What FAANG Company Should You Work For?

An Analysis of Employee Reviews on Glassdoor

Table of Contents

BACKGROUND 3
VALUE PROPOSITION 4
OBJECTIVE 4
HYPOTHESIS 4
OVERVIEW OF METHODOLOGY 5
METHODOLOGY 5
I) Data Acquisition and Exploration 5
II) Text Pre-Processing 6
III) Topic Modelling 6
IV) Bi-Gram Frequency 7
V) Sentiment Analysis 9
VI) Visualizations 11
RESULTS 12
Threats to Validity 13
Recommendations 13
To MMA Students 13
To FAANG Companies 14
Conclusion 15
Appendix 16

BACKGROUND

As the McGill MMA class of 2021 looks forward to graduating in a few months, much emphasis is currently being placed on job searching. As emerging Data Scientists, many of the students hope to work at tech-enabled companies. Of course, the most prestigious and notable of these companies are the FAANG companies.

FAANG is an acronym which encompasses the U.S. technology giants:

- **F**acebook - an online social media and social networking service company founded in 2004.
- **A**mazon - a diversified technology company operating in e-commerce, consumer electronics, and cloud computing industries established in 1994.
- **A**pple – a multinational technology company known for selling consumer electronics such as phones, tablets, and computers, founded in 1976.
- **N**etflix - a media provider that provides customers with subscription-based online streaming of films and TV shows .
- **G**oogle - founded in 1998 and specializing in providing internet-based services and products.

These are among the best-performing and most well-known technology companies in the world. To a certain extent, the role of Data Scientist at any of these companies is fairly similar. Therefore, choosing which company to target should largely depend on other parameters closely linked to the attributes describing the company, rather than role-specific features. When attempting to identify which company best suits one's ambitions, the answer lies in realizing the major differences between these types of companies - the culture, leadership, benefits, etc... - all of which contribute to a more holistic understanding of the organization.

Job sites such as Indeed, LinkedIn and Glassdoor are among the first places that come to mind when beginning one's job search. They offer a list of jobs at several companies, as well as reviews of these companies by current and past employees. These reviews are very important as they provide access to candid insights regarding the inner workings of a company and can help persuade or dissuade a student from applying to a company.

Also, due to the COVID-19 pandemic, job searching has become harder and more competitive than ever. Companies across all industries have been forced to adjust, and the FAANG companies are no exception. Despite the fact that many tech companies were at an advantage when the pandemic hit, compared to traditional trade companies, they have also had to make significant adjustments to the way in which they operate in order to ensure the safety of their employees, garner the trust of their customers, and maintain profitability. For instance, Google and Facebook extended a 'work-from-home' policy until Summer 2021 and are currently focusing on a permanent shift to remote or hybrid working models for employees.

Past statistics have shown that our generation changes jobs on average every 18 months. Due to the uncertainty brought about by the COVID-19 pandemic, researchers anticipate that the average tenure will increase, because job security is of the utmost importance nowadays. Therefore, as the MMA class embarks on their job searching journey, it is crucial to choose the right company to work for based on one's own work life preferences, because it is likely that leaving a job will be more difficult in the coming years.

VALUE PROPOSITION

We are creating a tool to help MMA students understand which company is better to target according to how current and former employees feel about certain aspects of work life at these companies. By examining reviews from Glassdoor, pre- and post-COVID, we will be able to uncover valuable insights which allude to the health of the company, and what employees enjoy/don't enjoy about working there. The goals of our solution are as follows:

- Help MMA job seekers identify which FAANG company fit their preference.
- Help FAANG companies identify which departments are unhappy .

OBJECTIVE

The insights we will derive are:

- Top 5 key topics that employees use to rate their experience at a company
    - Ranking each company based on their performance within these topics
- Difference in sentiments of former employees vs current employees
- Difference in sentiments across FAANG companies pre- and post-COVID
- Difference in sentiments across departments within each FAANG company

HYPOTHESIS

Based on our initial research obtained from general news and social media, we have formulated some hypotheses:

1. Google will have the best employee satisfaction pre- AND post-COVID.
2. Amazon will have the worst employee satisfaction pre- AND post-COVID
3. Overall, former employees will be more negative than current employees
4. The supply chain department at Amazon will have the highest dissatisfaction

OVERVIEW OF METHODOLOGY

We will be completing the following steps during our analysis:

1. **Data Acquisition and Exploration** – scraping the data from Glassdoor
2. **Data pre-processing** – preparing the text data for modelling and analysis
3. **Topic Modelling** – determining 5 key attributes that employees care about
4. **Bi-Gram Frequency Counts** – confirming the key topics, as results from topic modelling were unfavorable
5. **Sentiment Analysis** – uncovering employee attitudes pre/post COVID per department per company, as well as, former vs current employee
6. **Visualization** – word cloud, Tableau dashboard

METHODOLOGY

I) Data Acquisition and Exploration

We obtained reviews from Glassdoor by using a scraper. Glassdoor does not have a public API for reviews, therefore, we had to write a script to extract the data from the site into a CSV file. We obtained 2000 English-language reviews from former and current employees at each of the FAANG companies between the years of 2018 and 2021. It takes 4 hours to scrape 2000 reviews, therefore, it took 20 hours to obtain reviews from all 5 companies. Please note that during this report, 2018 & 2019 will constitute 'pre-COVID' years, and 2020 & 2021, will be referred to as 'post-COVID' years.

