Sentiment Analysis for Human Resources: A Comparative Analysis of Methods That Can Be Used Along with Modern Technologies

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This paper offers an integrated vision for supporting the challenges that most of organizations meet when discussing about human resources. One of scenarios addressed nowadays with analytics and AI is related to sentiment analysis that can contribute to employee retention, efficiency and development. The paper will provide an interesting approach that takes advantage of data with the power of cloud and natural language processing. The aim of this research will be to compare a cloud-based approach, integrated with artificial intelligence and a more classical one that uses R as development language for a lexicon-based analysis. Finally, it will be presented the benefits and ease of use for the technologies used, as well as for the results obtained.

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1 Introduction

Human resources in companies today include complex processes and associated costs. Management studies also suggest the fact that corporate culture has great impact on organizational behavior, especially in the areas of employee commitment, effectiveness and also corporate efficiency. [1]

Therefore, in order to address the biggest challenges existing in organizations worldwide, technology is the key, especially artificial intelligence that already has a big influence on employee engagement and retention.

Considering a dynamic workplace, where employees are trying to develop themselves, to seek purpose, observe and fight for opportunities, old practices of analyzing people and understanding their needs can take a lot more time with little results at the end. Non-satisfied work means also the lack of engagement and commitment from the employees, facts that are also leading to less productivity and efficiency [2].

With the help of artificial intelligence and the newest technologies proposed by the great leaders on the market, organizations can now easily understand what are the people's feelings towards the company they are working for, the work environment, relationships with the others colleagues, job life balance, opportunities to develop one's career and many other things.

Therefore, considering the technology and the need of observing the correlations between an employee feeling towards the workplace and the opportunities or problems that the employee faces because of the company culture and development, there is proposed a sentiment analysis that represents a special concept which derives useful insights. [3]

Language, in general, is used by someone to express the thoughts associated with the different experiences or relationships with the others. Using this kind of analysis, organizations can now observe important data in every sentence, review, comment or interaction that an employee has.

In this way, different problems like attrition, lack of efficiency or burden can be detected and prevented from time, saving a lot of money, but most important, creating a healthy environment where people enjoy their workday and feel committed and motivated to achieve more. [4]

This paper will focus on employee reviews on the company they are working for as dataset, considering also the existence of some variables that are presented for these employees like revenue, working years, job role, department, job level, etc. The sentiment analysis will be build using useful tool provided in cloud and data visualizations will be made using a business intelligence tool. The aim of this paper is to observe how can we adapt technology and artificial intelligence in an easy way so that an organization can address employee satisfaction and possible retention.

2 Sentiment analysis techniques and related work

Sentiment classification techniques can be divided using different approaches. The first one is the machine learning approach, followed by lexicon based and hybrid approach. The first one applies machine learning algorithms and also makes use of linguistic features.

The second one is based on a sentiment lexicon, which is in fact a collection of precompiled and known sentiment terms. This approach is also divided into dictionary-based type and corpus-based type, the last one using statistical or sematic methods to find sentiment polarity. The hybrid approach combines the two already mentioned approaches, as it is very common to use a sentiment lexicon in the majority of the methods existing nowadays. [4]

In addition, on the text classification methods that are using machine learning for their final conclusions, the learning methods can be supervised or unsupervised. The supervised ones make use of an amount of different labeled training texts, while the other ones are used when these labeled documents are harder to find. [4] [5]

The lexicon-based approach is also related to the possibility of finding the opinion lexicon which should be used in order to analyze the text. In this approach, there are two different methods: the dictionary based one, which depends on finding opinion seed words, followed by the search in the dictionary for synonyms and antonyms, while the corpus-based one begins with a seed list which includes opinion words, and then finds different opinion words in the larger corpus, so that to find opinion words with the same context orientation. [4] [6]

Sentiment Analysis can be considered, as per previous researchers, a very restricted NLP problem. On this type of analysis, the only necessary step is to understand if there are any positive or negative sentiments for each target sentence or text. However, despite all of these considerations, the methods discovered in this area are working correctly in terms of Information Retrieval. The only struggles existing, even after a lot of research year, are pointing to how to handle negations or the names entity recognition, as well as the challenges of dealing with irony or sarcasm. [7] [8]

