Romanian-Lexicon-Based Sentiment Analysis for Assesing Teachers' Activity

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Abstract
The students' feedback is important to measure and improve teaching performance. Many teacher performance evaluation systems are based on responses to closed question, but the free text answers can contain useful information which had to be explored. In this paper we present a lexicon-based sentiment analysis to explore students' text feedback. The data was collected from a system for the evaluation of teachers by students developed and used in our university. The students comments are in Romanian language so we built a Romanian sentiment word lexicon. We used this to categorize the feeback text as positive, negative or neutral. In addition, we added a new polarity - indifferent – in order to categorize blank and "I don't answer" responses.
Keywords:
sentiment analysis, students' feedback, teaching evaluation, lexicon based approach

1. Introduction

The students' feedback is very important in education field for both teachers and students. It can lead to improve teaching performance and learning experience. The feedback allows teachers to know the perspective of their students regarding the courses and help them make the right changes to increase the learning experience. Giving feedback, the students become more involved with their experience of learning.

Student satisfaction has become an important element to improve the quality process of higher education in most countries of the world [1]. Even if students' opinions can be collected in various ways, a simple and modern method is through online surveys. Usually, a feedback survey contains closed questions and open questions. Closed questions have multiple choice answers while the answers to the open questions are in a free form text with no given structure. It is easy to analyse and interpret the answers to closed questions through statistical and data mining methods. But the free text answers can contain more subtle information to be explored.

This type of data can be automatically analyzed through text mining techniques, particularly through sentiment analysis and opinion mining techniques.

In this paper we present a lexicon-based sentiment analysis to explore students' text feedback.

Even if there are other works in the literature dealing with sentiment analysis in education [2][3], the novelty of our work is given by the following: the dataset is original and represents real data collected in the teacher evaluation process carried out by students; a lexicon in Romanian was built for the analysis and a new polarity associated with "don't know" or "don't answer" responses was considered.

Our data set is collected over several years from the teacher evaluation activity by students using an application designed and implemented in "Ștefan cel Mare" University of Suceava. The app collects student responses to online surveys that target each teacher's work in a course, lab or project. Some of these data are analyzed through text mining techniques in order to create models for students' sentiments about teaching process.

The opinions of students are in Romanian, so we had to process Romanian feedback texts. In order to do this, we built a lexicon containing Romanian sentiment words specific to the education domain. In addition, we consider a new polarity that we named *indifferent* (*indiferent* in Romanian language).

We intend to use the results of the research in a recommendation system for the improvement and student-centeredness of the whole teaching process.

The rest of the paper is organized as follow. Section 2 introduces some basics about opinion mining and sentiment analysis. Section 3 presents the related work on using sentiment analysis. Section 4 shows the research methods and results. Section 5 and Section 6 presents discussions and conclusions respectively.

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2.Theoretical background

Opinion mining, also known as sentiment analysis is the computational study of the people opinions, feelings, attitudes, beliefs about the aspects of an entity[4][5]. Mainly sentiment analysis focuses on classify the impressions about a specific aspect as positive, negative or neutral or on detect specific emotions like happy, sad, angry.

Like other mining processes, opinion mining process consists of few steps: data collection, preprocessing, data analysis and visualization. The preprocessing step includes removing punctuations and digits, removing stop words, stemming, tokenization, part of speech tagging. This step depends very much on the language in which the text is written. There are two approaches for sentiment analysis: machine learning and lexicon-based approach[5][6].

Machine learning uses two different methods: supervised learning and unsupervised learning. In supervised learning the most common technique is classification, while for unsupervised learning clustering techniques are used.

In supervised learning, a dataset, for which each case contains a class label, is divided into two sets, the training set and the test set. The model is trained on the first set. Then, the built model is applied on the test set to assess its performances. These techniques are highly dependent on the size of training data set. Among the algorithms used we mention Naïve Bayes, Support Vector Machines, Logistic Regression, Decision trees [6][7][8].

Unlike the supervised learning, unsupervised techniques use previously unlabeled datasets and aim to create groups (clusters) of cases that are very similar within the group and different from one group to another. The accuracy of built models is also influenced by the size of dataset. Among the algorithms used we mention Word2Vec and k-means clustering[9].

In lexicon-based approach, a sentiment dictionary, which contains opinion words with an assigned sentiment score that describes how positive, negative, or neutral they are, is used.

The lexicon-based techniques match the data with sentiment words to determine the text polarity [5]. Unlike the machine learning based techniques, the lexicon-based techniques don't need very large amounts of data and requires less computational power[10][11].

