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Abstract

The advent of web 2.0 technologies represents a paradigm shift in how individuals collaborate in their businesses and daily lives. Web 2.0 opens new opportunities for businesses to reconsider their strategies and operating models by taking a customer-centric approach, which creates a competitive advantage. Business Process Management (BPM) is taking advantage from this phenomenon (aka social business processes or business processes 2.0), embracing ‘social’ and embed it through different stages of the BP lifecycle. This paper contributes by a novel framework for the real-time monitoring and improvement of business processes by analyzing the huge amounts of social data, providing visibility and control, which leads to informed decision making and immediate corrective actions. Thus, the proposed framework bridges in the gap between the social and business worlds. The applicability, efficiency and utility of the proposed approach is validated through its application on a real-life case study of a leading telecommunication company.

Keywords

Web 2.0 - Business Process Management (BPM) - Social business processes - Social data - Process improvement - Customer-centric - Human empowerment - Sentiment analysis - Tweets analysis - Clustering - Classification
Utilizing Twitter Data for Identifying and Resolving Runtime Business Process Disruptions

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Abstract. The advent of web 2.0 technologies represents a paradigm shift in how individuals collaborate in their businesses and daily lives. Web 2.0 opens new opportunities for businesses to reconsider their strategies and operating models by taking a customer-centric approach, which creates a competitive advantage. Business Process Management (BPM) is taking advantage from this phenomenon (aka social business processes or business processes 2.0), embracing ‘social’ and embed it through different stages of the BP lifecycle. This paper contributes by a novel framework for the real-time monitoring and improvement of business processes by analyzing the huge amounts of social data, providing visibility and control, which leads to informed decision making and immediate corrective actions. Thus, the proposed framework bridges in the gap between the social and business worlds. The applicability, efficiency and utility of the proposed approach is validated through its application on a real-life case study of a leading telecommunication company.

Keywords: Web 2.0 · Business Process Management (BPM) · Social business processes · Social data · Process improvement · Customer-centric · Human empowerment · Sentiment analysis · Tweets analysis · Clustering · Classification

1 Introduction

In contrast to web 1.0 that was limited to the passive viewing of content to users in a static way, the emergence of web 2.0 technologies allow users to communicate and collaborate [1] through using social media, which comes in many different forms, including blogs, forums, business networks, photo-sharing platforms, social gaming, microblogs, chat apps, and social networks. Social networks such as Facebook, Twitter, Wikis, etc., result in a massive amounts of data, however, data alone does not create competitive advantage. Only when companies analyze and act on data when competitive advantage and potential economic growth can be achieved.

On the other hand, business processes explicitly capture the set of activities participating in the accomplishment of a specific organizational goal, and their control flow [1]. Business Process Management (BPM) is the discipline that combines knowledge from information technology and knowledge from management sciences and applies this to operational business processes to enable their efficient design,
execution, control, measurement and optimization [1]. Recently BPM has gained much interest from the industrial and academic communities due to the promise it brings for increasing productivity and significant cost reduction. Therefore, business processes form the foundation for all organizations and subsequently business entities are striving for the utilization of information and communication technologies for their continuous improvement.

Social BPM (also known as business processes 2.0) represents a paradigm shift and a gateway to enhanced process efficiency [2]. Organizations taking social BPM initiative have recognized that its processes, supportive tools and technologies is the focal point of this shift, and that a customer-centric approach should be adopted that represents a collaborative effort between process designers and customers to improve the entire process. This creates a closed feedback loop from customers and other stakeholders for continuous BP improvement throughout the various stages of the BP lifecycle. Business process areas that are most prone to improvement include [2]: (i) **Collaborative process improvisation and implementation**: where feedback from social media is continuously collected and used to enhance process designs, as well as aiding the implementation through constructing the interplay between unstructured social data and BP implementation, (ii) **Process discovery and analysis**: this creates a communication loop involving not only process engineers, but customers as a key stakeholder, realizing a customer-centric approach. (iii) **Real-time monitoring**: the massive amount of social data is continuously monitored by tracking key people and events in real-time, which leads to informed decision-making and immediate (semi-automated) corrective actions, and (iv) **Spontaneous Status Updates and Feedback**: this ensures timely and effective process improvisations and enhancements during various BP stages, from design to implementation.

