A Decision Support Approach based on Sentiment Analysis Combined with Data Mining for Customer Satisfaction Research

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***Abstract*—This paper describes the application of a novel domain-independent decision support approach for Customer Satisfaction Research. It is based on customer satisfaction research through deep analysis of consumer reviews posted on the Internet in natural language. Artificial Intelligence techniques, such as web data extraction, sentiment analysis, aspect extraction, aspect-based sentiment analysis and data mining, are used for realization of consumer reviews analysis. In paper, specific Internet resources (such as yelp.com, tripadvisor.com, tophotels.ru) are used for accumulating customer reviews as a data source. This is performed in accordance with the quality standard ISO 10004 and proposed decision support approach, which allows for both qualitative and quantitative customer satisfaction surveys to be carried out. The output of the quantitative survey are values of customer satisfaction with product and each product's aspect. The output of the qualitative survey are significance values of products aspect for customers and identified latent relations between overall satisfaction with product and satisfaction with products' aspects. The proposed approach is performed as a prototype of a decision support system. To evaluate the efficacy of the proposed approach, two experiments on hotels and banks customer reviews have been carried out. The obtained results prove the efficacy of the proposed decision support approach for quality management and the concept of using it instead of classical methods of qualitative and quantitative research of customer satisfaction.**

Keywords-customer satisfaction research; decision support system; sentiment analysis; data mining.

I. INTRODUCTION

In order to provide product quality, a company should make effective managerial decisions. In the modern world, the efficacy of managerial decision-making process depends on the information available to the person that makes decisions and the depth of information analysis. Therefore, a company should develop processes of automated collection of information and its further processing and analysis. Decision-making should be based on the knowledge and principles obtained during the analysis of the collected data. In this article, we expand on our research work presented at The Third International Conference on Data Analytics (2014) [1].

Quality assurance is currently attained through a process approach based on the model of a quality management system [2] (see Figure 1). It describes the interaction of the company and the customer during the process of product production and consumption. To correct the parameters of a product's quality in order to improve it for the customer, the model has feedback. For companies, feedback during the process of quality management is the information about the level of customer satisfaction, which is expressed in the form of customer reviews about a product's quality. That is why customer satisfaction is key information for quality management that influences decision-making.

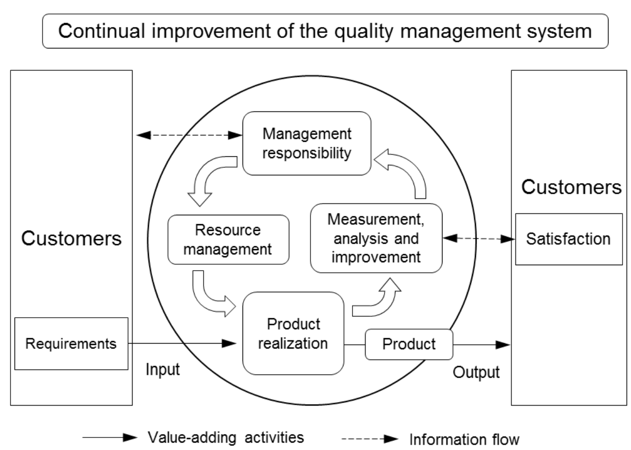

Figure 1. Model of a process based quality management system.

To collect data and evaluate customer satisfaction, International Quality Standards ISO 10004 (International Organization for Standardization) recommends using the following classical methods: face to face interviews, telephone interviews, discussion groups, mail surveys (postal questionnaires), on-line research and surveys (questionnaire surveys) [3]. However, these methods of collection and analysis of customer opinions have a number of significant drawbacks.

A general drawback of these methods is a large amount of manual work: preparing questions, creating a respondent database, mailing questionnaires and collecting results, conducting a personal interview, and preparing a report. All of these procedures make a research expensive. These methods cannot monitor customer satisfaction continuously. For this reason, monitoring is limited by a one-time period, because costs rapidly grow with an increase in the frequency of monitoring. There is no possibility for monitoring trends of customer satisfaction. It also has a negative influence on lengthiness of managerial decision making.

Another problem regards various scales for measuring customer satisfaction and their subjectivity perception. Value of customer satisfaction is estimated by abstract satisfaction indices that are difficult to understand, hard to compare and interpret. Furthermore, methods for data analysis recommended by ISO 10004 [3] allow detection of only linear dependencies and relations in data, such as linear correlation. Using only linear methods researcher could miss the impact of the mutual satisfaction of the product's aspects to the overall satisfaction with a product. In paper, an aspect means characteristics, attributes, and properties that characterize the products, e.g., a “phone battery” or “delivery period”.

The aim of this paper is the development of a decision support approach for quality management provided by analysis of customer reviews on the Internet with use of web data extraction, sentiment analysis, aspect extraction, aspect-based sentiment analysis and data mining that could overcome the aforementioned drawbacks of the classical approach for customer satisfaction research. The main contribution of our research is novel approach using results of sentiment analysis for further knowledge extraction about dependencies between overall satisfaction with product and product's aspects.

The remainder of this paper is organized as follows: in Section II, we focused on overview of recent solutions and frameworks for analysis of user generated content and their drawbacks. In Section III, we described architecture and workflow of proposed decision support system. In Section IV, we described using text mining and data mining techniques for qualitative and quantitative customer satisfaction surveys. In Section V, we provide two experiments of customer satisfaction research: 1) qualitative and quantitative surveys for two hotels and whole resort and 2) qualitative survey for Russian banks.

II. RELATED WORK

Applying Text Mining tools for analyzing customers' reviews posted on the Internet is not novel. There are many studies concerning models and methods for data collection, sentiment analysis and information extraction. Recent studies show acceptable accuracy of methods for sentiment classification. Gräbner et al. [4] proposed a system that performs the sentiment classification of customer reviews on hotels. The precision values are 84% for positive and 92% for negative reviews. Lexicon-based method [5] allowed the correct classification of reviews with a probability of about 90%. These achievements make sentiment analysis applicable for an application on quality management and customer satisfaction research.

Jo and Oh [6] and Lu et al. [7] considered the problems of automatically discovering products' aspects and sentiments estimation for these aspects, which are evaluated in reviews. For solving these problems, they suggested methods based on Latent Dirichlet Allocation [8] and its modifications.

A lot of social monitoring systems and frameworks have been developed for automatic analysis of reviews and topics. Liu et al. [9] presented framework called Opinion Observer for analyzing and comparing consumer opinions of competing products. This prototype system is able to visualize the strengths and weaknesses of each product in terms of various product features. For visualization it use actual number of positive or negative opinions normalized with the maximal number of opinions on any feature of any product. For experiments, authors used reviews on electronic products. Kasper and Vela [10] presented a web based opinion mining system for hotel reviews and user comments that supports the hotel management called BESAHOT. The system is capable of detecting and retrieving reviews on the web, classifying and analyzing them, as well as generating comprehensive overviews of these comments. Ganu et al. [11] focused on an analysis of free-text reviews by means of classification of reviews at the sentence level, with respect to both the topic and the sentiment expressed in the sentences. For experiments, authors used reviews on restaurants. Blair-Goldensohn et al. [12] proposed a system that summarizes the sentiment of reviews for a local service, such as a restaurant or hotel. In particular, they focus on aspect-based summarization models, where a summary is built by extracting relevant aspects of a service, such as service or value, aggregating the sentiment per aspect, and selecting aspect-relevant text. Bjørkelund et al. [13] described how the results of sentiment analysis of textual reviews can be visualized using Google Maps, providing possibilities for users to easily detect good hotels and good areas to stay in. Ajmera et al. [14] developed a Social Customer Relationship Management (SCRM) system that mines conversations on social platforms to identify and prioritize those posts and messages that are relevant to enterprises. The system aims to empower an agent or a representative in an enterprise to monitor, track and respond to customer communication while also encouraging community participation. Bank [15] proposed interactive Social Media monitoring system to extract related information from user generated content. One of the important contribution of this work was the proposition of new quality indeces. One of the important contribution of work was proposition of new quality indeces. The Relevancy Index states the importance of a given topic and provides a robust marketing and market penetration independent importance information. The Market Satisfaction Index provides the possibility to compare several product features among different products or manufacturers. The Product Satisfaction Index extracts the advantages and disadvantages of a product.

