

Capturing the Difference between Former and Current Employees' Emotional Attitudes based on the Online Reviews

Xiao Pan, Wenli Du, Zhuoming Ren*

Alibaba Business School Hangzhou Normal University Hangzhou, China

* Corresponding author: zhuoming.ren@hznu.edu.cn

Abstract

We take current and former employees as research objects, and analyze the textual and numerical data according to 41,000 anonymous reviews of employees from Amazon, Apple, Microsoft, and Google employees, which is collected from a workplace community, the *Glassdoor* website, that provides company reviews. We discuss the differences between former and current employees' needs for each of the four companies based on reviews on the *Overall Rating* of the employees and the five dimensions (*Work/Life Balance*, *Culture & Values*, *Senior Management*, *Career Opportunities* and *Salary & Benefits*). The results reveal that the current employees prioritize *Work/Life Balance* and *Senior Management*, while former employees value the company's *Senior Management* the most. Next, we explore the textual data of former and current employees' comments on the company: a text mining analysis of the high-frequency vocabulary of positive and negative evaluations and employees' suggestions for the company, and it is found that current employees have positive comments on the *Work/Life Balance* of the company, former employees have positive evaluations of the company's *Senior Management* and *Culture & Values* and both current and former employees are not satisfied with the company's *Senior Management*.

Keywords-Online reviews; Former employees; Current employees; Emotional attitudes

1. INTRODUCTION

At present, there are many perspectives of company evaluation, such as company revenue, company product and industry perception. However, the impact of employee sentiment and review together with employee satisfaction on company evaluation is often overlooked [1]. In reality, both positive and negative online customer reviews are perceived as useful information by consumers [2], and these reviews can affect future customers' decisions [3-4]. Similarly, when job seekers choose a company, they tend to trust the opinions of employees who have worked or are working within the company. Therefore, employee evaluation is not only the basis for job applicants to choose a company, but also a key factor in evaluating employee turnover and satisfaction [5-6].

The research on sentiment analysis has attracted more and more attention in the society today. There are many researches on sentiment analysis of employee reviews abroad. When performing sentiment analysis, a good

sentiment lexicon can make the researcher's work more effective, and some of the comparable renowned sentiment lexicons are SentiWordNet [7-9], General Inquirer [10], SenticNet [11-12] and so on. While the sentiment lexicon is applicable to a wider range of corpus, the machine learning is more accurate. Tsukioka et al. [13] used text mining and support vector machine for classification. Turney et al. [14] proposed a simple unsupervised learning algorithm that can classify reviews as either recommended (Thumbs Up) or not recommended (Thumbs Down). Poria et al. [15] introduced the first deep learning method and a set of heuristic language models for aspect extraction in opinion mining. Agarwal et al. [16] used a tree kernel function to perform sentiment analysis on Twitter data, and Tang et al. [17] developed a deep learning system (Coooollll) for message-level Twitter sentiment classification. In addition, sentiment analysis research has also been widely applied in scenarios such as corporate strategy, marketing activities, and product preferences. Bajpai et al. [18] put forward aspect-level sentiment analysis of individual company reviews, using

the extreme learning machine classifiers ELM and SVM to help users better understand the company profiles. Recupero et al. [19] designed and implemented an algorithm for calculating sentiment scores at the topic and sentence levels. In order to better understand the attitudes and behaviors of employees, Shah et al. [20] adopted HR Predictive Analytics (HRPA) approaches to assess them.

From the previous research progress whether it is based on textual or traditional numerical data statistics, it is based on data-driven verification of related management theories. Unlike previous researches, we collect the anonymous comment data of Amazon, Apple, Microsoft, and Google employees on the company from *Glassdoor.com*, a workplace community for corporate reviews and job searches in the U.S., create a dataset containing 41,000 anonymous comments, and perform data analysis on the dataset to understand the emotional attitudes of internal employees towards the company, especially the differences in the evaluations of the company between former and current employees.

2. DATASET COLLECTION

2.1. Dataset collection

The *Glassdoor.com* is one of the largest jobs and recruiting websites in the world, which covers more than 700,000 global companies and provides nearly 33 million anonymous salary reports and employees' reviews since 2008. The *Glassdoor.com* allows people to evaluate the companies they have worked for or are working for. The evaluation content includes numerical and textual data. The numerical data is the *Overall Rating* ranging from 1 to 5 stars, and the company's five dimensions: *Work/Life Balance*, *Culture & Values*, *Senior Management*, *Career Opportunities* and *Salary & Benefits*. The textual data includes *pros*(positive comments about the company), *cons*(negative comments about the company), *advices*(suggestions for the company) and *recommend* of the company (attitudes to recommend to friends). The accuracy of the data is very high because of the anonymity measures taken by the website to increase the credibility of the reviews.