However, the gap between the social and the business worlds is still non-tackled. In essence, the majority of the proposed solutions are taking a marketing or business perspective and lacking a structured approach with concrete IT implementation. The main contribution of this article is a novel runtime monitoring framework that incorporates and integrates the social and business realms, and utilizes social unstructured data for the identification and resolution of BP disruptions/disturbances taking a customer-centric approach. We define a BP disruption (disturbance) as any event that hinders a customer’s satisfaction in the delivery and/or operation of a specific service offered by a service provider. BP disruptions are domain-specific that need to be identified and analyzed for the considered domain; for instance, if we consider mobile services offered by a telecommunication company, customers might be complaining (that’s BP disruptions) of a network disconnect at a specific time period, slow internet connection, payment error, etc.

To achieve this, the framework entails: a formal approach with associated supportive tools that continuously collect social data; filter and analyze it on the basis of utilizing and integrating data mining and machine learning techniques; relate it to the business realm; identify and detect possible online BP disruptions; automatically propose a recovery plan; and visualize the results in a user-friendly dashboard by accommodating various stakeholders’ perspectives. The proposed framework addresses the “real-time monitoring” and “spontaneous status updates and feedback” challenges.
discussed above. To keep the discussion focused, the paper concerns itself with presenting in detail the peculiarities of the ‘analysis’ component of the framework.

To validate the applicability, efficiency and utility of the proposed framework, a prototypical implementation has been developed by considering Twitter as the social medium source of data, and applied on a case study of the Customer Relationship Management (CRM) BP of a leading telecommunication company. Our empirical results show that pairing the analysis of the social side with its equivalent business side provides visibility and control throughout the execution phase of the BP/lifecycle, which enables informed decision-making and immediate corrective action(s) taking. These collectively lead to enhanced customer relationship, continuous BP improvements, and ultimately, a competitive advantage creation.

The rest of the paper is organized as follows: Sect. 2 summarizes related work efforts. Section 3 discusses the proposed framework. In Sect. 4, we discuss in detail the analysis approach proposed as a vital component of realizing the proposed framework. Section 5 demonstrates the application of the analysis approach on a real-life case study. This is followed by Sect. 6, which presents the conclusions and highlights future work directions.

2 Related Work

With the growth of blogs, social networks and opinion mining, social data analysis becomes a field of interest for many researchers and practitioners. The majority of proposals in the literature consider Twitter as the target social media because Twitter is a widely used social media site for posting comments through short statuses called tweets [3]. Each tweet was of 140 characters and now it is expanded to 280 characters however, it still has a size limit that means it is easier to be analyzed. Moreover, one can keep track of tweets talking about a specific topic through using the hashtag symbol (e.g., #topic). The millions of tweets received every year could be subjected to sentiment analysis and many other types of analytics. However, handling such a huge amount of unstructured data is a tedious task to take up. In a parallel context, there are some studies that consider other social media sites, such as Facebook [4–8].

This article considers Twitter for the previously cited reasons, and therefore the next discussion will focus on summarizing related work efforts in this direction. One of the prominent areas of Twitter analysis is the indication/prediction of the level of satisfaction of the customer with respect to a specific service or product, which is widely known as sentiment analysis [9]. Sentiment analysis is a type of data mining that measures the inclination of people’s opinions through Natural Language Processing (NLP), computational linguistics and text analysis, which are used to extract and analyze subjective information from the Web, mostly social media and similar sources. The analyzed data quantifies the public’s sentiments or reactions toward certain products, people or ideas and reveal the contextual polarity of the information\(^1\). It is also called opinion mining.

