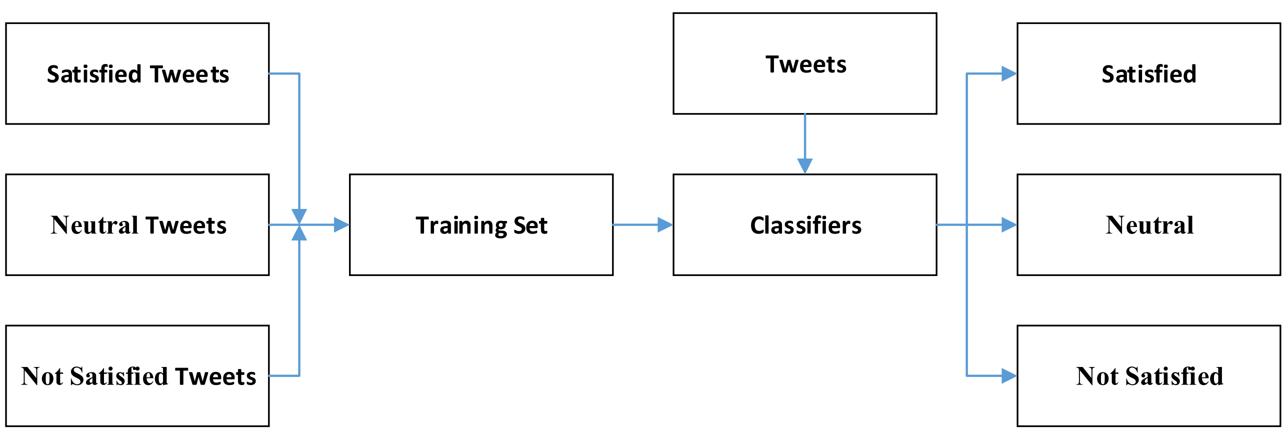

Figure 4: The Naive Bayes Classifier

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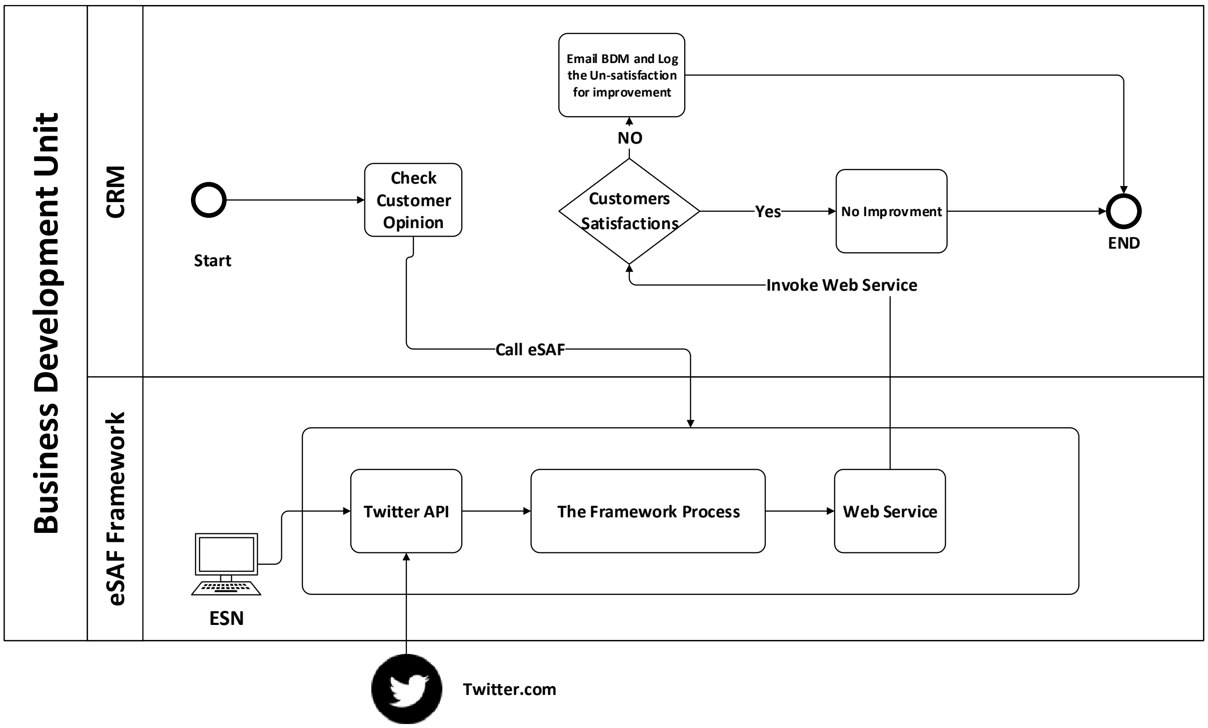