Upon acquisition of the data, we explored the variables and observations. We observed that there were a lot of duplicate reviews, therefore, we removed duplicates. As a result, we ended up with 500 unique reviews per company (Figure 1).

We extracted the 'Year' from the date column to create a new variable. This will be important in our trend analysis. Lastly, we created a new variable called 'department' by grouping the *job titles* into predefined categories (e.g. supply chain, marketing, technology, etc...). This is necessary for our sentiment analysis which is segmented by department. With this revised dataset (Figure 1), we proceeded to pre-processing and modelling.

company	year	review_title_o	pros_o	cons_o	department
amazon	2021	good	very good environment in the workplace\n	i have not find any deficiency in my workplace...	supply chain
amazon	2021	good service	hard working in this job\n	friendly working in management coverage\nadvic...	supply chain
amazon	2021	nothing	company provide a good salary\n	a lot of physical work\nhelpfu	supply chain
amazon	2021	amazing place to learn and grow	work on exciting products, growing businesses....	you work very hard but you learn a tonne and c...	admin
amazon	2021	good company with oppotunities	career opportunities; career opportunities; ca...	toxic competition culture; toxic competition c...	technology

Table 1 *- Sample of Data Scraped from Glassdoor*

II) Text Pre-Processing

Next, we applied a few standard pre-processing steps in order to prep the data for analysis.

1. *Expanding Contractions* - contractions are literary shortcuts – e.g. 'don't' instead of 'do not'. They are decontracted to facilitate the other pre-processing steps to follow.
2. *Tokenization* – each individual word is split into a token.
3. *Lower Casing* - transforming all words to lowercase is also a very common pre-processing step.
4. *Removal of Punctuations* - punctuations are removed since they serve little value once we begin to analyze our data.
5. *Removal of Stopwords* - stopwords are typically useless words and do not add much meaning to a sentence (e.g. you, it, are, a, etc...).
6. *POS Tagging* - apply parts of speech tags, in other words, determine the part of speech (ie. noun, verb, adverb, etc.) for each word. To prep the words for NLTK's word lemmatizer, which is the next step in pre-processing, we further convert the speech tags to wordnet's format.
7. *Lemmatization* - lemmatization considers the context of a word/sentence and converts the word to its meaningful base form (e.g. 'driving' becomes 'drive').
8. *Selection of Unique Nouns only* – we will be using nouns to perform topic modelling, as we believe they will provide the optimal topic groupings. We will also remove duplicates of words in each review.

III) Topic Modelling

After obtaining all unique nouns from the reviews, we proceeded to Topic Modelling. Topic modeling is a popular statistical tool for extracting latent variables from large datasets. Its goal is to determine the characteristics that data points share, i.e., determine what concepts a document is discussing. [1] One of the most popular methods of topic modelling is Latent Dirichlet Allocation (LDA). LDA represents documents as a mixture of topics, and the topics contain words with certain probabilities. In our case, each review will be classified as a 'document'. LDA is a generative model, meaning that it tries to backtrack from the documents to find a set of topics that are likely to have generated to a collection. To build our model, we did the following:

1. Created a Document Term Matrix using a list of all unique nouns
2. Built the LDA model, and specifying *num_topics*=5
3. Visualized the topics with pyLDAvis [Appendix 1]

Despite its popularity, topic modelling is prone to serious issues with optimization, noise sensitivity, and instability which can result in data which is unreliable. This was the case with our analysis. The topics generated by the LDA model were poorly defined and difficult to interpret. We were able to vaguely establish the following topics for *pro* and *con* sections of the reviews across all companies:

---

[1] https://www.sciencedirect.com/science/article/pii/S0306437920300703

PRO: Company, Perks, Benefit, Work, People, Opportunity (Appendix 2]
CONS: Team, People, Management, Process, Customers (Appendix 3]

However, these results were not satisfactory. As such, we calculated the frequency of the nouns to extract the most mentioned topics.