In this paper, we use the official API of the *Glassdoor.com* to collect anonymous reviews from employees of four companies - Amazon, Apple, Microsoft, and Google - about their own companies, creating a dataset containing 41,000 reviews. The number of reviews for each company is 10,350 for Amazon, 9,926 for Apple, 10,876 for Microsoft, and 9,848 for Google. The data of the four companies are all around 10,000, and there is not much difference from each other. The dataset specifically covers company name, evaluation time, employee attributes (former or current employees), numerical and textual appraisal data.

3. RESULT ANALYSIS

After processing the data, we analyze the online reviews of the employees of Amazon, Apple, Microsoft, and Google based on employee attributes, namely, current employees and former employees.

3.1. Numerical data analysis of the company's reviews by former and current employees

For the five dimensions (*Work/Life Balance*, *Culture & Values*, *Senior Management*, *Career Opportunities* and *Salary & Benefits*) of the company, statistics are compiled on whether former and current employees have different tendencies. First of all the evaluation levels of each company's employees on the five dimensions of the company are divided into two categories: former and current employees. It can be seen from Figure 1 that current employees' evaluations of the company in five dimensions are higher than those of former employees. In the two dimensions of *Culture & Values* and *Salary & Benefits*, current employees' rate higher than 4 stars, but the two dimensions of *Work/Life Balance* and *Senior Management* are only scored a little above 3.5 stars, which shows that current employees prioritize the company's *Work/Life Balance* and *Senior Management*. However, former employees value the company's *Senior Management* most.

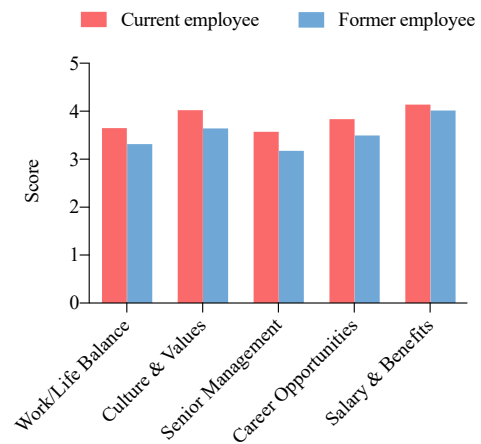


Figure 1. The evaluations of the five dimensions of the company by former and current employees of the four major companies.

After directly comparing the evaluations of the five dimensions of the company by current and former employees of the four companies as a whole, the evaluations of the five dimensions of the company are then categorized according to company and employee attributes and the ratings are displayed using radar chart, as shown in Figure 2. Figure 2(a) is the evaluation ratings of Amazon's current and former employees about the company's five dimensions, from which it can be seen that the evaluations of current employees in the five dimensions are higher than those of former employees,

and the evaluations of the three dimensions of *Work/Life Balance*, *Culture & Values* and *Senior Management* by former employees are below 3 stars. Figure 2(b) is Apple where all five dimensions are rated higher by current employees than by former employees, although all dimensions except *Culture & Values* and *Salary & Benefits* are rated slightly above 3 stars. Figure 2(c) shows that Google's current and former employees' assessments of the company's five dimensions are relatively similar. The evaluations of current employees are slightly higher than those of former employees, almost similar, and the current employees rate the company more than 4 stars in every dimension, which shows that Google is well received by the employees. The Figure 2(d) presents that the current employees of

Microsoft rate the company higher than former employees on all five dimensions; however, in the *Senior Management* dimension, former employees rate the company less than 3 stars. In general, current employees are willing to rate the company positively than former employees.

3.2. Textual data analysis of the company's reviews by former and current employees

In the section, we use word cloud to visualize the frequency of positive (e.g. *pros*) and negative (e.g. *cons*) evaluations of the company by former and current employees.