The studies of previous research shows that NLP needs to deal with different levels of analysis. Depending on what is the form of the target subject (either text, document of even linked sentences) different NLP and types of sentiment analysis can be applied. Hence, it is very important to distinguish the levels of the analysis that will determine the tasks of the analysis: document level, sentence level or entity level. [9]

Many papers in this research area are following the general strategies. For example, the paper presented by Vechtomova and Karamuftuoglu [10] proposed the use of lexical cohesion, more clearly, the use of physical distance between the collocations in order to rank the documents. In the same time, Vechtomova furtherproposes another approach where it is measured the distance between subjective words. [11]

Other examples are those that applied the already known supervised methods of Artificial Neural Networks and Support Vector Machines in order to classify sentiments, which are most of the time used for Information Retrieval. [12]

Lastly, Hu and Liu [13] presented also an important strategy of the dictionary-based approach. In this one, a set of opinion words is collected manually and this set is grown by searching in different parts (like the well-known corpora WordNet or thesaurus), so that further synonyms and antonyms can be searched. The new words are next added to the seed list and then the next iteration is triggered. All this process stops when no other words are found. However, this dictionary-based approach has major disadvantages, such as the inability to distinguish opinion words

that are related to a specific context. Qiu and He used the same approach to identify sentiment sentences in the advertising area. Their proposal in this context was to have a syntactic parsing, as well as a sentiment dictionary and a proposed rule for topic word extraction, which finally showed effectiveness in the extraction of advertising keywords and also in ad selection. [14] [15]
The current paper offers a comparative approach between two ways of building sentiment analysis, along with finally observing the results obtained through a business intelligence tool, as well and their associated quality. A first sentiment analysis will use the inbuilt capability of a business intelligence tool in order to make a brief analysis on text data. The second approach will take into consideration cloud technologies and how the latest services in artificial intelligence can offer great results without efforts and code writing. In the same time NLP was used in order to offer the final results. In order to observe the lexicon-based approach, a script written in R was used, R being one of the most important tools in data analysis.
A business intelligence tool takes the results of the analysis of sentiment, to compare the results and view the conclusions in the most presentable way.

2.1 Power BI as business intelligence tool for visualizations

Power BI is a cloud-based or desktop-based service from Microsoft which enable organizations to analyze data with a better efficiency and speed. This is one of the most used tools in industry, which can connect multiple type of data in a flexible way, so that is can be analyzed. This tool also has a drag and drop interface and tasks like comparing, sorting or adding new measure are very fast and easy to perform. [16]
This power visualization tool provides different capabilities like interactive dashboards, data warehousing and data discovery, it is also very easy to scale across the entire organizations and has the ability to load customer visualizations.

2.2 Azure Cognitive Services for text analytics

This cloud service offers a Text Analytics API, a service that provides Natural Language Processing features for text mining. This includes also sentiment analysis, opinion mining, key phrase extraction, language detection and names entity recognition. [17]

NLP can be used to classify different documents. The output of it can be used for subsequent processing and search. Also, this can be used in order to summarize text, action performed by identifying some of the entities presented in the document. In the same time, these entities can also be used so that we can tag different documents with relevant key words, action that enables search and also retrieval based on the content.
Entities can be also combined into topics, along with summaries that are describing the important topics presented in each document. All the topics that are detected can be used for categorizing the document navigation, or even to help in enumerating the related documents, considering the topic selected.
In additional, NLP can be also used for scoring the text considering the sentiments expressed, or even assess the tone which can be positive or negative. All the approaches that were previously explained use different techniques for natural language processing:

- Tokenizer, which means the action of splitting the text into words and phrases.
- Stemming and lemmatization, which contains the normalizations of the words, so that all the different forms existing in the text to map to the canonical words with the same meaning.
- Entity extraction, action that identifies the subject in the proposed text.
- Speech detection, which performs the action of identifying the text as a verb, participle, verb phrase, noun, and so on.
- Sentence boundary detection, which helps in detecting the complete sentences within the existing paragraphs of the text.