Table 1 *- Noun Frequency of Pro Reviews*

	word	frequency
5	work	654
18	benefits	547
8	people	434
26	pay	327
3	company	314
13	culture	293
0	environment	278
30	place	161
12	opportunities	139
25	team	137
53	time	133
2	job	121
94	perks	101

Table 3 *- Noun Frequency of Con Reviews*

	word	frequency
2	helpfu	1271
3	management	633
7	work	632
18	hours	307
5	advice	302
40	company	284
43	people	280
32	time	267
273	helpful	194
11	culture	192
20	balance	191
266	employees	172
115	cons	154

From Table 2 above, we can easily identify the top topics in the *pro* section of the reviews. We categorized the top 5 topics as: Pay, Environment, Perks, Work Life, Benefits.

However, in Table 3, which displays the *con* topics, they are difficult to group together or interpret. We can identify certain features such as 'management', 'Work', 'Culture', but it is not as clear. Therefore, we tried another approach: Bi-grams.

IV) Bi-Gram Frequency

An *n*-gram is a sequence of *n* words. By this notion, a 2-gram (or bi-gram) is a two-word sequence of words like 'work life' or 'good salary'. We chose to use bi-grams in order to identify words that co-occur together with the topic words previously identified through topic modelling. This provides another layer of confirmation of the topics. With bi-grams, we can also get an indication of the sentiment of the topic as the nouns could be paired with adjectives.

To begin, we used the *CountVectorizer* library, specified *ngram_range* as (2,2) and obtained a frequency table of all the bi-grams in both the *pro* and *con* columns.

We then scanned through the list to identify common themes that emerged. Using the insights we gained from topic modelling, we anticipated what the topics in the *pro* table would be. Since the topics from the *con* list in topic modelling was inconclusive, we looked through the list and generated 5 common themes/topics which came up frequently: Environment, Work Life, Management, Career Growth, Support. (Please see Appendix 4 for more details on how these categories were formed).

We used these topics and performed a find/replace function to substitute the bigrams with their corresponding topic. Following this, we obtained the normalized frequency of the topics per department by dividing the number of times the topic appeared by the number of reviews.

***Table 2** - Bigram Frequency Per Department for PRO Reviews*

	company	department	word	freq
0	amazon	supply chain	Pay	0.262987
1	amazon	supply chain	Benefits	0.233766
2	amazon	supply chain	Work Life	0.292208
3	amazon	supply chain	Environment	0.285714
4	amazon	supply chain		0.685065
5	amazon	supply chain	Perks	0.022727
6	amazon	admin	Environment	0.544304
7	amazon	admin	Pay	0.164557
8	amazon	admin	Work Life	0.392405
9	amazon	admin	Benefits	0.063291

***Table 5** - Bigram Frequency Per Department for CON Reviews*

	company	department	word	freq
0	amazon	supply chain	Management	0.340909
1	amazon	supply chain	Work Life	0.762987
2	amazon	supply chain	Support	0.233766
3	amazon	supply chain	Environment	0.058442
4	amazon	supply chain	Career Growth	0.071429
5	amazon	supply chain	work life	0.003247
6	amazon	admin	Management	0.316456
7	amazon	admin	Work Life	0.696203
8	amazon	admin	Environment	0.025316
9	amazon	admin	Career Growth	0.050633

Through this analysis, we gained an understanding of what attributes employees from different departments at FAANG companies tend to praise, and what attributes they tend to criticize. Using this information, the MMA students could see where their preferred FAANG company falls short according to others who previously worked in the technology/analytics departments, and where the company excels.

Figure 1 and Figure 2 below summarize our Topic analysis. We created a custom dashboard in Tableau to visualize all our findings. We go into more detailed explanation of the graphs and findings in the *Recommendations* section of this report.