Figure 5: Oman Air Business Process in the CRM

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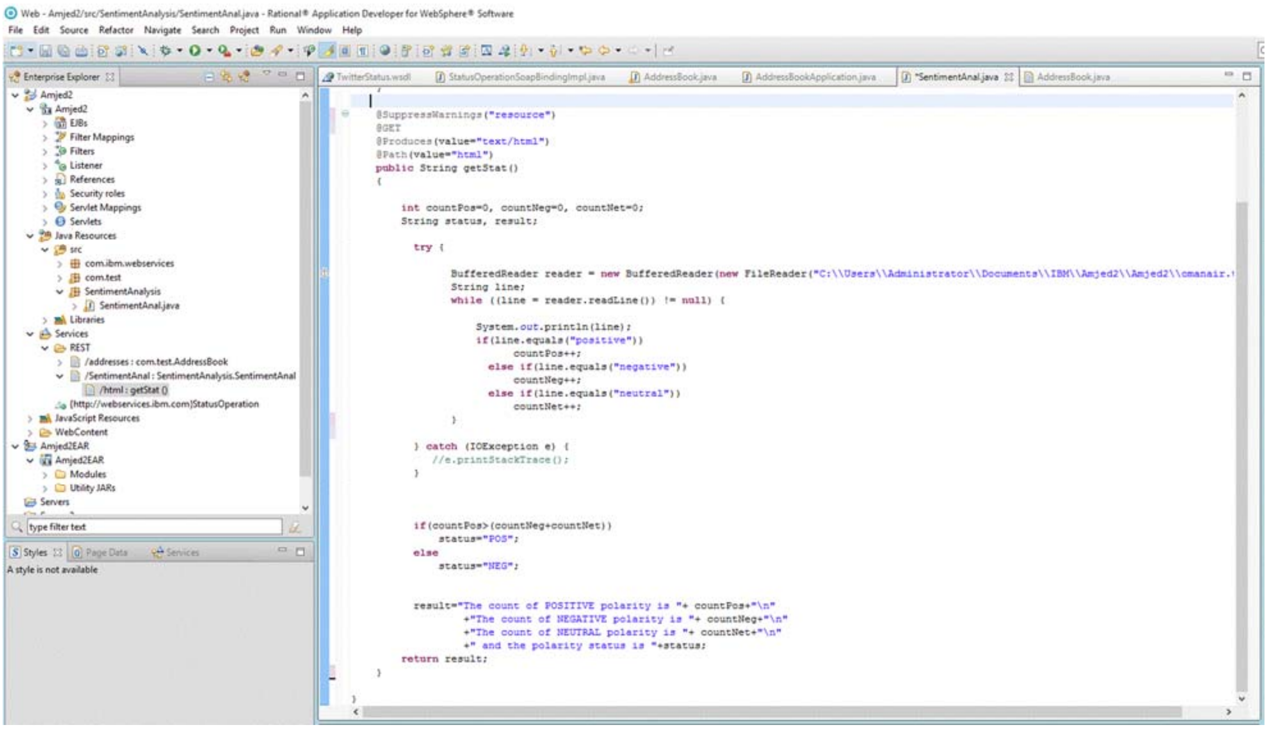