In choosing the analysis tool, it was considered that Azure Cognitive Services Test Analysis API provides pre-trained models as service, the REST API capability offering the tokenizer property, as well as the part of speech tagging. It can be used for entity identification and extraction, for detecting the topic, for analyzing the sentiments, for language detection or spell checking.

2.3 Tidy Text in R for lexicon-based analysis

Tidy Text is an effective package build in R for text mining. Tidy text format can be defined as a table with one token per row. In the same time, a token is an important unit of text (for example, a word) that we are interested to use in our analysis. Tokenization, as expressed before, is the process of splitting the text into token. This package provides the functionality of tokenizing strings by words and also convert the data into one term per row format. In this way, by keeping the text we want to analyze in tidy tables, we can use different toll for manipulation.
In addition, in order for us to arrive to individual tokens (get through the process of tokenization), we will use a specific function like "unnest_tokens()" that will help us to transform the data.

3 Comparative application of sentiment analysis

3.1 Dataset

The sample dataset used for the analysis that will be made using the technologies presented, contains different details about the employee of an organization (monthly revenue, job satisfaction, work life balance, age, department, education, business travel) which activated in IT industry. The data includes, apart from information associated with the employees, the surveys that each of the employee has offered the company at the end of 2019. Considering the surveys, not all of the employees have offered feedback.
Moreover, the initial dataset did not request further changed or cleaning as this was automatically generated from the HCM that takes care of all the human resources associated processed and data.

3.2 Dataset analysis and results

In order to be able to observe some conclusions regarding the employee and their sentiment towards the company they are working for, this paper will firstly look into the characteristics that are showing some patterns or problems in human resource area.

The initial dashboard designed in order to observe the perspective of employee details is observed in Figure 1.

Fig. 1. Dashboard of general analysis for the analyzed employees

As showed above, it may be observed that the average age on the people working in the company is 36.92. Most of the people have similar number of working companies before, in average, however we may see that the roles with very high engagement like managers and directors have stayed in the company, with the current manager, for a very long time. Again, it is observed that the people with the highest experience and seniority are the ones that have worked the highest number of years, therefore the seniority comes clear from the entire experience accumulated.

In the same time, we can conclude that those that are seniors have stayed a lot more at the company, facts that can show us that the company has been keeping the people with a lot of experience and in the management roles in.

Of course, the average monthly incomes seem correlated with the ideas already underlines, as well as with the seniority and responsibilities that the people are having in the company.

On a brief analysis made with the in-build text analysis capability that the tool offers, it can be seen an overall perspective of the survey the employee has offered to the company on the review in Figure 2, presented below.

Fig. 2. Dashboard of sentiment analysis obtained with in-build tool from Power BI

It is observed an average score of sentiment that is not that high and it is not entirely correlated, for example, with the work life balance feelings. It is also easily to conclude that those that do not have great experience, lots of years in company or management roles are offering the smallest scores (0.54 for B2B operations and 0.47 for Sales).

The words that are most used in the survey seem to point to the team, to the work developed in the team, to associated issues like development, career, promotion, benefits.

Also, we are able to see that the surveys obtaining the lowest scores cannot be associated with working overtime.

For the next step in analyzing the survey we will use, as previously explained, the Azure Cognitive Services API. In order to do this, the Azure Cognitive Service will be provisioned in Azure and a service of type Text Analysis is configured.

Next, we will include the API returned by this in order to make analysis on the data we want to observe the sentiment for.

Using Power BI or Postman, we can retrieve the predictions after requesting this, obtaining a JSON file as seen in Figure 3.

```
{
  "documents": [
    {
      "id": "1",
      "sentiment": "positive",
      "confidenceScores": { "positive": 1.0, "neutral": 0.0, "negative": 0.0 },
      "sentences": [
        {
          "sentiment": "positive",
          "confidenceScores": {
            "positive": 1.0,
            "neutral": 0.0,
            "negative": 0.0
          },
          "offset": 0,
          "length": 64,
          "text": "Working from home is one of the best benefits I could ever want."
        },
        {
          "sentiment": "positive",
          "confidenceScores": {
            "positive": 1.0,
            "neutral": 0.0,
            "negative": 0.0
          },
          "offset": 65,
          "length": 25,
          "text": "I'm really happy with it."
        }
      ],
```


Fig. 3. JSON file content obtained after applying the pre-trained mode provided by Azure Cognitive Services

The file generated not only contains the predictions, but also the scores for every survey offered.