In some related work, authors pay attention to relations between overall ratings of products, and ratings of products' aspects evaluated in the review. Wang et al. [16] formulated a novel text mining problem called Latent Rating Analysis (LARA). LARA aims at analyzing opinions expressed in each review at the level of topical aspects to discover each individual reviewer's latent rating on each aspect as well as the relative importance weight on different aspects when forming the overall judgment. For solving this problem probabilistic rating regression model is used. For experiments, authors used reviews on hotels. De Albornoz et al. [17] aimed to predict the overall rating of a product review based on the user opinion about the different product features that are evaluated in the review. For experiments, authors used reviews on hotels.

Wachsmuth et al. [18] formulated and validated an important hypothesis that the global sentiment score of a hotel review correlates with the ratio of positive and negative opinions in the review's text and that the global sentiment score of a hotel review correlates with the polarity of opinions on certain product features in the review's text.

The main drawback of these considered systems is that they can provide entirely only a quantitative survey of customer reviews, i.e., they can provide measurement of the degree of customer satisfaction with a product and its aspects. Qualitative survey were usually only conducting the extraction of products' aspects. However, estimation of the significance of each products' aspects for the customer is missed. The information about products' aspects that influence customers' satisfaction and relative importance of products' aspects for the customers is missing, as well as an insight into customer expectations and perceptions.

The most related work to this problem is [19]. It is dedicated to the topic of aspect ranking, which aims to automatically identify important aspects of product from online consumer reviews. Most proposals used a probabilistic model with a large number of parameters that lead to low robustness of the model. Total weighting values of aspects are calculated as the average of the weighting values by each review. Finally, significance values of aspects are estimated independently of an opinion's sentiment, e.g., in real life, we can discuss in review about bad "signal connection", but we usually omit comments in case of good "signal connection", because it must be in phone. In our paper, we estimate significance values of aspects in accordance with their positive and negative sentiments. In this manner, it is possible to use the Kano's model of customer satisfaction [20], which classifies customer preferences into four categories.

In this paper, for qualitative survey is used a novel approach based on transformation results of sentiment analysis and aspect-based sentiment analysis, such as sentiment labels of reviews and mentions about product's aspects in reviews, into boolean data. After that, boolean data is processed with a data mining tool – decision tree (see Section IV). Qualitative survey aims to identify how the sentiment of reviews depends on the sentiment of different products' aspects. In other words, how overall customer satisfaction with product depends on the customer satisfaction with a product's aspects. Decision tree performs this aim and identifies latent relations between the sentiment of reviews and sentiment of a product's aspects. Also using the decision tree allows to estimate the significance of product's aspects for the customers. Output of qualitative survey are significance values of product's aspects for customers and identified latent relations between satisfaction with product and satisfaction with each product's aspect, which produced as rules extracted by the decision tree. The availability of both quantitative and qualitative surveys allows realizing Intelligent Decision Support System for Quality Management in accordance with quality standard ISO 10004.

III. THE PROPOSED DECISION SUPPORT APPROACH

The suggested approach to decision making in product quality management accomplished through unification of methods for collecting and processing text data into Intelligent Decision Support System (IDSS). The architecture (subsystems and contained modules) of the obtained IDSS is presented in Figure 2. The subsystem of monitoring and data collection fills the warehouse with customer reviews and other relevant information. It also supports the actuality of data via automated monitoring of Internet resources and carries out data cleansing. In the subsystem of monitoring and data collection is realized methods of web data extraction. The data storage subsystem provides safe-keeping and integrity of collected reviews and results of data processing. In the subsystem of data analysis are realized methods of aspect extraction, sentiment analysis of reviews, aspect-based sentiment analysis, and decision tree. In subsystem of user interaction is visualized results of analysis.

In Figure 3, the algorithm of the IDSS is presented. It consists of four stages. The first stage includes collection of reviews from Internet resources, data cleansing and loading reviews into the database. IDSS is able to actualize data everyday and to correct current customer satisfaction that allows provide continuous monitoring. The second stage performs processing collected reviews. It includes preprocessing procedures, such as preparing training samples of reviews for sentiment classifier, text lemmatization, and encoding text of reviews in vector form. Processing procedures include extraction of a product's aspects, training of the classifier and sentiment analysis of reviews and aspect-based sentiment analysis.

The third stage is the quantitative survey. The quantitative survey is based on sentiment analysis of reviews entirely, and aspect-based sentiment analysis of sentences with mentions of a product's aspects. Sentiment classification is attained through binary scale – positive and negative sentiments. As a measure of the customer satisfaction with product is used a ratio of positive reviews to the sum of positive and negative reviews. As a measure of the customer satisfaction with product's aspects is used a ratio of positive sentences with mentions of a product's aspect to the sum of positive and negative sentences with mentions of a product's aspect. The output of the quantitative survey is values of customer satisfaction with a product and each product's aspect.

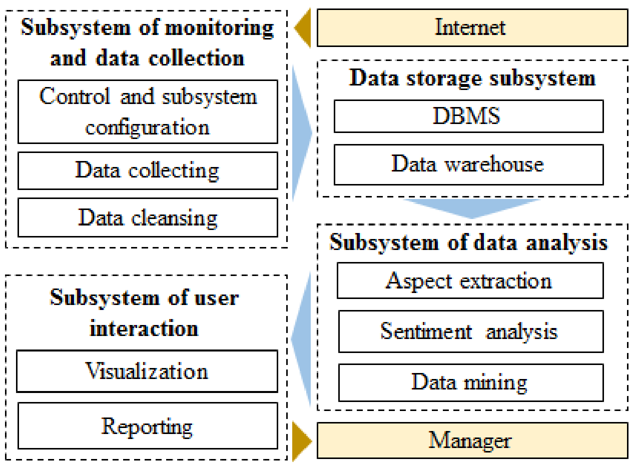

Figure 2. The architecture of Intelligent Decision Support System for product quality management.

The fourth stage is the qualitative survey of customer satisfaction. It is based on transformation results of sentiment analysis into Boolean data and following constructing of decision tree on it. The qualitative survey aims to identify how sentiment of review depends on the sentiment of different aspects of a product. Decision tree performs this aim and identifies latent relations between sentiment of a review and sentiment of a product's aspects. The output of the qualitative analysis is significance values of a product's aspects for customers and identifying latent relations extracted by decision tree. Managerial decision development and making is carried out on the basis of the performed quantitative and qualitative surveys.

IV. Applied Artificial Intelligence Techniques

In this section are described implemented AI techniques for customer satisfaction surveys and support decision making.

A. Data collection

Nowadays there are a large number of Internet resources where users can leave their opinions about products and services. The most popular examples of review sites are tophotels.ru (635 thousand reviews), yelp.com (53 million reviews), tripadvisor.com (130 million reviews). Similar resources continue to gain popularity. As opposed to social networking services, the advantage of review sites lies in their purpose - accumulation of customer reviews. One more advantage is that many of such resources have moderators of reviews and confirmation of author's objectivity, e.g., registration procedure.