\[^{1}\] https://www.techopedia.com/definition/29695/sentiment-analysis.
Conversely, few studies exist in the literature that attempt to embrace ‘social’ and embed it with BPM, which is known as social business processes or business processes 2.0. In the following, prominent work efforts in Twitter analysis and the few attempts towards social business processes are discussed and appraised against the approach presented in this paper. The main contribution of this article as compared to related work efforts is the establishment of a formal framework that bridges in the gap between the social and the BP worlds, embracing ‘social’ to BPM for disturbances/deficiencies analysis, identification and their proactive correction.

2.1 Twitter Data Analysis

**Sentiment Analysis for Market Research using Text Mining.** Text mining is a technology that attempts to extract meaningful information from unstructured textual data. The study in [7] describes a case study that applies text mining to analyze unstructured text content on Facebook and Twitter sites of three largest pizza chains. The study revealed that Domino’s Pizza got higher level of commitment and consumer engagement than the other two pizza chains through the number of posts and user comments on social media.

Analogously, in [10] the authors proposes a sentiment analysis method based on N-gram classification approach to measure the reputation of a given company by using particularly tweets of Twitter. A given tweet has either negative or positive impact on the company’s reputation or product. Similar approaches are also proposed in [12–14]. While the proposals in this category aims at getting insights about the weak points of a specific business by utilizing sentiment analysis, they do not link these insights to the business process realm. This is tackled in our approach in the ‘analysis’ component/phase of the framework through first clustering the data to identify the classes/clusters of disturbances and any unforeseen/unexpected patterns.

**Improving Sentiment Score Results by Using Sentiment Analysis.** Another track in the same area of research is analyzing the social side for improving the sentiment score or the sentiment results by using domain ontologies [15–18]. The authors in [14] conducted sentiment analysis based on a domain ontology to produce more accurate results than any other sentiment analysis classification. The domain ontology has been developed using a semi-automated ontology learning technique that deploys text-mining techniques via user-friendly interface that reduces development time and complexity called OntoGen. Ontologies enable the sharing of a common understanding of the domain of interest among people and software tools; enable the reuse and extension of the domain knowledge; make assumptions regarding the domain explicit; separate domain knowledge from the operational knowledge; and enable the analysis of the knowledge leading to improved decision making. We regard the integration of ontologies to our proposed framework as future work direction.

**Prediction Using Sentiment Analysis.** This track combines sentiment analysis with machine learning techniques to predict something about a product or service [19–21]. The study in [20] analyzed how machine learning techniques and twitter sentiment analysis can be used to predict stock market fluctuations. The authors applied various
machine-learning models such as Linear Regression, Support Vector Machines (SVM) and Neural Networks and tuned them up in order to maximize the efficiency. The authors worked on historical data of stocks taken from Yahoo Finance website and built a classifier based on the Movies Reviews dataset, which we consider as an incompatible issue. The study concluded that stock markets are heavily sentiment driven. Similarly, the study in [21] uses sentiment information mined from current movie tweets for predicting movie’s performance. The authors developed a prototype, which may be useful to marketers in the of course correcting marketing campaigns to garner positive sentiments before the release of the movie. Similarly, studies in [8, 22, 23] take the same direction.

The approach proposed in this paper is tightly related to this category, however, we can distinguish ourselves by: (i) a comprehensive framework for disruptions monitoring, analysis, planning of corrective/proactive plans and their execution; the article focuses on presenting the details of the analysis component, (ii) the proposed “analysis” component integrates clustering and classification techniques to get insights and visibility over unexpected/unforeseen patterns, while all related work efforts directly conduct classification, (iii) the clustering activity has the main objective of linking the classification/prediction results to the BP world.