3.Related work

Last time, sentiment analysis has been widely used in various fields. One of the most popular uses of sentiment analysis methods is consumers' opinions analysis. In [12] authors have processed more than 5000 online reviews using a dictionary of positive and negative words and WEKA classifiers. They classified the reviews into positive, negative, neutral or undefined and gave the overall polarity of reviews. In the paper [13] 300 product reviews from Amazon have been analyzed using SentiWordNet lexical resource. Authors of [14] have studied a dataset containing tweets of product reviews of five famous manufacturers (Unilever, Samsung, Procter and Gamble, Mobilink and GlaxoSmithKline). They used two approaches – text based and emoticon based - and found the polarity of reviews.

Another popular use of sentiment analysis is for movie reviews analysis. In [11] authors used lexicon-based method to classify movie reviews into positive, negative and neutral. They collected data from Twiter and processed them using R language. The authors of [15] used eight classifiers on almost 43 thousand movie reviews from IMDB. They performed classification to label reviews as being either positive or negative and obtained an accuracy ranged from 79.51% to 96.01% for the 8 classifiers.

Other areas have benefited from sentiment analysis techniques, like elections or employees job satisfaction.

In the last years students' opinions were analyzed to evaluate teachears' activity and courses.

In [2] a raw dataset, containing opinions of students from eleven high schools in Romania, related to various aspects of the educational process, was used. They were collected through a Google Docs form and classified through the Orange environment, making a comparative study of the obtained results using the Ekman and Plutchik models. Each model extracts from the analyzed texts, a different emotion, based on which the students' sentiments towards the educational process are analyzed.

In [10] a system which measure the teachers' performance by automatic analysis of students' feedback is presented. The feedback is in text form and is processed using lexicon-based approach and

Vader Lexicon as source to determine the polarity of opinions. The [5] paper also considered a lexicon-based approach but created an English sentiment words list. This list contains opinion words regarding the academic field, some of them are not included in the Vader or Afinn lexicons. The results of feedback analysis are showed as strongly positive, moderately positive, weakly positive, strongly negative, moderately negative, weakly negative or neutral. The authors of [16] have collected the feedback text from the students at a Finnish university and have analysed the ones written in English. They used R programming language and Syuzhet library to find out the polarity for each feedback text. In addition, they have used NRC Emotion Lexicon to classify feedback texts in NRC categories (anger, fear, anticipation, trust, surprise, sadness, joy, disgust).
In [17] a lexicon approach, with InSet Lexicon to analyse the students' feedback written in Indonesian language, was used. The authors of this paper have made two types of analysis, document level and sentence level. The document level analysis provided 90.9% accuracy. In the case of sentence level analysis, the authors added some words to InSet lexicon to fit with educational domain.

4.Working Methodology

We proposed to carry out an analysis of students' opinions regarding their learning experience using text mining techniques. For this purpose we used R programming language and R packages for data science like tidytext, tidyr and wordcloud.
Fig. 1 presents the workflow of the analysis process.

Data Set Description

As we mentioned before, data were collected from the online application for teachers' evaluation. This application was developed in the University of Suceava (Romania) and has been used for several years to evaluate teachers by students. The evaluation is performed by students on condition of anonymity. The evaluated teacher does not have direct or indirect access to the identity of the evaluator.

The students answer to several questions, some of them in the form of closed questions, others in the form of free answer (open questions).
Samples of closed questions are presented below:

- *Obiectivele cursului au fost clar definite?* (Where the course objectives clearly defined?)
- *Conţinutul cursului a fost bine structurat?* (Was the course content well structured?)
- *Noţiunile cheie au fost suficient prezentate?* (Was the key notions sufficiently presented?)
- *Expunerea profesorului a fost clară?* (Was the teacher's presentation clear?)
- *Profesorul a încurajat participarea studenţilor la discuţii?* (Did the teacher encourage students to participate in the discussions?)
- *Criteriile de evaluare au fost clare?* (Where the evaluation criteria clear?)

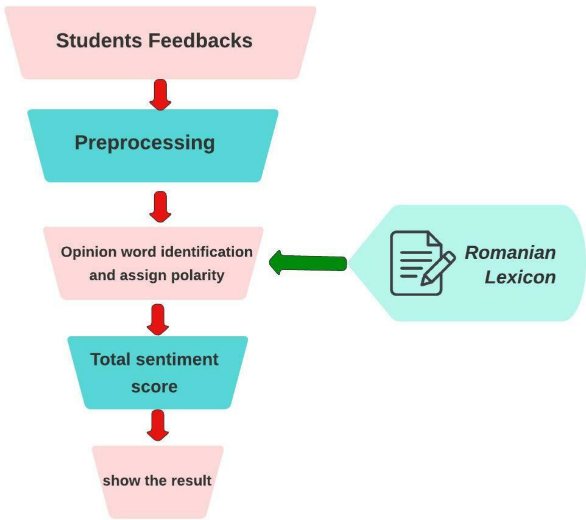

Fig. 1 The sentiment analysis workflow

The answer options for these types of questions are: *da* (yes), *nu* (no), *nu știu* (I don't know), *nu răspund* (I don't answer).
Samples of open questions are:

- *Care credeţi că este trăsătura de personalitate definitorie pentru stilul didactic al titularului acestei activităţi?* (What do you think is the defining personality trait for the teaching style of the owner of this activity?)
- *Ce aspecte consideraţi că ar trebui îmbunătăţite?* (What aspects do you think should be improved?)
- *Cum apreciaţi conţinutul şi utilitatea chestionarului?* (How do you assess the content and usefulness of the questionnaire?)

The result of evaluation is based on the closed questions, while the responses to other questions have purely an informative role.
We consider, for our project, the first open question.
For information privacy reason, we can use only the evaluations of those colleagues who have agreed to participate to this project.
The data collection was done manually and includes results of evaluations from five academic years (2016-2017, 2017-2018, 2018-2019, 2019-2020 and 2020-2021). Fig. 2 shows a sample of the source data. It can be seen that in some questions the answer is a single word and in others it is a complex sentence. Some students chose to use the options offered in the closed questions, i.e. *nu știu* (I don't know), nu *răspund* (I don't answer) or the abbreviated options *ns,* respectively *nr*.

Care credeţi că este trăsătura de personalitate definitorie
exigenta
este o profesoara buna
NS
calm
explica bine
...
nr
Bunatatea
Intelegatoare
Amabilitate
Bunatatea.
comunicativa
Preda foarte bine si se intelege.
Intelegatoare
de treaba calma
Profesionalism
Eficienta in prezentarea materialului predat
Organizare

Fig. 2 Sample of the dataset

Data Preprocessing

Data preprocessing consists of removing stop words, numbers and punctuation, turning capital letters into lowercase letters, and tokenizing. The Romanian dictionary available online at https://countwordsfree.com/stopwords was used to remove stop words. Fig. 3 shows two samples from the list of stop words in this dictionary. After preprocessing, a data set with 402 observations was obtained.

Modelling

The lexicon-based method was used for sentiments analysis. This method consists of using a lexicon in which the words are associated with a score that represents a positive, negative or neutral character.

6	aceia	214	să
7	acel	215	săi
8	acela	216	sale
9	acele	217	şapte
10	acelea	218	şase
11	acest	219	sau
12	acesta	220	său
13	aceste	221	se
14	acestea	222	şi
15	aceşti	223	sînt

Fig. 3 Samples of Romanian stop words

For English language there is the the Bing lexicon, which includes positive or negative labeled words.
In order to perform the analysis of data set in Romanian language, we built a lexicon in Romanian. It contains 107 words specific to the educational field and was made in two stages. In the first stage, the words were taken from the corpus, and in the second stage the collection was expanded using synonyms. 57 words were labeled with *pozitiv* (positive), and 50 words were labeled with *negativ* (negative). Sample of such words are shown in fig. 4.

	word	sentiment			
20	corecta	pozitiv	68	iresponsabila	negativ
21	corectitudine	pozitiv	69	incorect	negativ
22	creativitate	pozitiv	70	incorecta	negativ
23	devotat	pozitiv	71	indiferent	negativ
24	devotata	pozitiv	72	indiferenta	negativ
25	empatie	pozitiv	73	ingamfat	negativ
26	empatic	pozitiv			
27	empatica	pozitiv			
28	exigent	pozitiv			

Fig. 4 Words from Romanian lexicon built for sentiment analysis

In the analysis stage, based on the Romanian lexicon, the polarity of the personality traits indicated in the students' answers was established.
Of the 237 ratings collected, 107 contain words that represent sentiments that can be labelled positively or negatively. The others contain answers of the form "I don't know"/"I don't answer", answers for which no associated label was found in the Romanian lexicon (eg, "Strictly on the subject") or which cannot be

associated with a sentiment (eg, “how should I know?”).