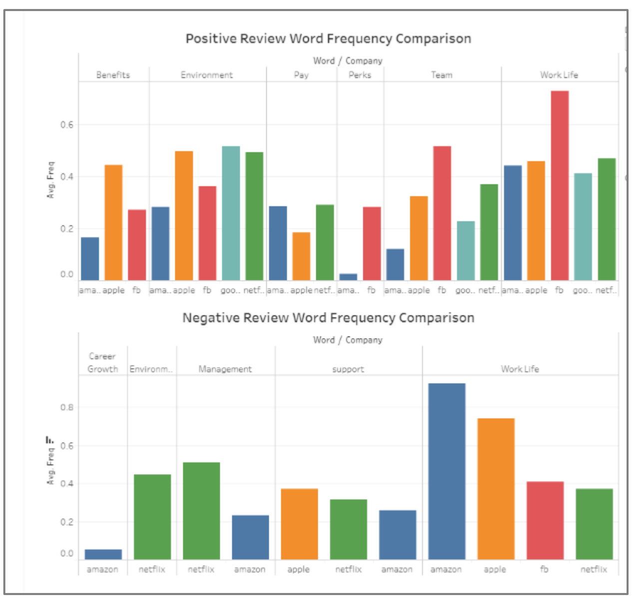


***Figure 2** - Topic Frequency Comparison Across All Companies*

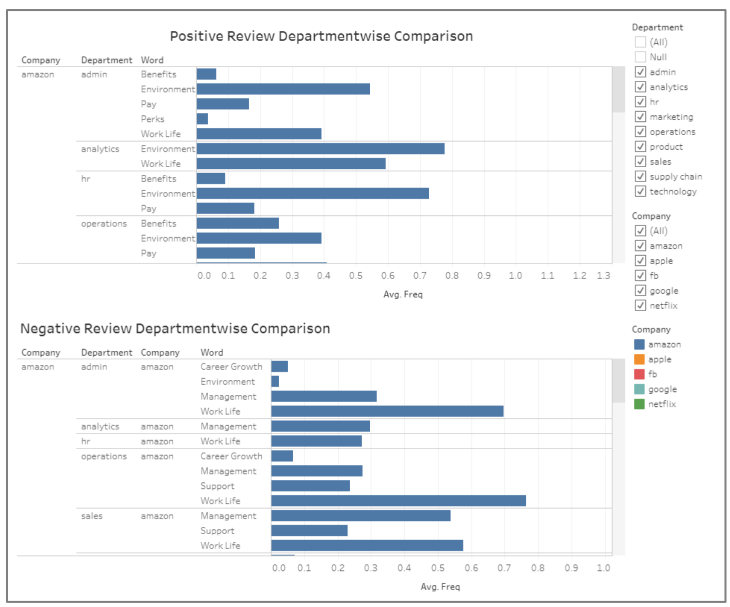


***Figure 2** - Dashboarding Tool Created to Visualize the Difference in Topic Frequencies Across Different Departments Across Different Companies*

V) Sentiment Analysis

Building upon the topic and bi-gram analysis, we performed sentiment analysis to derive more information to serve our initial objectives. Sentiment Analysis – otherwise known as opinion mining – is the most common text classification tool that analyses a message and tells whether the underlying sentiment is positive, negative our neutral. [2] In essence, it is the process of determining the emotional tone behind a series of words, used to gain an understanding of the attitudes, opinions and emotions expressed within an online mention.

We performed sentiment analysis using *Vader SentimentAnalyzer*. The VADER algorithm outputs sentiment scores to 4 classes of sentiments (negative, neutral, positive, compound). The metric we used to calculate sentiment was the *compound score*. This is because compound score is computed by summing the valence scores of each word in the corpus, adjusted according to the system rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). This is the most useful metric if you want a single unidimensional measure of sentiment for a given sentence.[3]

We thus calculated the sentiment of the *pro* and *con* sections of all reviews. We segmented the data by employee status (current vs former), year, and company, to derive richer insights.

Table 3 *- Snippet of the Output Which Displays the Average Sentiment Score For Each Company, In Different Years, and also Segregates Current and Former Employers.*

			pros_sentiment	cons_sentiment	department
			mean	mean	
employee_status	year	company			
current employee	2018	apple	0.691979	0.043635	(current employee , 2018, apple)
		fb	0.966033	0.405033	(current employee , 2018, fb)
		google	0.705200	0.111200	(current employee , 2018, google)
		netflix	0.737444	0.198860	(current employee , 2018, netflix)
	2019	amazon	0.589601	0.041835	(current employee , 2019, amazon)
		apple	0.646700	-0.028045	(current employee , 2019, apple)
		fb	0.210750	0.296750	(current employee , 2019, fb)
		google	0.704675	-0.015025	(current employee , 2019, google)
		netflix	0.710827	0.255090	(current employee , 2019, netflix)
	2020	amazon	0.529605	-0.009160	(current employee , 2020, amazon)
		apple	0.628829	0.056194	(current employee , 2020, apple)
		fb	0.761044	0.127806	(current employee , 2020, fb)
		google	0.602282	-0.002351	(current employee , 2020, google)
		netflix	0.564054	0.240614	(current employee , 2020, netflix)
	2021	amazon	0.521198	-0.069346	(current employee , 2021, amazon)
		apple	0.693370	-0.028117	(current employee , 2021, apple)
		fb	0.643532	0.049681	(current employee , 2021, fb)
		google	0.612717	0.045396	(current employee , 2021, google)
		netflix	0.550252	0.093187	(current employee , 2021, netflix)

Interestingly, we found that the sentiment scores for the *pro* reviews were all fairly positive, but so were those for the *con* reviews for the most part. By interpreting the compound score, this alludes to the fact that the positive and negative reviews were not as polarizing as we had expected.

---

[2] https://towardsdatascience.com/sentiment-analysis-concept-analysis-and-applications-6c94d6f58c17

[3] https://blog.quantinsti.com/vader-sentiment/

Following on from this, we found the sentiment scores of the different departments across all five FAANG companies. This will enable us to understand which departments are more or less satisfied with their employer. Figure 4 below shows the visualization of our data.