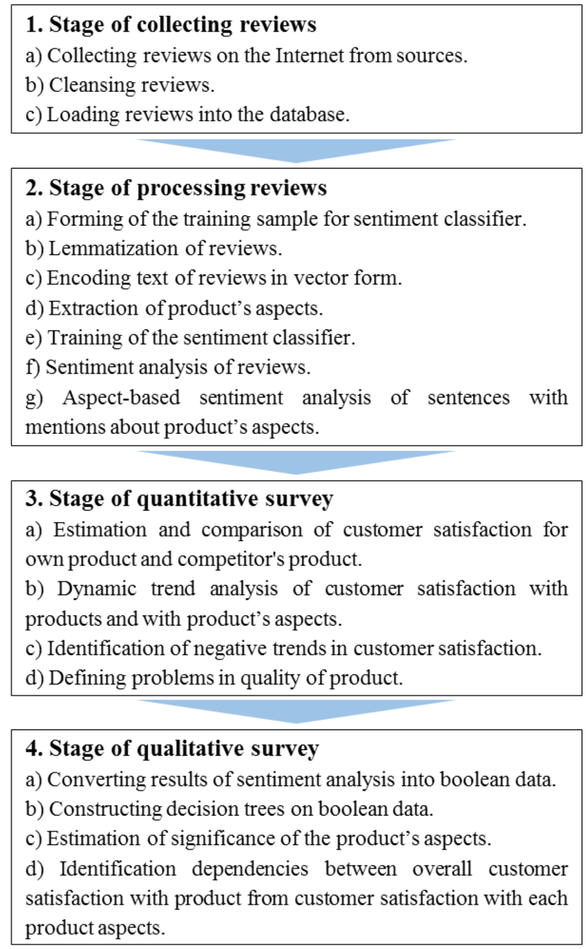

Figure 3. Working algorithm of Intelligent Decision Support System

There are two main types of collecting data from the Internet resources of customer reviews: 1) by using API (Application Programming Interface), and 2) by web data extraction. API is a set of ready-to-use tools - classes, procedures, and functions - provided by the application (Internet resource) for using in an external software product. Unfortunately, only a few resources that accumulate reviews have API.

In this paper is used the second method for data collection – web data extraction. It is a process of automated content collection from HTML-pages of any Internet resource using special programs or script. Related work is presented in [21][22]. Scheme of reviews collection is presented in Figure 4. Web pages of review sites have specific HTML-structure that includes separate blocks with the name of a product or company, author's review, and other blocks with additional information, such as date, place. Therefore, all reviews are clearly identified in relation to the object of review. It significantly simplifies the process of data collection in contrast to collecting messages from social networking services.

Input: review site

1. Gathering links on pages with reviews or generating links by using a template.
2. Setting boundaries for a content by using a HTML-structure.
3. Collection data on the set of links.
4. Cleaning data and removing duplicates.
5. Loading data into the database.

Output: set of customers' reviews *D*

Figure 4. Algorithm of web data extraction

B. Sentiment Analysis

After data collection, it is possible to process review data with Text Mining tools. In this paper automatic sentiment analysis of reviews is used to evaluate customers' satisfaction with product and product's aspects. Sentiment stands for the emotional evaluation of author's opinion about a product that is referred to in the reviews.

There are three main approaches to sentiment analysis: 1) linguistic, 2) statistical, and 3) combined. The linguistic approach is based on using rules and vocabularies of emotionality words [23][24]. This approach is quite time-consuming due to the need of compiling vocabularies, patterns, and making rules for identifying sentiments. However, the main drawback of this approach is the impossibility to get a quantitative evaluation of the sentiment. The statistical approach is based on the methods of supervised and non-supervised machine learning (ML) [25][26]. The combined approach presupposes a combined use of the first two approaches.

In this paper we used methods of supervised machine learning – naïve Bayesian classifier and Support Vector Machines. Text sentiment evaluation can be expressed quantitatively. Their realization in IDSS is based on techniques described by Pang and Lee [25][26]. More detailed information about implemented methods of sentiment analysis used in this paper can be found in our previous work [27][28]. In Figure 5 algorithms of learning and classification for naïve Bayes classifier based on Multinomial model are presented. An advantage of these ML methods that they are quite easy in software implementation, and do not require making linguistic analyzers or sentiment vocabularies. They are able to evaluate sentiment quantitatively. For sentiment classification is used binary scale - positive and negative tonality. We use vector representation of review texts with help of the bag-of-words model. As attributes, we consider bit vectors - presence or absence of the word in the review text, and frequency vectors – a number of times that a given word appears in the text of the review. Lemmatization is also used. We also used lemmatization that transforms all the words of the review to the initial form.

Learning of naive Bayes classifier
Input: training set of reviews $D' = \{(d_1, c_1), \ldots, (d_m, c_m)\}$, set of classes $C = \{positive, negative\}$.

1. Extract all words from *D'* to the vocabulary *V*
2. For each $c \in C$ do
   3. Count documents N^c in each class *c*
   4. Calculate probability $p(c) = N^c / N$
   5. For each $w_t \in V$ do
      6. Count number of occurrences $K^c_{w_t}$ of word w_t in each class
      7. Calculate prob. $p(w_t \mid c) = (K^c_t + 1) / \sum_{t=1}^{|V|} (K^c_t + 1)$

Output: V, $p(c)$, $p(w_t \mid c)$

Classification with naive Bayes classifier
Input: review *d* from set *D*, *V*, $p(c)$, $p(w_t \mid c)$

1. Extract all words from *d* to the vocabulary V_d
2. For each $c \in C$ do
   3. Calculate $score[c] = \ln p(c)$
   4. For each $w_t \in V_d$ calculate $score[c] \mathrel{+}= \ln p(w_t \mid c)$
5. If $score[pos] > score[neg]$ than $d \in positive$ else $d \in negative$

Output: sentimental label *Sent* of review *d* (positive/negative)

Figure 5. Algorithm of naïve Bayes classifier

C. Aspect-based Sentiment Analysis

Sentiment Analysis of reviews allows the evaluation of overall customer's satisfaction with product. However, it does not clearly show what customers like about a product and what they do not like. To answer this question, it is necessary to perform an aspect-based sentiment analysis. An aspect means characteristics, attributes, and properties that characterize the products, e.g., a "phone battery" or "delivery period". However, one product can have a great number of aspects. Furthermore, aspects in the text can be expressed by words-synonyms, e.g., "battery" and "accumulator". In this case, it makes sense to combine aspects into aspect groups.

Aspect-based sentiment analysis of the review is a more difficult task and consists of two stages – identifying all product's aspects and determining the customers' sentiment of the comment on them. To complete the task of the aspect-based sentiment analysis, we developed a simple algorithm (see Figure 6). Aspects extraction based on the frequency of nouns and noun phrases mentioned in reviews based on work [29].

A frequency vocabulary [30] (created on text corpus) that helps to compare the obtained frequencies from reviews with frequencies from corpus is used to identify aspects. The nouns with maximum frequency deviations are claimants to be included into aspect groups. Clustering of the nouns into aspect groups was carried out manual. It should be noted, that if a sentence includes nouns from several aspect groups, then it would refer to opinion about each aspect group of these nouns.

Aspect extraction
Input: set of reviews D

1. Extract all nouns S from the set of reviews D.
2. Count the frequency of nouns $\forall t = 1, |S| : f_t = N_t / N$ in the whole set of reviews D, where N – number of appearances of all words, N_t – number of appearances of the t noun.
3. Count the difference $\forall t : \Delta_t = f_t - f_t^v$ between the counted frequencies f_i and vocabulary frequencies f_t^V.
4. Sort the set of nouns S in descending order Δ_t.
5. Divide the set of nouns S from $\Delta_t > 0$ into aspect groups.

Output: set of aspect groups and aspect words

Aspect-based sentiment classification
Input: sentiment classifier, set of aspect groups and aspect words

1. Divide a set of reviews into set of sentences.
2. Perform sentiment classification for each sentence.
3. Check each sentence for the condition: if a sentence has a sentiment score (negative or positive) greater than a threshold h and contains at least one noun from any aspect group, then this sentence is labeled as an opinion (negative or positive) about the given product's aspect.

Output: labeled sentences with mentions about product's aspects $\{Neg_{i1},\ldots,\ Neg_{im},\ Pos_{i1},\ldots,\ Pos_{im}\}$

Figure 6. Algorithm of aspect-based sentiment analysis

The results of sentiment analysis and aspect-based sentiment analysis can be presented in the form of text variables $Obj = (\mathrm{Re}\,v_i, Sent_i, Neg_{i1},\ldots,Neg_{im}, Pos_{1i},\ldots,Pos_{im})$, where Obj – a object or a product, Rev_i – text of the i review, $Sent_i$ – sentiment label of i review, Neg_{ij} – negative sentences with mention about the j aspect group in the i review, Pos_{ij} – positive sentences with mention about the j aspect group in the i review, i – number of review, j – number of aspect group, m – amount of aspect groups.