**Social Business Process Management.** Some research efforts in this direction view social BPM as designing and implementing business processes socially using any enterprise collaboration platforms, such as Yammer, and Chatter, or by employing hybrid Wikis. Prominent work efforts in this direction are: [25, 26]. Another stream of research in social BPM utilizes social BP. At diagnosis time, a BP execution component is implemented to discover and build the networks of social relations between the business process components (task, machine, person) based on process execution logs as well as the BP model. This is mainly reported in [26], where a model is being introduced (called SUPER standing for Social based bUsiness Process managEment fRamework) that leverages social computing principles for the design and development of social business processes). SUPER identifies task (t), person (p), and machine (m) as the core components of a business process. The authors defined all social relation states of t, p, & m. At diagnosis time, authors implemented a social analysis component to discover and build the networks of social relations between the business process components (t, p, m) based on process execution logs as well as the BP model. Every time a task is suspended, its resource is checked to identify the reason of being idle.

The work in [27] built a platform that bridges in the gap between the social and the business world through meet-in-the-middle platform, just for integration purposes without any analysis and/or improvement mechanisms.

The work in this paper proposes a novel approach for the analysis and resolution of BP disruptions through the utilization of social data and by integrating clustering and classification techniques. The clustering technique aids us to identify disturbances patterns and unforeseen/unexpected patterns and link them to the BP world, and then the classification approach aims at predicting future disturbances. Therefore, we consider our approach to fall under the categories of “Social BPM” and “Prediction Using Sentiment analysis”. To the best of our knowledge, such an integration does not exist in the literature.
3 Proposed Social BPM Monitoring Framework

Figure 1 presents a schematic view of the proposed framework for Social BP monitoring and improvement.

![Proposed framework diagram]

The framework is presented as an instantiation of the well-recognized IBM MAPE-K adaptation loop [29, 30], which is an efficient and novel approach for self-adaptation in autonomic computing. Autonomic computing is a computing environment with the ability to manage itself and dynamically adapt to changes in accordance with business policies and objectives [30]. As discussed in [31], self-adaptiveness in the general level inhibits a number of self-* properties in the major level, including self-configuring, self-healing, self-optimizing and self-protecting. We consider the approach presented in this article to fall under the self-healing category. Self-healing is the capability of the system (BPM in our case) of discovering, diagnosing and reacting to disruptions [30].

Self-healing can be classified into self-diagnosing and self-repairing, where the former concerns itself with diagnosing errors, faults and failures, and the latter focuses on recovering from detected disturbances. While the focus of the proposed framework is to provide an integrated approach for self-diagnosis and self-repairing by exploiting social media for BP improvement, due to space limitations and to keep the next discussion focused, this article focuses only on presenting the details of the proposed
self-diagnosis approach. The other components will be presented in future publications by referring to the framework.

The upper part of Fig. 1 represents the five MAPE-K self-adaptation loop components corresponding to its acronyms: that’s: K: Knowledge, M: Monitoring, A: Analysis, P: Planning, E: Execution and K: Knowledge.

The knowledge component in our framework constitutes the interlink between: (i) execution log(s), which maintains and relates business process execution logs, and (ii) social logs. This includes a structured representation of social data, e.g., tweets, in addition to predicted & extracted features that entails more value to the business (details are presented in Sect. 4). The knowledge component is the backbone of the four MAPE activities defined next.

The monitoring component constitutes monitoring running BP instances, which has been continuously acknowledged in the literature as key to ensure the successful completion of running BP instances. With the advent of web 2.0 technologies and their growing adaptation in business organizations, social artefacts and social events (see the bottom-right of Fig. 1) bring together the key parties and events, which can naturally be used to track key people and events in runtime. This enables quick decision making and inferring (semi-) automated corrective/prevention actions. Complex Event Processing (CEP) [32] is adopted by the proposed framework for realizing this component by applying our previous work in this area as reported in [34, 35]. CEP technology mainly combines data from multiple sources to infer events or patterns that suggest more complicated circumstances. For example, if we consider that the BP model under consideration is the Customer Relationship Management (CRM) BP of a telecommunication company as introduced in Sect. 5, then the events of interest are the problems/disruptions that hinder customers’ satisfaction, e.g., a customer complaining about extra charges added to her mobile phone bill, or a customer suffering from no network coverage in his/her area etc.