Figure 9: RESTful Web Service

Table 3: ESN Standards

ESN Standard	Specifications	Example Products
ActivityStrea.ms	JSON and XML are core format of activity streams formats and extensions.	JSON Activity Streams 1.0 Atom Activity Streams 1.0, Activity Base Schema, Socialtext
OpenSocial	Used for building portable and reusable gadgets written by HTML5 and JavaScript	Google, IBM Connections , Atlassian Activity Streams ,JIVE Social Business Platform.
Open Graph Protocol	Set of HTML metadata attributes.	Facebook, Microsoft Yammer

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Table 4: Sentiment Analysis Studies using Naive Bayes

Study	Study	Results
[22]	The Authors used three classifiers to compare their performance in Facebook status update (positive or negative).	Naïve Bayes has the best performance in precision compared to Rocchio and Perception classifiers
[23]	Introduces a strategy to classify tweets sentiment using Naive Bayes techniques.	The accuracy of using Naive Bayes algorithm was 90% ± 14% measured by the total number of correct classified tweets.
[24]	Data mining was used to discover followers and increase Twitter engagement followers for products and services using the Naïve Bayes algorithm.	Increased engagement followers by 69% and accuracy of Naïve Bayes classification reached 90.31%. Used data testing from tweet product and 80.91% from data testing tweet services.
[10]	Proposed a model to improve learning process of teaching by analyzing Tweets by students and comments by teachers.	The study used Naïve Bayes classifier to classify emotions and polarity.
[25]	Analyzed a large amount of Twitter by using Naïve Bayes, SVM and Maximum entropy.	Naïve Bayes shows better results and accuracy compared to others algorithms.
[26]	Compared classification algorithms on Swahili language	The Author compared Naïve Bayes and J48 classification algorithms and found that Naïve Bayes perform better on Swahili tweets compared to J48 classification algorithm

Table 5:Confusion Matrix

		True Condition	
		Positive Condition	Negative Condition
Predicted Condition	Prediction Positive	True Positive (TP)	False Positive (FP)
	Prediction Negative	False Negative (FN)	True Negative (TN)

Table 6 Real Tweet

Text (Tweet)	Sentiment (class Label)
Thanks @omanair for excellent service from Katmandhu to London. Really well looked after n good clean plane. https://t.co/GCw19jZyIO	satisfied
@omanair are the meals on board still normal service in Ramadhan Month flight?	not satisfied
@notabrownbag Yes, we can. Please DM us the booking reference of both guests to do the needful. https://t.co/hJSM4Kk0h5	neutral

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Table7: Final Tweets Classification Sentiment and Prediction

Text	Confidence			
	neutral	satisfied	not satisfied	Prediction (Sentiment)
@omanair Do you have through checkin with Singapore Airlines?	1.0	.0	.0	neutral
#هاشتاق_عمان: We welcome you to fly in the unique comfort of Oman Air! https://t.co/Johrgf0Sxf	.0	1.0	.0	satisfied
@omanair thank you...hope i fly soon with u	.0	1.0	.0	satisfied
We welcome you to fly in the unique comfort of Oman Air! https://t.co/W1ns6mBNhu	.3	.3	.3	neutral
Full Video: https://t.co/7fAG8P7kFO #iamnarcis #travel #video #first #omanair #oman #muscat… https://t.co/cFI1CUlmjE	1.0	.0	.0	neutral
Thanks @omanair for excellent service from Katmandhu to London. Really well looked after n good clean plane. https://t.co/GCw19jZyIO	.0	1.0	.0	satisfied
@omanair are the meals on board still normal service in Ramadhan Month flight?	.0	.0	1.0	not satisfied
@qatarairways @flydubai @emirates @GulfAir @EtihadAirways @MAS @omanair @KuwaitAirways @Official_PIA pls join the… https://t.co/ujVLfTdT0z	1.0	.0	.0	neutral
@notabrownbag Yes, we can. Please DM us the booking reference of both guests to do the needful. https://t.co/hJSM4Kk0h5	1.0	.0	.0	neutral