D. Data Mining

The present paragraph suggests an algorithm of the following processing of results of sentiment analysis and aspect-based sentiment analysis. The aim of the developed algorithm is to discover latent knowledge that can be used for decision support in product quality management. To realize this algorithm we use the Data Mining method – decision tree, since it is easy to understand and interpret results. It also can explain relations between overall sentiment of review and sentiment of each aspect group by means of Boolean logic.

Input: positive and negative sentences with mentions about product's aspects $\{Neg_{i1},\ldots,\ Neg_{im},\ Pos_{i1},\ldots,\ Pos_{im}\}$, vector of sentimental labels *Sent* of reviews.

1. Convert a text data $Obj = (\mathrm{Re}\,v_i, Sent_i, Neg_{i1},\ldots,Neg_{im}, Pos_{1i},\ldots,Pos_{im})$ into a boolean type by the following rules:
2. If $Sent_i = negative$, then $newSent_i = 1$, else $newSent_i = 0$
3. If $Neg_{ij} \neq null$, then $newNeg_{ij} = 1$, else $newNeg_{ij} = 0$
4. If $Pos_{ij} \neq null$, then $newPos_{ij} = 1$, else $newPos_{ij} = 0$
5. Creating a decision tree where the variable $newSent_i$ is a dependent variable from $\{newNeg_{i1},\ldots,\ newNeg_{im},\ newPos_{i1},\ldots,\ newPos_{im}\}$
6. Estimation significances of aspect groups and interpretation of extracted rules

Output: significance values of product's aspects, latent relations between satisfaction with product and satisfaction with aspects

Figure 7. Algorithm of data mining

The developed algorithm of knowledge discovery includes procedures presented in Figure 7. The main idea of this algorithm is to convert results of aspect-based sentiment analysis to Boolean data considering both positive and negative mentions about product's aspects. Then we apply decision tree for obtained Boolean data. The described algorithm allows understanding of which sentiment sentences about a product's aspects influence the overall sentiment of review or, in other words, what product aspects influence customer satisfaction and in what way. The constructed decision tree model allows the consideration of the influence on overall satisfaction with product of not only each satisfaction with some product's aspect, but also mutual presence of satisfaction and dissatisfaction with different product's aspects in the review. In other words, this approach is able to identify non-linear dependencies between overall satisfaction with product and satisfaction with product's aspects. The decision tree model also allows the detection of the most significant product's aspects that are essential for the customer.

In Figure 8 an example of decision tree model is presented. Nodes of the decision tree are the sentiment aspects' variables, i.e., presence or absence in the review sentimental sentences (positive or negative) with mention about some aspect from aspect group. Edges of the tree are the values of aspect variables, i.e., 1 is presence, 0 is absence. Leaves present overall sentiment of review, i.e., each branch leads to either a positive review or a negative review that meets customer satisfaction or dissatisfaction in dependence, which product's aspects satisfy or dissatisfy the customer.

The decision tree model can be expressed both in the form of Boolean functions (see Eq. (1)) in a disjunctive normal form, and in natural language as rules:

$$\begin{aligned}&Rule\ \ \#1:\ \overline{Neg.a.g.\#2} \to Pos.\ review\\&Rule\ \ \#2:\ Neg.a.g.\#2 \cap \overline{Pos.a.g.\#3} \to Neg.\ review\\&Rule\ \ \#3:\ Neg.a.g.\#2 \cap Pos.a.g.\#3 \cap \overline{Pos.a.g.\#1} \to Neg.\ review\\&Rule\ \ \#4:\ Neg.a.g.\#2 \cap Pos.a.g.\#3 \cap Pos.a.g.\#1 \to Pos.\ review\end{aligned}, \quad (1)$$

where $Neg.a.g.$ – negative mention about some aspect group in review, $Pos.a.g.$ – positive mention about some aspect group in review, $Pos.\ review$ – positive review, $Neg.\ review$ – negative review.

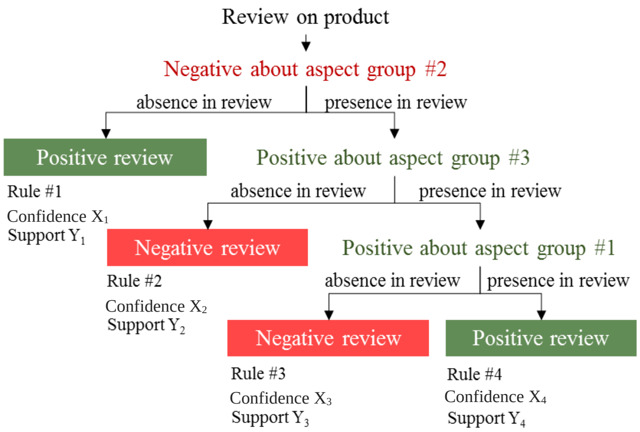

Figure 8. Example of the Decision Tree model

Each rule is characterized by measures of confidence and support. The confidence shows what percentage of reviews containing conditions of some rule, has the same sentiment corresponding to this rule. The support shows percentage of reviews that contain conditions of some rule regarding the entire number of reviews.

E. *Measures for customer satisfaction*

As a measure of the customer satisfaction with product is used a ratio of positive reviews to the sum of positive and negative reviews. The score of customer satisfaction *CS* by product is calculated by (2):

$$CS = \frac{Z^{pos}}{Z^{pos} + Z^{neg}} \cdot 100\%, \quad (2)$$

where Z^{pos} – the number of positive reviews, Z^{neg} – the number of negative reviews.

As a measure of the customer satisfaction with product's aspect groups is used a ratio of positive sentences with mentions of a product's aspect to the sum of positive and negative sentences with mentions of a product's aspect. The score of customer satisfaction cs_j with *j* product's aspect group is calculated by (3):

$$cs_j = \frac{z_j^{pos}}{z_j^{pos} + z_j^{neg}} \cdot 100\%, \quad (3)$$

where z_j^{pos} – number of positive sentences containing mention about the *j* product's aspect group, z_j^{neg} – number of negative comments containing mention about the *j* product's aspect group. Unlike indices in [3] (which often represent the average subjective values obtained with using rating scales) proposed measures show the ratio of positive / negative reviews to total number of reviews. It gives more clearer for understanding of monitoring results.

Significance of aspects group shows how much the sentiment of a review depends on the aspect group in positive and negative sentences, i.e., significance of product's aspects for customers. Let the number of aspect groups is *g/2*, then the number of independent sentimental variables *g*. According to the methodology described in [31] the equation (4) for calculating the significance of variable *m* is:

$$Sign_m = \frac{\sum_{j=1}^{k_m}\left(E_{m,j} - \sum_{i=1}^{q_{m,j}} E_{m,j,i} \cdot \frac{Q_{m,j,i}}{Q_{m,j}}\right)}{\sum_{l=1}^{g}\sum_{j=1}^{k_l}\left(E_{l,j} - \sum_{i=1}^{q_{l,j}} E_{l,j,i} \cdot \frac{Q_{l,j,i}}{Q_{l,j}}\right)} \cdot 100\%, \quad (4)$$

where k_l – number of nodes that were split by attribute *l*, $E_{l,j}$ – entropy of the parent node, split by attribute *l*, $E_{l,j,i}$ – subsite node for *j*, which was split by attribute *l*, $Q_{l,j}$, $Q_{l,j,i}$ – number of examples in the corresponding nodes, $q_{l,j}$ – number of child nodes for *j* parent node.

V. EXPERIMENT

A. *Qualitative and quantitative surveys for hotels*

The proposed approach can be applied for one language (English or French or German etc.). The approach is sensitive for reviewer's eloquence, command of the language, richness of expression, because we don't use specific techniques for this. Nevertheless, we assume that the sensitivity to linguistic peculiarities of review's text will decline with an increase in the training sample.