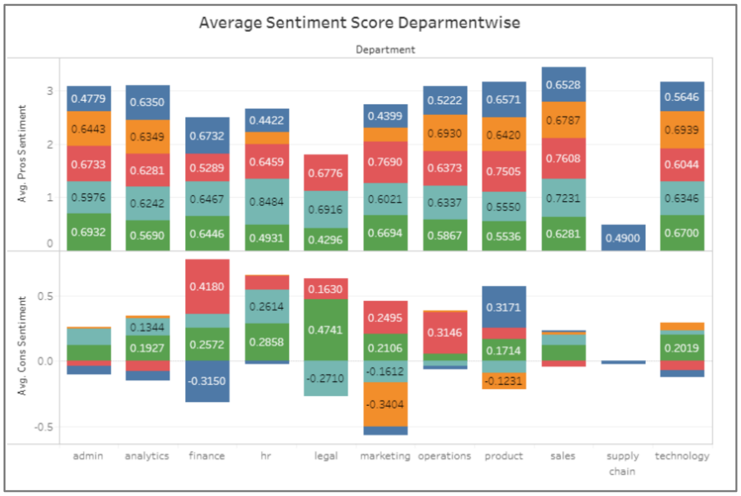


Figure 4 - Average Sentiment Score Across Different Departments at Different Companies

In addition to this, we found the difference in sentiments between the reviews given by former and current employees. This will enable us to test one of our initial hypotheses.

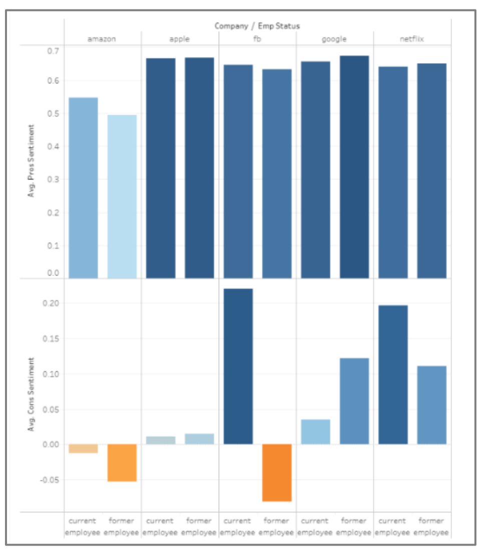


Figure 5 - Difference in Sentiment Score Between Current and Former Employees

Lastly, we found the overall company sentiments per year. This will enable us to understand how employee attitudes have change pre- and post- COVID.

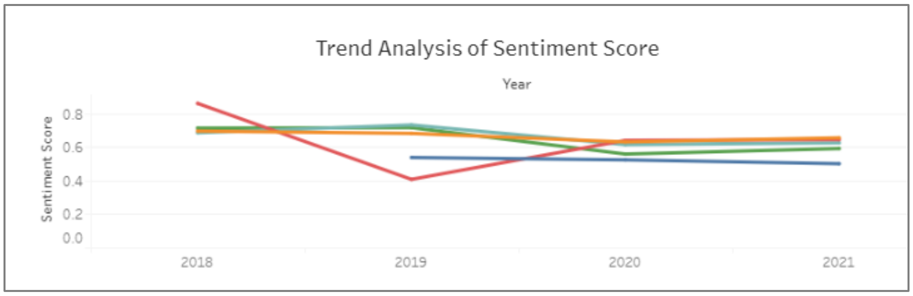


Figure 6 - *Trend Analysis of Employee Sentiments Pre- and Post-COVID Across All Companies*

VI) Visualizations

In order to easily interpret the plethora of insights we generated through our analysis, we performed extensive data visualization using [Python](#) and [Tableau](#).

We used Tableau to visualize all aforementioned bi-gram and sentiment analysis insights. Using Python, we generated word clouds to better identity the topics in the *pro* and *con* reviews.

Figure 7 *- Word Cloud of all PRO Reviews*

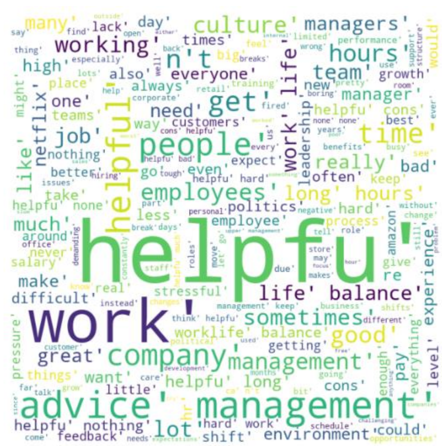


Figure 8 *- Word Cloud of CON Reviews*

RESULTS

Here are the results, as they pertain to our hypotheses:

Hypothesis 1: *Google will have the best employee satisfaction pre- AND post-COVID.*

Overall, Google has held a 1st or 2nd position across the years in terms of overall sentiment score. Just like the other FAANG companies, there was a slight decline in sentiment score from 2019 to 2020, but it has also increased in 2021 [see Figure 6 above]. As previously mentioned, Google was very quick to react to COVID by establishing a work-from-home policy, which we assume greatly improved their employees' attitudes during the pandemic.