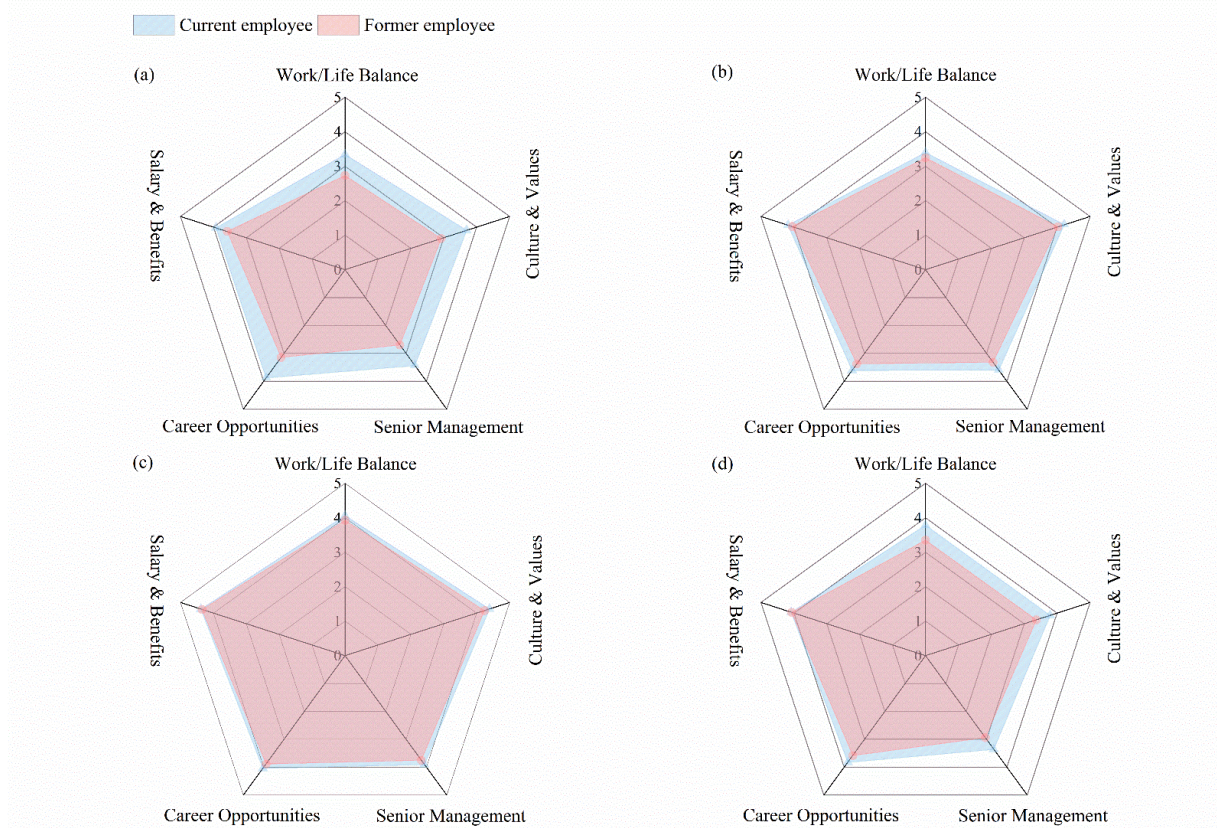


Figure 2. The evaluations of the five dimensions of the company by former and current employees. (a) A radar chart of Amazon employees' evaluations of the company's five dimensions; (b) A radar chart of Apple employees' evaluations of the company's five dimensions; (c) A radar chart of Google employees' evaluations of the company's five dimensions; (d) A radar chart of Microsoft employees' evaluations of the company's five dimensions.

Based on whether the employee is a former or current employee, we divide the *pros* and *cons* of the text data in the dataset into four parts: “the current employee's favor of the company”, “the former employee's favor of the company”, “the current employee's objections to the company” and “the former employees' objections to the company”, shown in Figure 3. Figure 3(a) indicates that current employees are more in favor of the company's *Work/Life Balance* (visible from words such as “work life”

and “life balance”), while the words “team” and “culture” in Figure 3(b) present that former employees are more positive about the two aspects of *Senior Management* and *Culture & Values*. Figure 3(c) reflects that current employees have higher expectations for the company's *Senior Management* (“manager”, “team”, etc. in the Figure 3(c)). The former employees also agree that the company's *Senior Management* needs to be strengthened, in Figure 3(d).



Figure 3. Word clouds of employees' pros and cons of the company. (a) The word frequency graph of current employees' favor of the company; (b) The word frequency graph of former employees' favor of the company; (c) The word frequency graph of current employees' objections to the company; (d) The word frequency of former employees' objections to the company.