Therefore, in order to further analyze these results, we can use the files in Power BI again and also make connections between the results and the details previously known about the employees.

After importing the results file into power BI, it can be seen next in Figure 4 what are the sentiment predictions on the employees analyzed based on different variables.

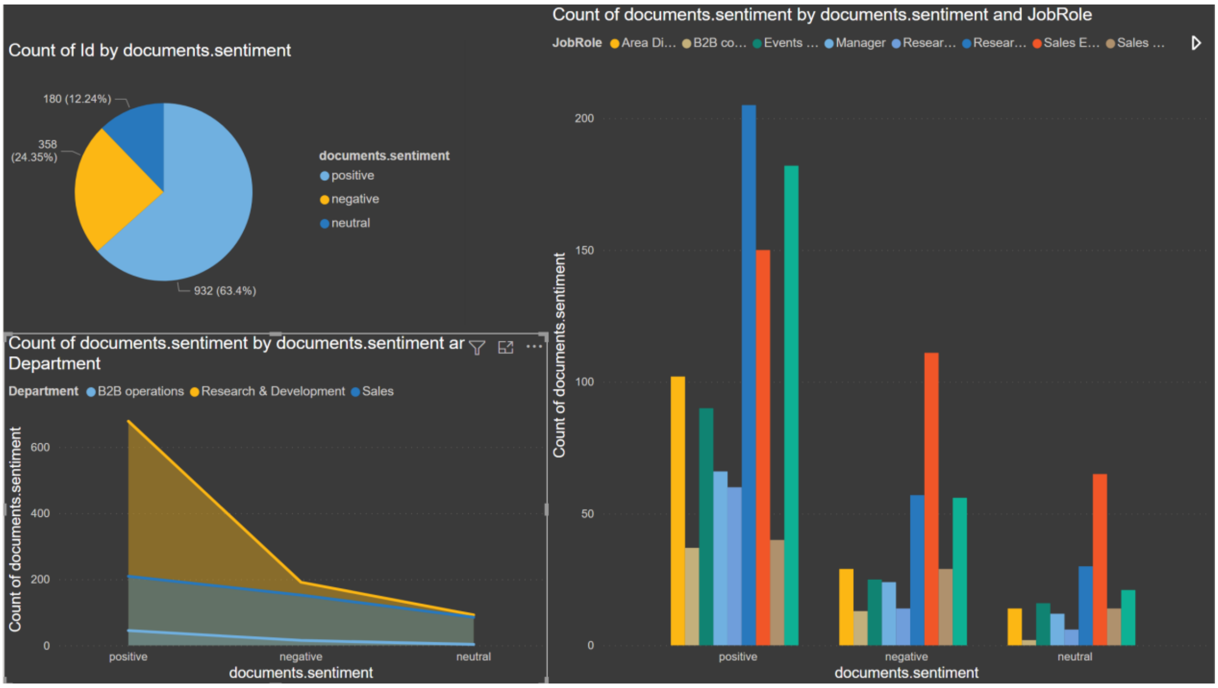

Fig. 4. Dashboard of sentiment analysis obtained with Azure Cognitive Services

From this visualization, most of the employees have expressed positive surveys, about 63.4% from the total. Even though the neutral ones can be interpretated as positive or negative, it is nice to observe the small number of strong negatives.

Even though the research and development department had the most answers in the survey, most of them are positive anyway. However, it is observable a balanced number of positives and negatives for B2B operations and Sales departments.

The last chart shows that Sales department has again most of the people offering bad surveys, helping us to conclude (along with the initial analysis) that the lack of experience the benefits associated with this job role can be an issue for our employees. Of course, since we are talking about two departments that have offered much more bad surveys then the other one, we can look at managers of these, their organization and workload.