Efficacy evaluation of the developed IDSS was performed on the data obtained from 635,824 reviews about hotels in the Russian language. The reviews have been collected from the popular Internet resource tophotels.ru for the period of 2003-2013. The initial structure of the collected data consisted of the following fields: hotel name; country name; resort name; visit date; review's text; author's ratings of placement, food, and service. The data was preprocessed and loaded into the database SQL Server 2012.

Classifying of overall sentiment about product used a binary scale (negative and positive). A training set of positive and negative reviews was formed using the collected data on an author's ratings of placement, food, and service. The review site tophotels.ru uses a five-point grading scale. A review can have a maximum total rating of 15 points, and minimum total rating of 3 points. The training set included 15,790 negative reviews that have 3 and 4 total points, and 15,790 positive reviews that have 15 total points. We did not use the author's ratings for further data processing. Classification of another 604,244 reviews was carried out using a trained classifier.

For the purpose of training an effective sentiment classifier, the accuracy of classification was evaluated for machine learning methods and some peculiarities of their realization (see Table I). The measure accuracy as a ratio of the number of correctly classified reviews to total number of reviews was used to estimate classification accuracy. Accuracy estimation was performed on two sets of data. The first set (Test No. 1) represented a training set of strong positive (15,790) and strong negative reviews (15,790). Classifiers were tested by using cross validation by dividing the first set into 10 parts. The second set (Test No. 2) included random reviews from initial set of reviews (635,824) with different total points (3-15 points) and was labeled manual (497 positive and 126 negative). It was used only for accuracy control of the classifier that had been trained on the first data set.

TABLE I. COMPARISON OF METHODS FOR SENTIMENT CLASSIFICATION

#	Machine learning methods	Vector	Accuracy		
			Test No. 1	*Test No. 2*	*Base line*
1	SVM (linear kernel)[b]	Frequency	94.2%	83.1%	72.8%
2	SVM (linear kernel)	Binary	95.7%	84.1%	82.9%
3	NB[a]	Binary	96.1%	83.7%	81%
4	NB	Frequency	97.6%	92.6%	78.7%
5	NB (stop-words)	Frequency	97.7%	92.7%	-
6	Bagging NB	Frequency	97.6%	92.8%	-
7	NB (“negations”)	Frequency	98.1%	93.6%	-

a. Naïve Bayes Classifier. b. Support Vector Machine

To estimate influence of negative particles “not” and “no”, the tagging technique was used; for example, the phrase “not good” was marked as “not_good”, and was regarded by the classifier as one word. This negation technique allowed the increasing of sentiment classification accuracy (see classifier #7). Accuracy values are presented in the Table I. We used results obtained by Pang and Lee [19] for movie-review domain as a base line. Our results of classification accuracy looks better than the base line. This can be explained that we used more large training sample (31,580 vs 2,053). The most efficient ML method was Naïve Bayes classifier with negation technique (classifier #7). In Figure 9 are presented ROC-curves classifiers #4 and #7. The classifier #7 was trained on the training set and was used for further sentiment analysis of unlabeled reviews.

Using the aspect extraction algorithm (Section III), we extracted the nouns that were divided into seven basic aspect groups (see Figure 10): “beach/swimming pool”, “food”, “entertainment”, “place”, “room”, “service”, “transport”. The following step was extracting and sentiment classification sentences with words from aspect groups using classifier #7. However, not all sentences with aspects had a clearly expressed sentiment; therefore, the sentences with poorly expressed sentiment were filtered out using threshold *h*. Threshold *h* was chosen empirically and it allowed to cut sentences with weak sentiment. This algorithm of aspect-based sentiment analysis (Figure 6) is very simple and primitive, but it allows to realize its main aim - to identify sentences with strong sentiments (that form overall sentiment of review) with mentions about product's aspects, and filter out sentences with weak sentiment or without mentions about product's aspects.

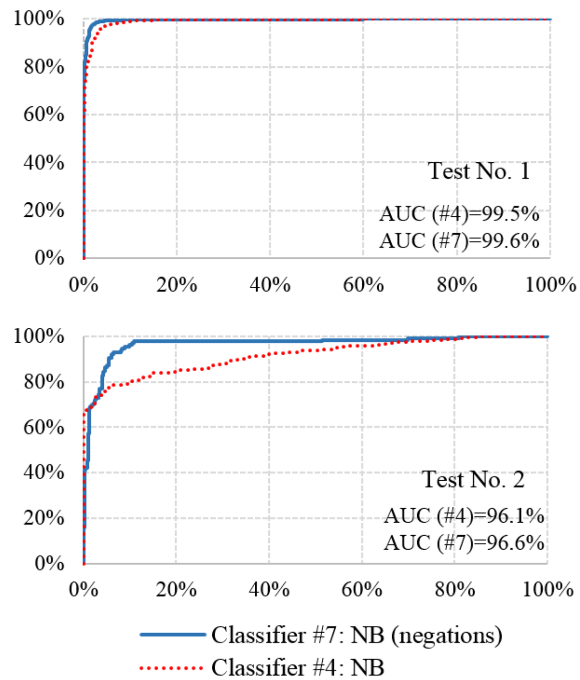

Figure 9. Comparison of ROC-curves for classifiers #7 and #4

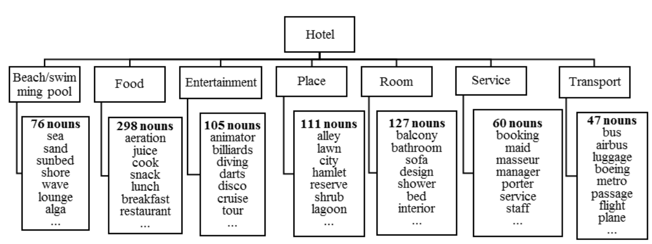

Figure 10. Aspect groups of object “hotel”

In present work we give an example of qualitative and quantitative surveys for two 5-star hotels “A” (1692 reviews) and “B” (1,300 reviews) located on the resort Sharm el-Sheikh (63,472 reviews) in Egypt. Firstly, we will make a quantitative survey, measure customer satisfaction, compare it with average satisfaction in the whole resort, detect negative trends by each hotel's aspect group, and identify problems in the quality of hotels.

The dynamics of customer satisfaction calculated by equation (2) is presented in Figure 11. Concerning the hotel “A”, there is a positive upward satisfaction trend from 2009, and it fixes on the average-resort level in 2013. Concerning the hotel “B”, in 2012 there was a sharp satisfaction decline and the same sharp increase in 2013. We can also notice that on a monthly graph (Figure 12). For the hotel “B”, satisfaction decrease started in June 2012, and stopped in October 2012. Then, customer satisfaction grew to the level that was higher than the average resort level being ahead of its competitor – hotel “A”.

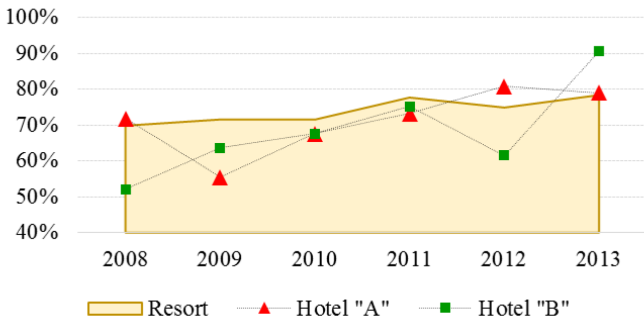

Figure 11. Dynamics of the consumer satisfaction by years.

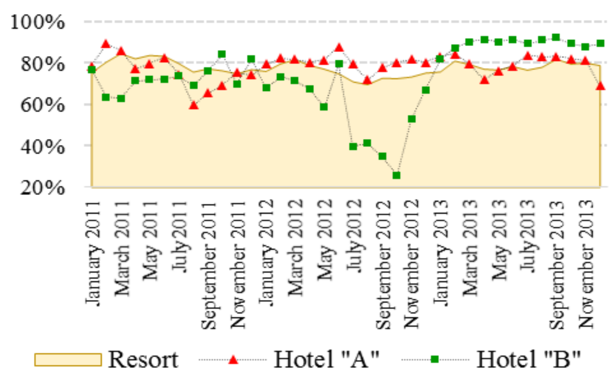

Figure 12. Dynamics of the customer satisfaction by months.