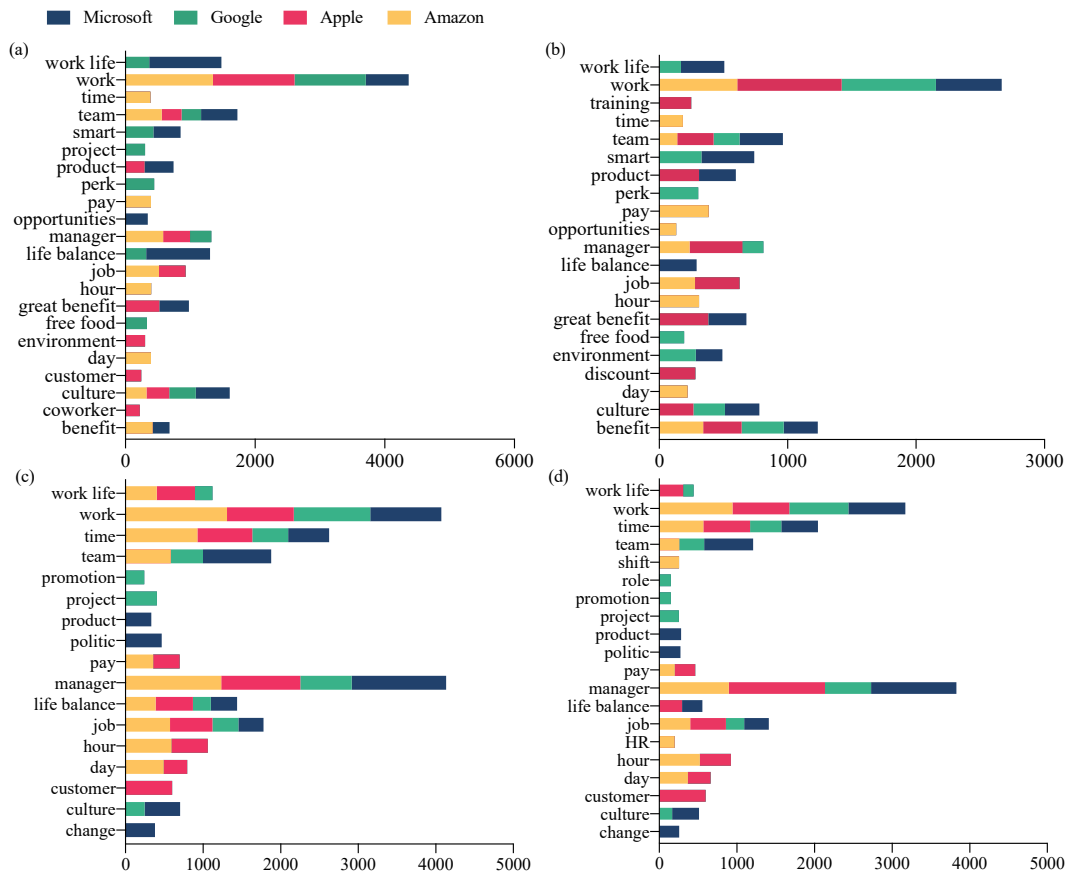


Figure 4. High-frequency vocabulary in the employees' pros and cons of the company. (a) High-frequency vocabulary in the current employees' favor of the company; (b) High-frequency vocabulary in the former employees' favor of the company; (c) High-frequency vocabulary in the current employees' objections to the company; (d) High-frequency vocabulary in the former employees' objections to the company.

Next, the top ten most frequent terms of positive and negative evaluations of the former and current employees of the four companies are displayed in a histogram as Figure 4. From Figure 4(a) and (b), it's clearly that both current and former employees have a more optimistic view on the company's *Senior Management* (as evidenced by the words "team") and *Culture & Values* (seen from "culture"). Figure 4(c) and (d) tell us that both current and former employees have higher expectations regard for the company's *Senior Management* (from words such as "manager") and *Work/Life Balance* (from words like "time", "day" and "hour", etc.). From Figure 4(c), it is evident that current employees are more dissatisfied with their company's *Work/Life Balance*, and this problem exists in every company. The word "role" in Figure 4(d) emphasizes that former employees consider that the company's *Senior Management* needs to be strengthened.