Of course, we can add the those with management positions like managers and directors have the smallest amount of bad survey, fact that explains for us their overall feeling in comparison to their benefits and seniority.

Lastly, one more method for sentiment analysis is developed in R. This one, as expressed before, will use predefined lexical dictionaries (lexicons). Considering the method chosen, we will use different libraries, depending on the step we want to achieve. Firstly, coming from the original data set to the tidy one, it will be used “tidy test” to perform the tokenize process. In addition, we will use “dplyr” and “tidyr” in order to get the sentiment lexicon.

Finally, we will arrive to the summarized text and observe the results again in Power BI.

The general lexicon that will be used is “nrc”, from Saif Mohammad and Peter Turney. The analysis will start with the tokenizer step, along with getting the sentiments and removing stop words, if there are any.

```
test<-test$Survey

test_tidy<-test%>%
  unnest_tokens(word, Survey)
```

Fig. 5. Code of unnest function used in R code for lexicon analysis

After applying the unnest_tokens function previously presented in Figure 5, it is now easy to see that data in a more “tidy” format, as observed below in Figure 6.

	Id	Age	word
1	80	46	bad
2	80	46	bad
3	80	46	single
4	80	46	promotion
5	80	46	days
6	80	46	lost
7	80	46	energy
8	80	46	caring
9	80	46	anymore
10	80	46	job
11	80	46	outstandingly
12	101	37	home
13	101	37	benefits
14	101	37	happy

Fig. 6. Data resulted after applying previously unnest_tokens function

After this, we will create the test with nrc, that will provide the sentiments for the survey analyzed, as per Figure 7:

```
test_nrc<-test_tidy %>% inner_join(get_sentiments("nrc"))
test_nrc_sub<-test_tidy %>% inner_join(get_sentiments("bing")) %>%
  filter(!sentiment %in% c("positive", "negative"))

test_nrc
```

Fig. 7. Sample code of applying “nrc” lexicon on the test data

The newly obtained data will have some sentiments associated with every word, based on how the library works, and this can be observed in Figure 8.

	Id	Age	word	sentiment
1	80	46	bad	anger
2	80	46	bad	disgust
3	80	46	bad	fear
4	80	46	bad	negative
5	80	46	bad	sadness
6	80	46	bad	anger
7	80	46	bad	disgust
8	80	46	bad	fear
9	80	46	bad	negative
10	80	46	bad	sadness
11	80	46	promotion	positive
12	80	46	lost	negative
13	80	46	lost	sadness

Fig. 8. Data resulted after joining the dataset obtained previously with "nrc" lexicon

The results obtained will be saved in a table and imported back to Power BI.
Finally, on Fig. 8, it can be observed that most of the feelings obtained from the analysis are positive, however we may see what feelings are associated with every positive or negative result. This is a capability obtained from R analysis, in addition to the general sentiment that we could get from the previous NLP analysis performed with Azure Cognitive Services.
Based on the job roles of departments, it is easy to conclude what are the employees' feelings towards their organization, and also what is every sentiment percentage from the general feeling.