Based on the monitoring results, the analysis component is responsible for performing complex data analysis and reasoning, by the continuous interaction with the knowledge component. Particularly, the analysis component carries out processing, correlation, and analysis of event streams to detect the occurrence of disturbances. To realize this component, our analysis approach exploits and integrates data mining and machine learning techniques, i.e., clustering and classification techniques. The next discussion focuses on presenting in detail the concrete analysis approach that realizes this component, which represents the main focus of this article.

Based on the results of the analysis component, the planning component is responsible for establishing a preventive/corrective action plan to avoid/minimize the impact of the problems detected by the analysis component. The action plan will be mainly constructed semi-automatically by a planning agent that infers from the knowledge base -based on the history of recovery plans- the most appropriate recovery plan(s), ranked based on a number of selected features. Then, the BP expert can make the final decision through the intuitive interaction with the dashboard.

Finally, the execution component involves the automated application of the self-healing plan produced from the planning component to the respective running BP instance. For example, if the analysis component detects a network degradation issue, and the planning component proposes the recovery plan as including an ad-hoc BP
activity that assigns extra minutes to the affected customer, then the execution component actually sends signals to the BP execution engine to execute this ad-hoc BP instance in the new planned sequence. The work to realize the concrete approach of the related planning and execution components is ongoing and will be considered for future publications.

4 The Analysis Approach: Integrating Data Mining and Machine Learning Techniques

Figure 2 depicts the major activities of the analysis approach as described in the framework presented in Sect. 3. Starting from the left hand-side of the figure, users of Twitter typically tweet by complaints/compliments/inquiries of the service provided by a specific service provider, for example, services of a telecommunication company as used as the running scenario in this article. Once the tweets are received, they are stored in its raw format, so that they can be eventually used for learning and analysis purposes. When sufficient amount of raw tweets data is available in the raw tweets log, the flow then goes to the “Filtration” activity. This activity is required to remove tweets of positive sentiment since we are only concerned with negative tweets representing complaints/problems the customer is facing.

![Fig. 2. Activities of the proposed analysis approach](image-url)
Then the process goes to “clustering tweets” activity. The main objective of clustering here is to identify the labels/topics of problems faced by the customers, and to detect any unforeseen/unexpected patterns. Clustering is unsupervised machine learning problem and is performed in our approach by using Twitter LDA [35] (Latent Dirichlet Allocation). Twitter LDA is a text data mining clustering algorithm to extract hot topics from text. It includes a two-step approach to twitter data analysis. The first is to generate a topic model and the second to cluster tweets into topic-based categories. Twitter LDA clusters the tweets by automatically inferring/identifying hot topics (customer’s problems in our case), and then generating a number of tweets clusters based on these topics.

Then, the flow goes to the “Labelling” activity, which is responsible for annotating each tweet by one or more problem topic(s), identified by the prior “Clustering” activity. The “Labelling” activity operates semi-automatically, such that it refers to a dictionary we have built representing the words that are related to each problem topic, and requires an expert’s validation. If a tweet contains words that are not defined in the dictionary, the human expert will be prompted to manually decide on the label. These annotation labels that we call problem topic labels are required for the next classification activity that builds the prediction model.