4. CONCLUSION

The paper focuses on the two directions of former and current employees, and analyzes the sentiment of various aspects of the company based on the evaluations of the company by former and current employees, so as to provide different insights into the future development of the company. From the above-mentioned comparative data analysis results of former and current employees, it can be concluded that the company's five dimensions (*Work/Life Balance*, *Culture & Values*, *Senior Management*, *Career Opportunities* and *Salary & Benefits*) do not affect each other. Each dimension is independent and has a significant impact, and both former and current employees attach great importance to these five dimensions. Meanwhile, current employees prioritize the two dimensions of the company's *Work/Life Balance* and *Senior Management*, while former employees value the company's *Senior Management* most. Moreover, the management systems of many companies lead to a lack of the ability to maintain a balance between life and work, which is believed to be a relatively intuitive and clear indicator of the company's development. In the future work, the paper will expand the dataset of company employee reviews at the first and then develop a model of employees' emotions towards the company so that a more comprehensive dimensional sentiment analysis can be conducted.

ACKNOWLEDGMENT

The work is partially supported by National Natural Science Foundation of China (Grant Nos. 61803137), Natural Science Foundation of Zhejiang Province (Grant Nos. LY21F030019).

REFERENCES

- [1] Moniz A, de Jong F. Sentiment analysis and the impact of employee satisfaction on firm earnings[C]//European Conference on Information Retrieval. Springer, Cham, 2014: 519-527.
- [2] Cheng Y H, Ho H Y. Social influence's impact on reader perceptions of online reviews[J]. *Journal of Business Research*, 2015, 68(4): 883-887.
- [3] Xu X, Wang X, Li Y, et al. Business intelligence in online customer textual reviews: Understanding consumer perceptions and influential factors[J]. *International Journal of information management*, 2017, 37(6): 673-683.
- [4] Viglia G, Minazzi R, Buhalis D. The influence of e-word-of-mouth on hotel occupancy rate[J]. *International Journal of Contemporary Hospitality Management*, 2016.
- [5] Costa A, Veloso A. Employee Analytics through Sentiment Analysis[C]//SBBB. 2015: 101-112.
- [6] Stamolampros P, Korfiatis N, Chalvatzis K, et al. Job satisfaction and employee turnover determinants in high contact services: Insights from Employees' Online reviews[J]. *Tourism Management*, 2019, 75: 130-147.
- [7] Esuli A, Sebastiani F. Sentiwordnet: A publicly available lexical resource for opinion mining[C]//LREC. 2006, 6: 417-422.
- [8] Hamouda A, Rohaim M. Reviews classification using sentiwordnet lexicon[C]//World congress on computer science and information technology. sn, 2011, 23: 104-105.
- [9] Ohana B, Tierney B. Sentiment classification of reviews using SentiWordNet[J]. *Proceedings of IT&T*, 2009.
- [10] Stone P J, Dunphy D C, Smith M S. The general inquirer: A computer approach to content analysis[J]. 1966.
- [11] Cambria E, Poria S, Bajpai R, et al. SenticNet 4: A semantic resource for sentiment analysis based on conceptual primitives[C]//Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers. 2016: 2666-2677.
- [12] Cambria E, Speer R, Havasi C, et al. Senticnet: A publicly available semantic resource for opinion mining[C]//AAAI fall symposium: commonsense knowledge. 2010, 10(0).
- [13] Tsukioka Y, Yanagi J, Takada T. Investor sentiment extracted from internet stock message boards and IPO puzzles[J]. *International Review of Economics & Finance*, 2018, 56: 205-217.
- [14] Turney P D. Thumbs Up or Thumbs Down?

- Semantic Orientation Applied to Unsupervised Classification of Reviews[C]. meeting of the association for computational linguistics, 2002: 417-424.
- [15] Poria S, Cambria E, Gelbukh A. Aspect extraction for opinion mining with a deep convolutional neural network[J]. Knowledge-Based Systems, 2016, 108: 42-49.
- [16] Khan F, Apoorva M, Meghana M, et al. Sentiment Analysis Of Twitter Data[J]. International journal of engineering research and technology, 2018, 4(27):100-105.
- [17] Tang D, Wei F, Qin B, et al. Coooolll: A deep learning system for twitter sentiment classification[C]//Proceedings of the 8th international workshop on semantic evaluation (SemEval 2014).2014: 208-212.
- [18] Bajpai R, Hazarika D, Singh K, et al. Aspect-Sentiment Embeddings for Company Profiling and Employee Opinion Mining[J]. arXiv preprint arXiv:1902.08342, 2019.
- [19] Recupero D R, Presutti V, Consoli S, et al. Sentilo: frame-based sentiment analysis[J]. Cognitive Computation, 2015, 7(2): 211-225.
- [20] Shah N, Irani Z, Sharif A M. Big data in an HR context: Exploring organizational change readiness, employee attitudes and behaviors[J]. Journal of Business Research, 2017, 70: 366-378.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