Hypothesis 2: *Amazon will have the worst employee satisfaction pre- AND post-COVID*

We were correct in our hypothesis. Figure 6 shows that Amazon was generally ranked lowest pre- and post- COVID. In 2019, Facebook scored lower than Amazon, however, we believe this occurred due to the Cambridge Analytica scandal that the company was wrapped up in. The scandal started in early 2018 but we believe it took some time before the feelings of employees started showing up more and more on job review platforms. In fact, a former product designer at Facebook stated that because of the scandal "Morally, it was extremely difficult to continue working there as a product designer" [4].

Hypothesis 3: *Overall, former employees will provide more negative reviews than current employees*

As seen in Figure 5, this hypothesis is validated. Overall, the sentiment scores of former employees for both *pro* and *con* reviews tend to be lower than those of current employees. However, this is not the case for Google, which further strengthens our claim in hypothesis 1.

It is intuitive to reconcile why sentiments of former employees are lower. While still employed at a company, there is a higher risk of being laid off if you are caught being openly negative about your employer, therefore, current employees are more cautious and less likely to offer candid negative reviews.

Hypothesis 4: *The supply chain department at Amazon will have the highest dissatisfaction*

This was proven to be untrue, as the marketing department at Apple had the lowest average sentiment score between pros and cons (-0.34) of any department at any company. Moreover, within Facebook itself, the finance department had a lower sentiment score (-0.31) than the supply chain department (-0.023)

[4] https://www.businessinsider.com/why-facebook-employees-quit-2019-2

Threats to Validity

Despite the extensive nature of our analysis, it is important to note that there are several factors which pose a threat to the validity of our results.

Firstly, the size of our dataset was fairly small. As previously mentioned, during the data exploration phase, we eliminated duplicate values which left us with less than an average of 500 observations per company. With a small dataset, variability and noise have a greater effect on the outputs of our models. Therefore, it is important to get a larger dataset and re-evaluate our analysis. As part of this, we were unable to gather reviews published in 2018 for Amazon. Nonetheless, given the size of our dataset, we were able to uncover meaningful insights that align with information and events that are prevalent in the news and social media, therefore, there is still a good level of validity to our results.

In addition, the subjectivity with which we selected the topics during the topic modelling and Bi-Gram frequency analyses also poses a threat to validity. As seen in the LDA plot, there are several overlaps between categories, which makes it difficult to fully distinguish between themes.

Recommendations

To MMA Students

Everyone has their own opinions about what they want in a job. Some people care much more about pay than culture, and others value a work-life balance over everything else. To make recommendations, we looked at the *pro* section of the reviews, as we felt that if a person is willing to go out of their way to write something in that section, it is more likely that it is true. Meanwhile, we feel that people could have other reasons for writing what they do in the *con* section, especially if they are a former employee. Therefore, we make the following recommendations to students based on the five topics we gathered from the data:

1. If you are someone who values benefits, you should apply to work at Apple. When talking about benefits as a *pro* of working at the company, Apple employees mentioned this aspect way more than any of the other company. The average frequency of the topic "benefits" for Apple was 0.46, the next closest being Facebook at 0.23.
2. If you are someone who values work environment, you should try to work at Facebook. The environment topic was a common theme across the pros sections of the reviews, but Facebook employees mentioned it more than the employees of any other company, with an average frequency of 0.79.
3. If you are someone who cares most about salary, you should target either Amazon or Facebook. The topic "pay" is most mentioned with these two companies, as the average frequency of this topic in reviews for Facebook is 0.24 and 0.21 for Amazon.
4. If you are someone who values perks, you should try to work for Netflix. Employees at Netflix mentioned perks in the *pro* of their reviews much more compared to the employees at the

other companies. The average frequency for this topic at Netflix was 0.28, with Apple being the next closest at 0.15.

5. Lastly, if you value work life, you should target Facebook. Facebook employees mentioned work life very often in their reviews as an advantage of working for the company. In fact, the average frequency for the "work life" topic in these reviews was 0.93 for Facebook employees.

To FAANG Companies

Our analysis not only showed valuable information for job seekers, but it also gave insights into where these companies can improve their employee satisfaction. Our sentiment analysis segmented by department (Figure ##), showed which departments are the most unhappy/happy within these tech giants. Based on this analysis, we make the following recommendation.