The “Creation of the Prediction Model” activity applies the Sequential Minimal optimization (SMO) classification technique [36]. Our selection of this technique is based on an analytical evaluation of the accuracy of several evaluation techniques, which includes: Random Forest [37], Naïve Bayes [38], Naïve Bayes Multinomial [39], Sequential Minimal optimization (SMO) [36] classification algorithms. The evaluation accuracy of SMO was 76.7% in our controlled experiment. We have used WEKA for this purpose, which implements a large collection of machine learning algorithms for data mining tasks². The goal of this activity is to build a prediction model that once given a new tweet, it predicts whether it represents a problem and then identifies its problem topic. Then, afterwards, this tweet associated with its predicted topic label will be stored in a transient data store (called New batch of tweets in the diagram) that receives batches of new tweets outputted from the prediction model for applying further analysis steps on them (The batch size could be adjusted by size or on daily basis according to the density of the tweets received).

Following the two-fold classical machine learning methodology, first, the model is trained; second, the model is tested to determine its accuracy. Typically, classification of texts usually follows a mathematical approach by representing words as vectors called wordToVector representation, then the selected classification algorithm works on classifying these vectors and building the prediction model.

After building the prediction model and being deployed for the analysis of new streamed tweets, “Getting the thread of each tweet” activity is responsible for organizing each tweet with its replies sequentially to be viewed as a dialogue between the customer and the service provider in an easy to visualize way. This component is implemented in Python programming language.

The tweet thread is then given as an input to “Detecting the customer satisfaction/dissatisfaction” activity, which indicates whether the customer of this tweet thread is satisfied, dissatisfied, neutral, or incomplete thread (incomplete occurs when the customer does not reply). In other words, this activity concerns itself with computing the sentiment score of the customer’s tweet thread, and then amending it with the result of the sentiment score.

“Detecting the delta time for each thread” activity computes the time between the user tweet and the company’s reply (i.e., retweet). In many organizations, there is a violation if the company took longer time than allowed to reply to the customer. This metric/feature will be added to detect time violations, which can be tuned according to the company’s policies.

Afterwards, these extracted measures are added to the social log (see Fig. 4 for a snapshot of the social log) and then presented on the dashboard for business experts, by highlighting/alerting events that need attention. This is considered as the output of the analysis component in our proposed framework demonstrated in Sect. 3. The social log is formed from 8-tuple as follows:

< id, t, twt, Pid, username, Pb, Sent, Res >

Where:
- **id**: tweet id.
- **t**: timestamp of the tweet.
- **twt**: tweet text.
- **Pid**: parent id of the tweet that detects whether the tweet is a retweet or it’s the first tweet.
- **Username**: name of the user who sent the tweet.
- **Pb**: problem topic predicted by the classifier.
- **Sent**: sentiment of the tweet whether it is positive, negative, or neutral.
- **Res**: result of the issue between the client & the service provider. It can be satisfied, unsatisfied, not complete case, or neutral.
- **time measure** is a calculated measure not added in the social log.

The next Planning component as presented in the framework in Sect. 3 also follows a machine learning technique, which assumes that the business expert first (semi-automatically) decides on how to respond to sufficient number of detected disruptions/problems by the aid of the clusters inferred in the analysis phase (the results of the “Clustering” activity in Fig. 2). These clusters will point to relevant BP activities/fragments that the business expert needs to interrogate to resolve the detected disruptions. The resolution plan/actions decided by the business expert for each disruption is/are also stored in the repository, along with an indication of how much the customer was satisfied with this reconciliation. This data is then used to build a new classification model, which is capable of automatically inferring the possible recovery plan/actions to resolve future detected violations. Given the fact that humans/experts should always be in the loop, during the Execution phase, the business expert has to
check the automatically generated recovery plan and can make modifications, if needed. The details of our integrated “Planning & Execution” approach is left for a next publication.

5 Application of the Analysis Approach on a Case Study

In order to validate the applicability, efficiency and utility of the proposed analysis approach described in Sect. 4, we have considered a real-life case study of a leading telecommunication company that provides mobile communication services, and applied the analysis approach on. For this purpose, we have collected tweets using Java twitter API\(^3\), by filtering them based on #TheCompanyName. The attributes of interest include tweet ID, created (which specifies the date and time of the tweet), text of tweet, user name of the sender, parent ID, and sentiment score (‘0’ means neutral, ‘+ve’ integer means satisfied, and ‘-ve’ integer means unsatisfied). Figure 3 shows excerpt of the collected tweets.