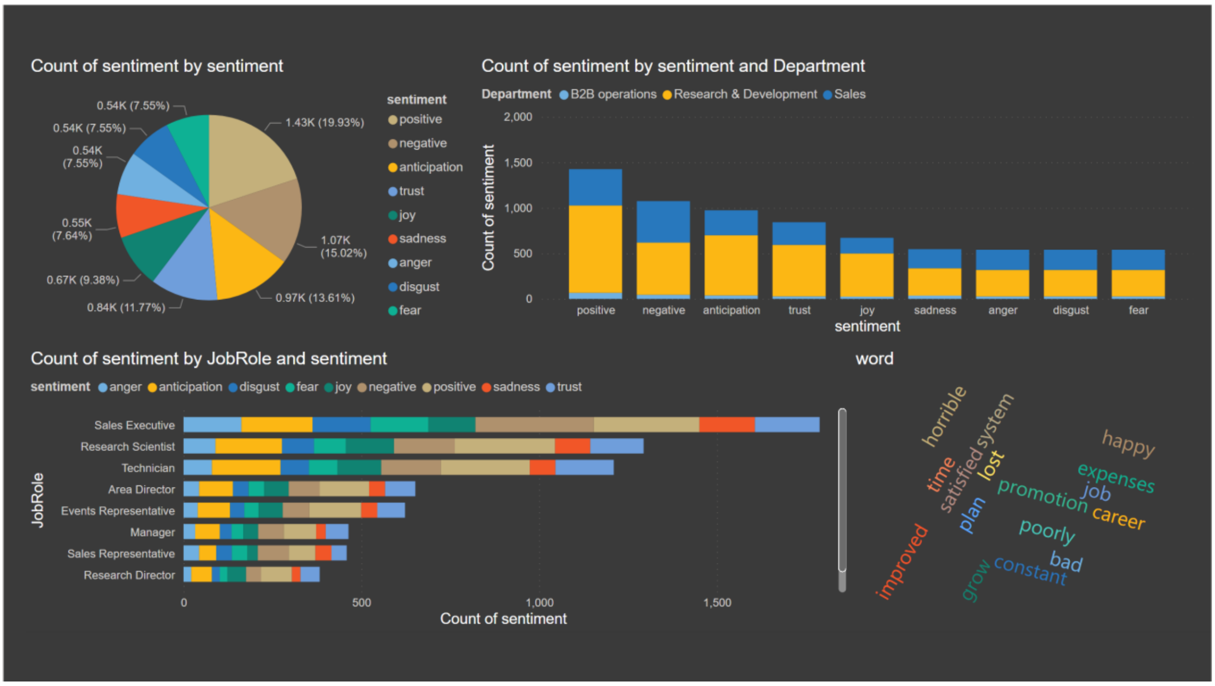

Fig. 8. Dashboard of sentiment analysis obtained with R using tidy text

Finally, using here a word chart based on the results get from R, we may see different details related to employee feeling at work and career and development.

4 Conclusions

Even though sentiment analysis has developed a lot though the years and we have many methods and possibilities to achieve it, there are plenty of combinations that can provide still important results that can be taken into consideration for business purposed.

This paper has showed a comparative approach between a cloud-based solution that is easy to apply and offers good results and a classic lexicon-based approach that requires a little more knowledge and code writing.
Considering the details presented on these two methods, we cannot say that one has performed better than the other one, especially since the results have different forms. However, we can conclude that a cloud-based approach with artificial intelligence included, which also contains predefined algorithms

that have been trained before, will clearly perform better, especially in terms of time and integration (between cloud-based application, even from the same vendor).
In the same time, a more classical approach like the lexicon one from R might mean lower costs and possibility to observe even more details in data, like specific sentiments, not only a positive and negative tag on every work. However, this approach requires more time and the integration with a business intelligence tool requires more attention and work.
Moreover, even though there were considered two different types on analysis performed in different environments, the data analysis has been built in the same business intelligence tool. This choice not only did it offer a very easy way to observe and compare the data, but it has also required less time to integrate and link all the dataset obtained from all the tests performed.
Nonetheless, it is important to specify that one of the approaches used in this paper with artificial intelligence has made use of an unsupervised algorithm. This was chosen because of the data needed to be analyzed (since we did not have pre-known sentiments for all the surveys gathered from employee). Therefore, it was hard to understand how classification models using supervised algorithms performs and which of the existing one would have been the best for our sentiment analysis. Classification is one of the methods often used in other research papers and, even for the organization considered, this would have been a good test. So, for future research and based on the possibilities that we have on this are, collecting data with the associated sentiments that can help us to build and train a model can be considered.
Finally, as specified previously, the data was already cleaned and structured. This comes from the fact that, for a short survey, the company offered a clear way to collect this feedback, also based on the person responding on it. However, the sentiment analysis has multiple ways of applicability, all of them very useful for the business decisions. Therefore, we can consider in the future another area where this type of research can be done, offering much more unstructured data.

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