1. Employees from Apple's marketing department leave the most negative reviews. The sentiment score for the pros section was barely positive (0.26), and the sentiment for the cons section was the most negative of any department at any company (-0.34). Apple should look at how they are treating the employees in their marketing department, as they are leaving poor reviews on Glassdoor.

We also looked at how average sentiment changes in reviews between current and former employees at these companies. When looking at the pros section of the reviews, there was not much of a change in the sentiment if an employee was no longer with the company. However, there was one major discrepancy, and that was between current and former employees at Facebook in the cons section of their reviews. Current Facebook employees are very positive when mentioning the disadvantages of working at Facebook (average sentiment score of 0.22). However, the former employees were much more negative (average sentiment score of -0.08). This was the biggest difference we saw for any company. Therefore, we make the following recommendation:

2. This makes it clear that Facebook employees that leave are rather disgruntled and leaving because they did not enjoy working for the company. Therefore, Facebook should interview employees that are leaving to understand why they are leaving, in hopes that they can stop more people from leaving, or at least stop them from leaving on a bad note.

Conclusion

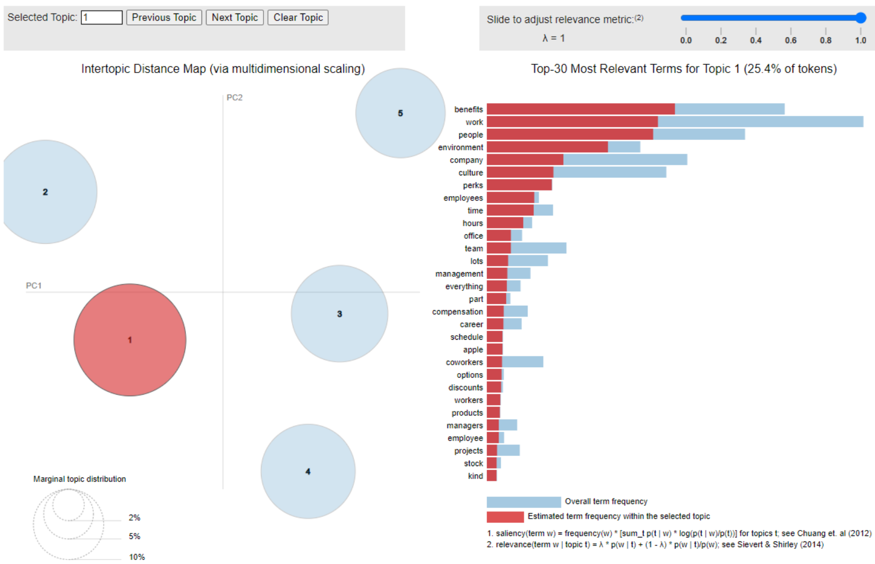
Our hypotheses were fairly intuitive and aligned with what is most often heard in the news, on social media, and in the public. Consequently, it was encouraging to see that our analysis also aligns with these general views. It showed that popular views such as "Amazon employees hate their jobs" or "Google is a very fun place to work" are backed up by data. This convinces us that our analysis makes sense, and further confirmed our views of these companies.

However, it is worth noting that our analysis was not extremely conclusive. One issue that we ran into was the amount of data that we could run the analysis on. Because of the large number of duplicate reviews on Glassdoor, our dataset was not as large as we would have liked. This made our methods more sensitive to noise, especially the topic modeling. We do believe that the sample size was still large enough to draw the conclusions that we did, but more data would have made the conclusions more concrete.

In terms of next steps, we could solidify our findings by not only gathering more data, but also by looking at other data sources. It is very possible that the reviews on Glassdoor are inherently biased, as Glassdoor forces people to review a company when they sign up for an account. We could cross-reference our findings from this analysis with data from LinkedIn and Indeed to further confirm our conclusions. More data, from multiple sources, would be sure to show precisely how employees at these companies feel about their company, along with what they would want to improve, and thus make it easier for us to make recommendations to the company on how to improve the employee experience, as well as affirm our recommendations for which FAANG company the MMA students should work for.