Most assessments were associated with a single sentiment but there are also assessments that contain two words for which an associated sentiment was found in the lexicon – for some of them it was the same sentiment and for others it was different sentiments. In fig. 5 it can be seen that the assessment with number 175 contains a word associated with a positive sentiment and a word associated with a negative sentiment, while the assessment with number 178 contains two positive sentiment words.

	nrEvaluare	sentiment	n
79	168	pozitiv	1
80	172	negativ	1
81	175	negativ	1
82	175	pozitiv	1
83	178	pozitiv	2
84	182	pozitiv	1
85	183	negativ	1
86	188	pozitiv	1
87	189	pozitiv	1
88	190	pozitiv	1
89	191	pozitiv	1

Fig. 1 - The result of polarity assign

The score associated with an evaluation is given by the difference between the number of positive sentiments and the number of negative sentiments. Finally, if the score has a value greater than zero the sentiment associated with the evaluation is POSITIVE, if the value of the score is less than zero the sentiment associated with the evalation is NEGATIVE, and if the score is zero the final sentiment is NEUTRAL. For instance, the assessment with number 31 (fig. 6) contains a word associated with a positive sentiment and no word associated with a negative sentiment, so the finall score is 1 i.e POSITIVE.

	nrEvaluare	negativ	pozitiv	sentiment	sentiment_final
17	31	0	1	1	POZITIV
18	32	0	1	1	POZITIV
19	34	0	1	1	POZITIV
20	35	1	0	-1	NEGATIV
21	36	0	2	2	POZITIV
22	38	0	1	1	POZITIV
23	43	0	1	1	POZITIV
24	45	0	1	1	POZITIV
25	47	1	1	0	NEUTRU

Fig. 6 Final sentiment association

Thus, out of the 107 evaluations, 92 (85.98%) were labeled with POSITIVE, 13 evaluations (12.15%) were labeled with NEGATIVE, and 2 evaluations (1.87%) were labeled with NEUTRAL (fig. 7).

	sentiment_final	n
1	NEGATIV	13
2	NEUTRU	2
3	POZITIV	92

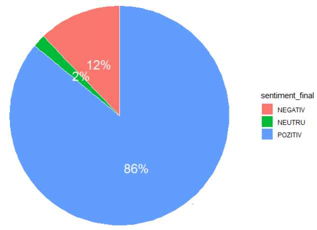

Fig. 7 Graphical visualisation of the result

Using the frequency of the terms, it can be found out which words contributed the most to a feeling. It is found that *înțelegătoare* (understanding) determined the POSITIVE sentiment the most, and *dură* (harsh) the NEGATIVE one (fig. 8 and fig. 9).

```
1      intelegatoare   pozitiv 12
2        seriozitate   pozitiv 11
3               calm   pozitiv  8
4              calma   pozitiv  7
```

Fig. 8 Words that determined the POSITIVE sentiment

```
1          dura    negativ 3
2    indiferenta   negativ 2
3    nepasatoare   negativ 2
```

Fig. 9 Words that determined the NEGATIVE sentiment

Fig. 10 shows the wordclouds representation of the words determining the postive and negative sentiments.

Fig. 10 Wordcloud visualisation of all words

In the next sentiment analysis we've made, we calculated the score by every academic year. The analysis is like the previous analysis and the result can be seen in fig. 11. The figure shows the numeric values. As seen in the figure, all results are greater than zero, so all are positive.

	anUniv	negativ	pozitiv	sentiment
1	2016-2017	4	15	11
2	2017-2018	4	24	20
3	2018-2019	4	20	16
4	2019-2020	3	18	15
5	2020-2021	0	23	23

Fig. 11 Sentiment analysis by academic year

In the next sentiment analysis, we calculated the score by academic year and by type of activity i.e. course or laboratory. Again, the result is positive for all cases, so we presented just numeric values of scores.

	anUniv	tipActivitate	negativ	pozitiv	sentiment
1	2016-2017	Curs	1	5	4
2	2016-2017	Lab	3	10	7
3	2017-2018	Curs	2	13	11
4	2017-2018	Lab	2	11	9
5	2018-2019	Curs	3	13	10
6	2018-2019	Lab	1	7	6
7	2019-2020	Curs	2	11	9
8	2019-2020	Lab	1	7	6
9	2020-2021	Curs	0	19	19
10	2020-2021	Lab	0	4	4

Fig. 12 Analysis by academic year and type of activity

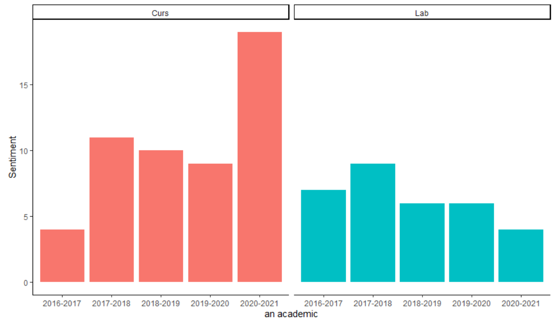

Fig. 13 Graphical visualisation of results by academic year and activity type

A new polarity proposal

In the following analysis, the answers I don't know, I don't answer (ignored in the first stage) were also taken into account. These answers were associated which the feeling of indifference.