![Table of raw tweets](image_url)

Fig. 3. Example of raw tweets

As shown in Fig. 3, the raw tweets cannot give clues about anything if left without further analysis. We will apply the analysis approach discussed in Sect. 4 on these unstructured/raw tweets.

First, the Filtration activity is applied to remove the tweets of positive sentiment since we are only concerned with unsatisfied customers/tweets. This activity resulted in 5,191 tweets.

Then the flow goes to the Clustering activity, where we run Twitter LDA [35] on the filtered dataset of tweets, and nine clusters were generated corresponding to nine topics of problems (Problem topic labels): (1) Internet (2) Customer-service (3) Mobile-
data/cellular (4) Network (5) Signal (6) Financial (7) Phone-services (8) Sales (9) Other⁴.

Then *Creation of the prediction model* is done using classification on WEKA. The previously mentioned topics of problems represent the annotation problem topic labels for the training step in the classification model. Then, 80% of the tweets are used as a training set and 20% as a testing set. Accordingly, we have 4,152 tweets as a training set and 1,039 tweets for testing purpose, which have been semi-automatically annotated with one or more of the nine identified topics above (as the result of the prior clustering activity). The annotations have been conducted by developing a python program to automatically detect the words of interest and suggest the annotations. For example, if annotation program finds in the tweet key-words like ‘credit’, ‘bill’, ‘billing’, ‘charge’, ‘overcharge’ and ‘credit card’ then it will annotate this tweet with ‘Financial’ as the problem topic. Having the data sets annotated, the classification model is then built.

The test data set is then used to estimate the accuracy of the generated prediction model. We have tested the model across several classification algorithms, including: Random Forest [37], Naïve Bayes[38], Naïve Bayes Multinomial [39], Sequential Minimal optimization (SMO) [36]. Our evaluation results showed that Sequential Minimal optimization (SMO) has the best results as will be demonstrated next in Sect. 5.1.

Fig. 4. Example of the created social log

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⁴ “Other” means that the person is tweeting by un-meaningful words or not a related tweet indicating a potential problem.
Then, getting the tweet’s thread, detecting customer satisfaction/dissatisfaction, and getting the delta time for each thread steps are done on our dataset (original data set of 8,719 tweet) to create the Social Log as illustrated in Sect. 4. A snapshot of the social log is depicted in Fig. 4.

By creating this social log from the raw tweets, the telecommunication company in our running scenario can gain profound insights and can take informed decisions. Aggregated statistical analysis could also be performed to get insights for example of the total number of satisfied/dis-satisfied customer and if they are in line with their strategic plans, and what recovery/correction actions they can take to alleviate any deficiencies.

5.1 Results and Discussion

This section demonstrates the results of the machine learning algorithms we used for testing the classification models we have deployed in our proposed framework. However, before showing the results we have to clarify the meaning of some key terms [40]:

- **True Positives (TP):** These are the correctly predicted positive values, which means that the value of actual class is positive, and the value of predicted class is positive.
- **True Negatives (TN):** These are the correctly predicted negative values, which means that the values of both the actual predicted classes are negative.
- **False Positives (FP):** These cases represent the situation when the actual class is negative and predicted class is positive.
- **False Negatives (FN):** These cases represent the situation when actual class is positive but the predicted class is negative.
- **Accuracy:** Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. One may think that, if we have high accuracy then our model is good enough. Nevertheless, accuracy is a great measure but only when you have symmetric datasets, where values of false positive and false negatives are almost the same. Therefore, you have to look at other parameters to evaluate the performance of your model.

\[
Accuracy = \frac{TP + TN}{TP + FP + FN + TN}
\]

- **Error rate (Err):** The complement of Accuracy is the error rate, which evaluates a classifier by its percentage of incorrect predictions. Accuracy and Err are general measures and can be directly adapted to multiclass classification problems.