To find reasons of hotel “B” satisfaction decrease, we will examine structure of customer satisfaction with product in Figure 13. We can see that in 2012, the hotel “B” on average was second to the hotel “A” in such aspects as “room” (Δ12%), “place” (Δ8%), “service” (Δ5%), “beach/swimming pool” (Δ3%) and “entertainment” (Δ3%). To complement the overall picture of the level of quality we have included in the analysis mentions about “theft” and “intoxication”. In 2012, the Hotel “B” had more registered cases of intoxication in September 2012, as well as cases of theft in August 2012 (see Figure 15). We should also note that one of the reasons of customer dissatisfaction with the hotel “B” was the initiated repair of hotel rooms and buildings, which, however, paid off in 2013. Customer satisfaction with the hotel “A” aspects conforms with the average resort level.

In 2013, customer satisfaction with product’s aspect groups with the hotel “B” exceeded the average level in all aspect groups (see Figure 14). Customer satisfaction with the hotel “A” dropped lower than average values in such aspects as “service” (Δ3%), “food” (Δ3%), “beach/swimming pool” (Δ3%) and “transport” (Δ4%). For hotel “A” manager arise questions like: which aspects are the most significant for the customer and that should be improved in the first place, is it possible to “substitute” the dissatisfaction with the service, e.g., by tasty food or employ new entertainer?

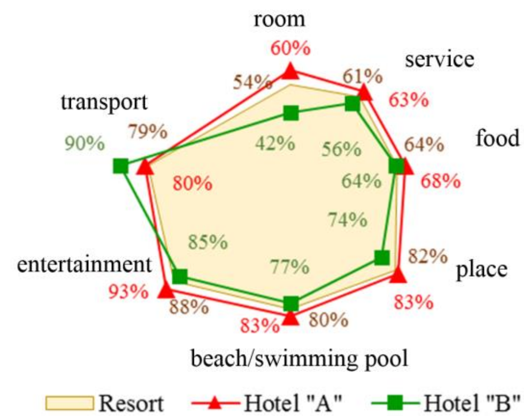

Figure 13. Comparison of the structure of customer satisfaction in 2012.

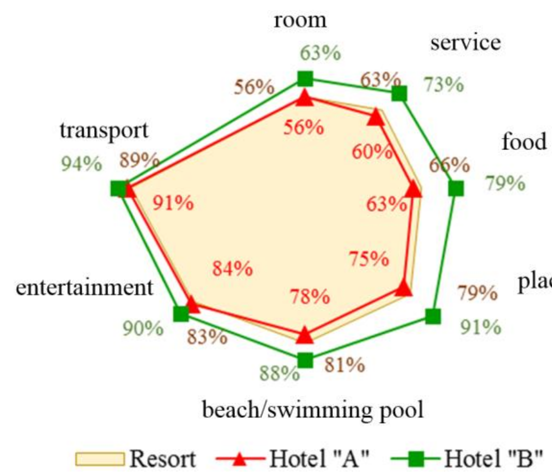

Figure 14. Comparison of the structure customer satisfaction in 2013.

Decision Trees were constructed using algorithm C4.5 and a tool “Deductor” [31]. At the first step was constructed a tree for the all hotels of resort. Extracted rules are represented in Table III. At the second step trees were constructed for hotel “A” and hotel “B”. Significance values of a product’s aspect groups are represented in Table II. In Figure 13, there are the decision trees created for hotel “A” and hotel “B”. Due to the large size of the produced decision tree of the whole resort we omitted it, but in the Table III its rules are presented that have confidence >80% and support >5% (it is five rules from 27).

By analyzing significance values (see Table II) of product's aspect group on overall review's sentiment (i.e., on customer satisfaction), we can say that the main factors of consumer dissatisfaction are a low service level (34.8%), problems with food (16%), and complaints about the hotel rooms (4%). The most critical aspect group for the hotel "B" is "room" (57.3%). In absence of negative opinions on the aspect group "room", the review would be positive with a confidence of 95.5% (see Table III, rule #10). That is why the repair that was performed facilitated to a significant increase of consumer satisfaction. The most critical aspect group for the Hotel "A" is "service" that corresponds with the resort in a whole.

	Hotel "A"										Hotel "B"								
	beach/swimming poo	food	entertainment	place	room	service	transport	intoxication	theft		beach/swimming poo	food	entertainment	place	room	service	transport	intoxication	theft
January-11	91%	65%	87%	84%	55%	60%	90%	1%	6%		86%	75%	85%	78%	57%	67%	73%	3%	0%
February-11	95%	82%	94%	75%	61%	80%	45%	0%	3%		93%	87%	43%	39%	28%	33%	37%	1%	0%
March-11	76%	70%	88%	88%	60%	78%	73%	0%	2%		81%	77%	55%	70%	31%	42%	52%	1%	0%
April-11	82%	67%	87%	81%	62%	65%	74%	0%	1%		82%	78%	70%	76%	42%	57%	68%	0%	0%
May-11	89%	68%	87%	81%	58%	57%	87%	2%	2%		82%	73%	77%	77%	44%	64%	71%	0%	0%
June-11	85%	77%	93%	78%	50%	62%	77%	1%	8%		84%	72%	83%	75%	48%	60%	79%	2%	0%
July-11	74%	68%	80%	64%	38%	38%	88%	5%	4%		81%	72%	87%	74%	46%	59%	84%	1%	0%
August-11	82%	62%	79%	67%	40%	41%	44%	7%	10%		76%	66%	87%	71%	43%	57%	85%	0%	3%
September-11	77%	58%	89%	70%	45%	47%	72%	8%	5%		86%	68%	91%	86%	50%	61%	86%	2%	1%
October-11	78%	59%	93%	80%	48%	54%	76%	5%	5%		89%	71%	91%	85%	56%	75%	93%	1%	1%
November-11	81%	63%	93%	80%	55%	65%	88%	4%	2%		79%	66%	84%	78%	47%	57%	90%	2%	2%
December-11	79%	63%	88%	87%	49%	62%	94%	4%	3%		88%	73%	87%	81%	49%	63%	89%	1%	3%
January-12	86%	64%	89%	86%	54%	61%	88%	3%	3%		84%	66%	86%	78%	42%	56%	95%	3%	3%
February-12	86%	64%	95%	87%	59%	63%	88%	2%	1%		84%	70%	87%	80%	46%	63%	94%	1%	2%
March-12	85%	71%	97%	90%	64%	68%	94%	3%	2%		88%	65%	89%	76%	39%	66%	97%	8%	5%
April-12	84%	69%	91%	86%	58%	64%	76%	3%	2%		81%	62%	85%	79%	40%	59%	93%	4%	2%
May-12	85%	70%	94%	86%	61%	67%	77%	5%	2%		77%	58%	71%	71%	32%	52%	80%	7%	1%
June-12	86%	69%	95%	88%	62%	69%	76%	4%	4%		88%	79%	86%	77%	52%	59%	90%	4%	1%
July-12	84%	67%	92%	85%	59%	60%	88%	5%	4%		69%	75%	93%	51%	26%	55%	45%	2%	0%
August-12	81%	64%	92%	81%	55%	57%	86%	5%	3%		62%	63%	80%	63%	30%	45%	56%	1%	7%
September-12	84%	70%	91%	79%	58%	68%	71%	5%	1%		63%	60%	73%	63%	33%	45%	78%	15%	4%
October-12	83%	68%	90%	81%	57%	63%	82%	3%	1%		62%	48%	87%	56%	35%	35%	72%	7%	2%
November-12	79%	66%	92%	83%	59%	62%	74%	2%	0%		75%	60%	93%	70%	47%	67%	86%	4%	1%
December-12	77%	66%	93%	80%	60%	62%	77%	2%	0%		83%	70%	92%	73%	53%	65%	85%	5%	0%
January-13	81%	68%	94%	82%	61%	64%	75%	3%	1%		92%	75%	94%	78%	57%	70%	92%	2%	4%
February-13	82%	66%	95%	85%	62%	64%	87%	1%	3%		88%	82%	95%	88%	61%	75%	96%	1%	2%
March-13	78%	61%	94%	81%	57%	57%	77%	1%	1%		93%	86%	95%	89%	66%	79%	98%	2%	1%
April-13	75%	58%	91%	82%	52%	57%	89%	3%	2%		93%	89%	95%	90%	74%	82%	99%	1%	0%
May-13	76%	59%	91%	83%	52%	59%	80%	2%	4%		86%	81%	92%	88%	67%	74%	97%	0%	0%
June-13	77%	62%	90%	81%	53%	59%	65%	2%	2%		88%	80%	95%	88%	62%	71%	91%	3%	1%
July-13	77%	66%	91%	83%	58%	63%	72%	5%	3%		89%	76%	94%	87%	61%	69%	89%	3%	3%
August-13	75%	67%	92%	89%	59%	63%	76%	2%	1%		87%	79%	92%	91%	63%	76%	94%	2%	2%
September-13	79%	67%	88%	94%	54%	57%	88%	1%	1%		84%	78%	94%	86%	65%	76%	86%	2%	2%
October-13	74%	64%	83%	88%	53%	50%	44%	7%	0%		88%	77%	95%	88%	59%	71%	85%	1%	3%
November-13	77%	63%	86%	86%	56%	57%	62%	3%	0%		89%	76%	94%	93%	59%	70%	90%	2%	2%
December-13	80%	63%	83%	88%	52%	58%	41%	4%	0%		86%	78%	94%	95%	61%	71%	91%	1%	1%