In this case the data preprocessing stage requires more operations than in the previous case. In addition to the stop words and punctuation marks removal, the turning of uppercase letters into lowercase letters and tokenization, the treatment of missing values as well as a "standardization" of the answers was also achieved. In the "standardization" step, the answers I don't know were transformed into ns (stands for *nu stiu* - I don't know) and I don't answer into nr (stands for *nu raspund* - I don't answer). The words ns and nr were added to the Romanian lexicon and assigned the *indiferent* (indifferent) polarity, this polarity being considered different from neutral.

In the case of missing values, we considered that the evaluating student chose not to answer the question, and thus we considered that the missing value is equivalent with the answer I don't answer/nr. Thus, for the treatment of missing values, we chose manual completion with value nr.

Another analysis has been made. 58 assessments were labeled with *indiferent* (indiffernet) label, 100 were labeled positively and 15 were labeled negatively.

Due to the fact that in the previous analysis a small number of assessments with two feeling were obtained, at this stage the analysis was performed at the word level. Fig. 14 shows the percentage representation of the results obtained.

	sentiment	n
1	indiferent	58
2	negativ	15
3	pozitiv	100

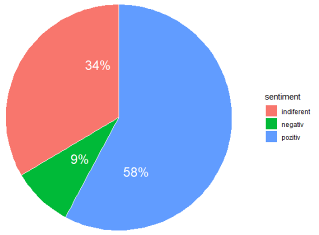

Fig. 14 The result of analysis including the *indifferent* sentiment

Using the new polarity of indifferent, we performed similar analyzes with the previous ones i.e. by academic year. The numeric results are shown in fig. 15 and the graphical representation are shown in fig. 16.

	anUniv	indiferent	negativ	pozitiv
1	2016-2017	15	4	15
2	2017-2018	13	4	24
3	2018-2019	11	4	20
4	2019-2020	10	3	18
5	2020-2021	9	0	23

Fig. 15 Sentiment analysis by academic year including *indifferent* sentiment

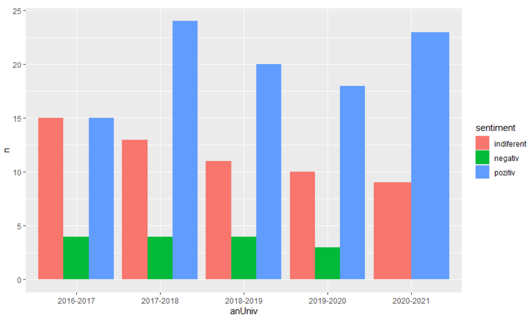

Fig. 16 Results of analysis by academic year including *indifferent* sentiment

5.Discussions

The results obtained in our analyses indicate that generally the sentiments expressed by our students' feedback are positive both for the entire analyzed period and for each individual year of this period.

The same trend was maintained when we took into account the blank answers and the I don't answer answers. 58% of the feedback from all analyzed years was positive while only 9% was negative. But, in this case, we noticed quite a large percentage (34%) of students who had an indifferent sentiment regarding the studied aspect of learning experience. However, a decreasing trend of this percentage was observed throughout the five academic years which was analyzed. Thus, in 2016-2017 academic year the percentage of feedback labeled with indifferent was 44.12%. This percentage decreased, reaching 28.13% in 2020-2021 academic year (fig. 17). This was surprising for us considering that in this year most teaching activities took place online.

anUniv	indiferent	negativ	pozitiv	proc_indif
2016-2017	15	4	15	44.11765
2017-2018	13	4	24	31.70732
2018-2019	11	4	20	31.42857
2019-2020	10	3	18	32.25806
2020-2021	9	0	23	28.12500

Fig. 17 – The percentage of indifferent feedback durin the five years

6.Conclusions

In this paper we have used lexicon-based sentiment analysis to explore the student' textual feedback. We collected data from the system for the evaluation of teachers by students developed in our university. All data collected are in Romanian language so, in order to process them, we built a Romanian sentiment word lexicon. The data was processed using R programming language.

By using lexicon-based approach the students' feedback comments was automatically analyzed to positive, negative, neutral polarity. Also, we added a new polarity, the indifferent polarity, in order to analyze the feedback of those students who don't want to answer to the considered question from the survey.

In the future we intend to extend the analysis to the other open questions of the survey and to correlate the results with those obtained by mining the responses to the closed questions.

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