\[
Err = 1 - Accuracy = \frac{FP + FN}{TP + FP + FN + TN}
\]

- **Precision:** Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. High precision relates to the low false positive rate.

\[
Precision = \frac{TP}{TP + FP}
\]
• **Recall (Sensitivity):** Recall is the ratio of correctly predicted positive observations to the all observations.

\[
Recall = \frac{TP}{TP + FN}
\]  

• **F1 score:** F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it is better to look at both Precision and Recall.

\[
F1 Score = \frac{2 * (Recall * Precision)}{Recall + Precision}
\]

Figure 5 shows the performance results of the four classification machine-learning algorithms, which are Random Forest, Naïve Bayes, Naïve Bayes Multinomial, SMO (Sequential Minimal Optimization). (The total number of instances here is 5191 tweet) SMO refers to the specific efficient optimization algorithm used inside the SVM Support Vector Machines implementation. From the results, one can see that SMO has the best results. As discussed in [41] SVM are supervised learning classification algorithms which has been extensively used in text classification problems due to the sparse high dimensional nature of the text with few irrelevant features.

Table 1 depicts the detailed accuracy measures by class for SMO classification algorithm, which has the best results in our case study.
6 Conclusions and Future Work

Business processes represent the foundation of all organizations, and as such, organizations are striving for their continuous improvement throughout the complete BP lifecycle. The emergence and the wide adoption of web 2.0 technologies represents a paradigm shift in how individuals collaborate in their businesses and daily lives, enabling organizations to take a customer-centric operating model, and subsequently achieve a competitive advantage. This paradigm shift is known as social business processes or business processes 2.0. This paper contributes with a novel framework that exploits the huge amount of social data (in particular twitter) to enable the identification and resolution of runtime business process disruptions (problems affecting customers’ satisfaction in different domains). The main objective of the framework is to inject self-healing capabilities into BPM systems, where the system is autonomously capable of discovering, diagnosing and reacting to disruptions. The paper then proposes a concrete analysis approach by utilizing and integrating text mining techniques (i.e. Twitter LDA), machine learning techniques (i.e. SMO, Naïve Bayes, Naïve Bayes Multinomial, Random Forest classification algorithms using WEKA) to realize the self-diagnosis component.

The proposed analysis approach has been implemented and applied on a real-life case study of a telecommunication company, and our evaluation study revealed that there exists a strong correlation between data analytics of the social side and improving its adherent twin; the business side. The huge amounts of data on the social side can always be utilized to enhance the business side, by removing the cover from many problems and violations that are taking place between users and the organization and can degrade their business if left unnoticed.

Ongoing and future work is going in a number of parallel and complementary directions. This includes:

- Incorporation and integration of other heterogeneous free text social media networks, such as Facebook, to extract more faithful knowledge, for better informed decision-making and better action taking.

<table>
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• Incorporation of ontologies to capture the semantics of the social and BP worlds, enable their semantic alignment and the integration of heterogeneous social media sources.

• Application of the proposed framework on enterprise social networks [42], which are dedicated private social networks adapted by organizations internally and externally to connect individuals who share similar business interests or activities. Although, we claim that our framework and results are applicable to enterprise social networks, however, this needs a dedicated experimental study for its validation.

• Intensifying the validation and evaluation of the proposed framework by considering other case studies from different industrial sectors, while comparing the domains that are more prone to the adoption of this technology.

• Accommodating with the large volume of today’s big data by incorporating a big data platform, such as Hadoop to support the scalability of the proposed framework and its underpinning approaches.

Acknowledgements. We wish to thank Dr. Ahmed Awad, Institute of Computer Science, University of Tartu, Estonia, for providing the essentials of the case study in this paper and for the fruitful discussions and advices.

References

30. IBM: An architectural blueprint for autonomic computing. IBM (2005)
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