Figure 15. Customer satisfaction with product's aspect groups by month.

Using significance values, we can relate each aspect group with Kano's model categories [19]. Negative mentions about aspect group "service" in review have high significance on customer satisfaction, but positive mentions have significance is near zero (34.8% vs. 0.7%). That's why we can say that aspect group "service" relates to "Must-be quality" of Kano's categories. This is interpreted as a positive mentions about aspect groups "service" do not have an influence on sentiment of review, i.e., on overall satisfaction with hotel. That means the consumer a priori awaits a high-level service as a matter of course.

TABLE II. SIGNIFICANCE OF PRODUCT'S ASPECT GROUPS ON OVERALL

Aspect group	Kano's model category	Sentiment of mention	Significance values		
			Resort	*Hotel "A"*	*Hotel "B"*
Service	Must-be quality	Negative	34.8%	60.2%	-
		Positive	0.7%	-	-
Food	One-dimensional quality	Negative	30.3%	27.2%	30.3%
		Positive	16%	-	-
Entertainment	Attractive quality	Negative	-	-	-
		Positive	8.5%	12.7%	12.4%
Room	One-dimensional quality	Negative	4%	-	57.3%
		Positive	2.1%	-	-
Beach/swimming pool	Attractive quality	Negative	0.2%	-	-
		Positive	2.5%	-	-
Place	Attractive quality	Negative	-	-	-
		Positive	1%	-	-
Transport	Indifferent quality	Negative	-	-	-
		Positive	-	-	-

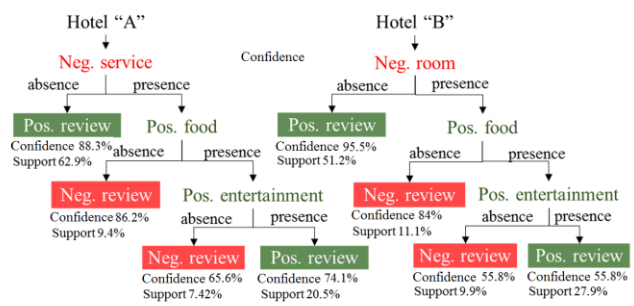

Figure 16. Decision trees for hotels.

For such aspect groups as "food" and "room" significance values are comparable (30.3% vs. 16% for "food" and 4% vs. 2.1% for "room"), that relates to "One-dimensional quality" of Kano's categories. That means that customer satisfaction rising with rising quality of aspect groups "food" and "room" and reducing when reducing quality of these aspect groups.

Aspect groups "beach/swimming pool", "entertainment" and "place" relates to "Attractive quality" because only positive mentions about them have a significance on customer satisfaction. That means that customer satisfaction rising with rising quality of aspect groups "beach/swimming pool", "place" and "territory", but does not reducing when reducing quality of these aspect groups.

In some cases, positive mentions about "food" and "entertainment" simultaneously in a review could substitute negative mentions about "services" and provide a positive review. That is why the hotel's aspects, which are contributing to customer satisfaction and important for both the resort and for the hotels, are good food and amusing entertainment activities. Customer satisfaction with these aspect groups can overlap dissatisfaction with "service" or "rooms" and make the customer overall satisfied (see Table III, rules #5, #7, #11).

TABLE III. RULES EXTRACTED BY USING DECISION TREES

#	Rules	S[a]	C[b]
	Extracted rules on resort reviews		
1	$\text{Food}^{+} \cap \overline{\text{Service}^{-}} \cap \overline{\text{Food}^{-}}$ = Positive review	37.2%	97.4%
2	$\text{Food}^{+} \cap \overline{\text{Service}^{-}} \cap \text{Food}^{-} \cap \text{Beach}^{+}$ = Positive review	11%	86.2%
3	$\overline{\text{Food}^{+}} \cap \overline{\text{Service}^{-}} \cap \overline{\text{Food}^{-}} \cap \overline{\text{Room}^{-}}$ = Positive review	10.6%	83.9%
4	$\overline{\text{Food}^{+}} \cap \text{Service}^{-} \cap \overline{\text{Entertainment}^{+}}$ = Negative review	6.9%	92.3%
5	$\text{Food}^{+} \cap \text{Service}^{-} \cap \overline{\text{Food}^{-}} \cap \text{Entertainment}^{+}$ = Positive review	5.8%	88.4%
	Extracted rules on Hotel "A" reviews		
6	$\overline{\text{Service}^{-}}$ = Positive review	62.9%	88.3%
7	$\text{Food}^{+} \cap \text{Service}^{-} \cap \text{Entertainment}^{+}$ = Positive review	20.5%	74.1%
8	$\overline{\text{Food}^{+}} \cap \text{Service}^{-}$= Negative review	9.4%	86.2%
9	$\text{Food}^{+} \cap \text{Service}^{-} \cap \overline{\text{Entertainment}^{+}}$ = Negative review	7.2%	65.6%
	Extracted rules on Hotel "B" reviews		
10	$\overline{\text{Room}^{-}}$ = Positive review	51.2%	95.5%
11	$\text{Food}^{+} \cap \text{Room}^{-} \cap \text{Entertainment}^{+}$ = Positive review	27.9%	81%
12	$\overline{\text{Food}^{+}} \cap \text{Room}^{-}$ = Negative review	11.1%	84%
13	$\text{Food}^{+} \cap \text{Room}^{-} \cap \overline{\text{Entertainment}^{+}}$ = Negative review	9.9%	55.8%

a. Support. b. Confidence

Then we compared frequency of nouns from aspect groups and significance values of aspect groups (see Table IV). As we can see, significance values do not correlate with frequency of nouns. For example, the most frequent aspect groups in reviews are "room" and "beach/swimming pool", but these aspect groups have low significance in contrast to "service" and "food". It also confirms the correctness of the chosen approach to the estimation of significance values of aspect groups.

TABLE IV. COMPARISON OF FREQUENCY OF NOUNS AND THEIR SIGNIFICANCE VALUES

Aspect groups	Number of nouns in aspect group	Frequency of nouns from aspect group	Significance values of aspect groups	
			Negative	Positive
Service	60	13.7%	34.8%	0.7%
Food	298	15.0%	30.3%	16.0%
Entertainment	105	8.9%	-	8.5%
Room	127	23.3%	4.0%	2.1%
Beach/swimming pool	76	25.1%	0.2%	2.5%
Place	111	8.8%	-	1.0%
Transport	47	5.1%	-	-

The performed qualitative survey allowed the detection of the main ways to increase customer satisfaction for hotel "A". The problem aspect groups identified through quantitative survey correspond to the most significant aspects detected during the qualitative research. Hotel "A" manager should firstly increase "service" quality, and then increase the quality of "food" and "beach/swimming pool" maintenance. "Transport" problems – concerning flights, early check-in, and baggage storage – are not significant for customers and can be solved in the frames of service improvement. The process of service quality increase can take much time; that is why organizing entertainment and animated programs together with enhancement of restaurant service could be immediate measures for increasing customer satisfaction. Specification of managerial decisions can be performed on the basis of the information on existing problems contained in negative reviews. The extracted sentences on aspects can be directed to the appropriate hotel services.

B. *Qualitative and quantitative surveys for banks*

For the qualitative and quantitative surveys for banks, we used small sample of consumer reviews – 1,153 reviews of Russian banks from site banki.ru. The sample consists of 304 positive reviews and 849 negative reviews in Russian.

It should be noted that the data is skewed towards negative reviews. This is because customers often leave a review in the case of dissatisfaction with the bank. In the absence of dissatisfaction, customers do not have a motive to leave a positive review. As we see studies in the respect of hotels and resorts, in contrast, show a skew towards positive reviews. We should note that identifying all of a product's aspects depends on reviewers' mentioning them all in the reviews. That is why very important to make satisfaction customer research using a large enough sample of positive and negative reviews, which would have covered mentions with all aspects of the product. In this case, the observing skew of positive and negative reviews has no effect on the significance values (4) of aspects and identified rules of decision trees (1) as for any other data mining problem. On the other hand, the skew is important for measuring customer satisfaction with product (2) and product's aspects (3).

To estimate accuracy of machine learning methods we used a cross-validation. Evaluation of the accuracy of the classifiers is calculated as the proportion of correctly classified positive and negative feedback on their total number. Results are presented in the Table V.

TABLE V. COMPARISON OF METHODS FOR SENTIMENT CLASSIFICATION

#	Machine learning methods	Vector	Accuracy
1	NB[a]	Binary	86.5%
2	NB	Frequency	86.8%
3	SVM (linear kernel)[b]	Binary	87.7%
4	SVM (linear kernel)	Frequency	85.0%
5	NB ("negations")	Frequency	88.0%

a. Naïve Bayes Classifier. b. Support Vector Machine

Accuracy values of the classification machine learning methods are comparable. For the sentiment analysis was chose Naive Bayes classifier with frequency vector. In this experiment, we also used tagging technique of negative particles "not" and "no". This technique has improved the classification accuracy to 88%. On the sample of bank reviews were extracted various aspects of banking.

Extracted aspects grouped by groups are shown in the Table VI. These aspect groups are used for the aspect-based sentiment analysis.

TABLE VI. ASPECT GROUPS OF OBJECT "BANK"

Aspect groups	Aspect nouns
Staff	Administrator, manager, supervisor, expertise, consultant, incompetence, maintenance, operator, guard, staff, employee, management, employees, specialist.
Credit	Profile, loan, debt, borrower, application, statement, mortgage, credit, lending limits, approval, waiver, redemption, delay, consideration.
Deposit	Contributor, deposit, contribution.
Card	Lock, ATM, release, holder, card, credit card, reissue.
Settlement and cash services (SCS)	Cashier, receipt, commission, transfer, assignment, debit, bill, terminal transaction.

Then we carried out quantitative and qualitative surveys of consumer satisfaction for four Russian banks: VTB24 (120 reviews), Alpha-Bank (131 reviews), Sberbank (232 reviews), Bank Russian Standard (86 reviews). The results of the quantitative survey are presented in the Table VII. Among these banks, the most satisfied customers are the customers of the VTB24 (35% positive reviews). Then follows Alfa-Bank and Sberbank (26.7% and 19.8%, respectively). At the last place is the Bank Russian Standard (14% positive reviews). These satisfaction values corresponds with customers' satisfaction values presented on the site as known as "People's rating".

TABLE VII. THE CUSTOMER SATISFACTION WITH ASPECT GROUPS AND OVERALL

	VTB24	Alpha-Bank	Sberbank	Bank Russian Standard
Staff	54%	48%	42%	38%
Credit	40%	25%	29%	28%
Deposit	100%	100%	69%	50%
Card	41%	48%	39%	29%
Settlement and cash services	42%	40%	31%	29%
Overall satisfaction	**35.0%**	**26.7%**	**19.8%**	**14.0%**
People's rating[a]	**38.6**	**37.1**	**32.7**	**31.6**

a. Ratings of banks, based on the assessments of customers, exposed on the Internet site banki.ru

Aspect-based sentiment analysis allowed evaluating consumer satisfaction with specific aspect groups of banking services. For example, although the first place in overall satisfaction, VTB 24 has a lower satisfaction on card products than those of Alfa Bank. However, there are problems with credit products at Alfa-Bank, because customers complain about unreasonable delay cases and the emergence of debt on loans.

Based on sentiment analysis reviews and aspect-based sentiment analysis we constructed decision tree. Obtained decision rules with confidence of more than 75% are shown in Table VIII. Rule #1 means that the absence of positive mentions about the staff and cards lead to negative reviews with confidence 92.9%. 60.2% of all reviews contain this rule. Positive mentions about staff without negative mentions about staff and settlement and cash services lead to positive reviews with confidence 79.4% (rule #2).

TABLE VIII. RULES EXTRACTED BY USING DECISION TREES

#	Rules	S[a]	C[b]
1	$\overline{Staff^+} \cap \overline{Card^+} = Negative\ review$	60.2%	92.9%
2	$Staff^+ \cap \overline{Staff^-} \cap \overline{SCS^-} = Positive\ review$	20.2%	79.4%
3	$Staff^+ \cap Staff^- = Negative\ review$	7.4%	85.9%
4	$\overline{Staff^+} \cap Card^+ \cap Card^- = Negative\ review$	4.1%	87.2%

a. Support. b. Confidence

Table IX shows the estimated values of the significance values of aspect groups for customers. The greatest impact on customer satisfaction have positive and negative mentions about bank' staff. Next in significance aspect groups are card products and Settlement and cash services. The rest of the aspect groups have significance values near zero.

TABLE IX. SIGNIFICANCE OF PRODUCT'S ASPECT GROUPS

Aspect groups	Kano's model category	Sentiment of mention	
		Negative	Positive
Staff	One-dimensional quality	19.5%	54.7%
Credit	Indifferent quality	0%	0%
Deposit	Indifferent quality	0%	0%
Card	One-dimensional quality	6.3%	14.9%
Settlement and cash services	Must-be quality	4.6%	0%

VI. CONCLUSION AND FUTURE WORK

Poor quality of products and services contributes to a decrease of customer satisfaction. On the other hand, under the conditions of stiff competition, there are no barriers for the consumer to change the supplier of goods and services. All these things can cause loss of clients and a decrease of a company's efficiency indexes. Therefore, maintaining high-quality standards should be provided by effective managerial decisions and based on opinion mining as a feedback.

The suggested conception of decision support based on the developed approach of text data processing and analysis allows performing quantitative and qualitative surveys of customer satisfaction using computer-aided procedures, and making effective managerial decisions on product quality management. The present conception allows effective reduction of labor intensity of customer satisfaction research that makes it available for use by a wide range of companies.

A prototype of IDSS was developed on the basis of the suggested conception. The performed experiment has proved its efficacy for solving real problems of quality management and consistency of the results obtained. IDSS enables companies to make decisions on quality control based on analytical processing of text data containing implicit information on client satisfaction.

Future research on the given topic can be devoted to automatic annotating of text data, representing text amount of review in the form of a summary, and extracting useful and unique information.

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