Appendix

Appendix 1: *LDA Visualization for the PRO topics*



Appendix 2: *Topic Modelling Output for the PRO Reviews*

```
[(0,
  '0.040*"salary" + 0.036*"company" + 0.029*"everything" + 0.026*"every" + 0.025*"product" + 0.022*"day" + 0.022*"skills" + 0.018*"everyone" + 0.016*"work" + 0.016*"managers"'),
 (1,
  '0.207*"work" + 0.086*"place" + 0.047*"balance" + 0.038*"life" + 0.035*"company" + 0.017*"’" + 0.012*"\'\'" + 0.012*"lunch" + 0.012*"around" + 0.011*"day"'),
 (2,
  '0.153*"company" + 0.102*"benefits" + 0.080*"culture" + 0.044*"pay" + 0.041*"google" + 0.036*"coworkers" + 0.033*"office" + 0.019*"none" + 0.018*"compensation" + 0.016*"options"'),
 (3,
  '0.146*"pay" + 0.077*"benefits" + 0.053*"time" + 0.032*"team" + 0.032*"fun" + 0.021*"feedback" + 0.020*"care" + 0.018*"tech" + 0.016*"schedule" + 0.016*"days"'),
 (4,
  '0.167*"people" + 0.094*"environment" + 0.090*"work" + 0.060*"culture" + 0.060*"benefits" + 0.049*"perks" + 0.022*"freedom" + 0.020*"&" + 0.018*"projects" + 0.013*"everything"'),
 (5,
  '0.065*"colleagues" + 0.061*"food" + 0.045*"people" + 0.036*"*" + 0.035*"leadership" + 0.032*"money" + 0.019*"communication" + 0.016*"problems" + 0.013*"like" + 0.013*"thing"'),
 (6,
  '0.086*"job" + 0.058*"hours" + 0.045*"experience" + 0.043*"employees" + 0.035*"environment" + 0.035*"benefits" + 0.023*"opportunity" + 0.022*"management" + 0.017*"lots" + 0.017*"products"'),
 (7,
  '0.087*"opportunities" + 0.052*"lot" + 0.048*"lots" + 0.047*"growth" + 0.039*"career" + 0.031*"culture" + 0.028*"benefits" + 0.020*"development" + 0.019*"team" + 0.017*"learn"')]
```

Appendix 3: *Topic Modelling Output for the CON Reviews*

```
[(0,
  '0.036*"management" + 0.031*"culture" + 0.031*"people" + 0.030*"company" + 0.029*"``" + 0.028*"\'\'" + 0.025*"team" + 0.016*"work" + 0.013*"employees" + 0.012*"growth"'),
 (1,
  '0.165*"helpfu" + 0.075*"cons" + 0.058*"none" + 0.058*"nothing" + 0.037*"management" + 0.036*"company" + 0.022*"advice" + 0.018*"place" + 0.017*"everything" + 0.017*"helpful"'),
 (2,
  '0.064*"’" + 0.048*"helpfu" + 0.045*"lot" + 0.032*"time" + 0.026*"people" + 0.025*"company" + 0.021*"like" + 0.018*"issues" + 0.017*"months" + 0.014*"get"'),
 (3,
  '0.094*"helpfu" + 0.065*"management" + 0.040*"advice" + 0.039*"people" + 0.029*"job" + 0.022*"things" + 0.014*"managers" + 0.013*"could" + 0.012*"use" + 0.012*"lot"'),
 (4,
  '0.120*"hours" + 0.057*"helpfu" + 0.048*"work" + 0.019*"day" + 0.018*"politics" + 0.014*"days" + 0.014*"changes" + 0.014*"shifts" + 0.014*"pay" + 0.013*"hour"'),
 (5,
  '0.154*"work" + 0.117*"helpfu" + 0.053*"balance" + 0.051*"life" + 0.036*"management" + 0.024*"environment" + 0.022*"advice" + 0.018*"times" + 0.017*"get" + 0.016*"pressure"'),
 (6,
  '0.029*"management" + 0.027*"like" + 0.022*"employees" + 0.018*"one" + 0.018*"job" + 0.014*"day" + 0.014*"employee" + 0.014*"without" + 0.013*"customers" + 0.013*"helpful"'),
 (7,
  '0.075*"time" + 0.068*"helpfu" + 0.026*"management" + 0.017*"years" + 0.015*"\'" + 0.014*"part" + 0.014*"advice" + 0.013*"roles" + 0.013*"office" + 0.013*"one"')]
```

Appendix 4:

In order to create more distinct topics, we used the find/replace function and grouped together bi-grams which shared the same theme. For example:

PRO

- *Benefits* – good benefits, 401k match, paternity leave, amazing maternity, unlimited vacation
- *Perks* – free meals, good perks, breakfast lunch, free netflix, discount amenities, new devices
- *Pay* – high salary, stock options, paid overtime, excellent pay, salary bonus, month reimbursed
- *Environment* – great company, culture great, environment friendly, culture transparency
- *Work Life* – flexible schedule, work life, lots opportunity, high performance, fun work

CON

- *Work Life* – long hours, physically demanding, heavy workload, extremely competitive
- *Management* – horrible management, extremely rude, micro management, management biased
- *Environment* – toxic culture, office politics, worst company, lack diversity, corporate groupthink
- *Career Growth* – limited career, hard move, lose job, fire people, challenging grow, climb ladder
- *Support* – high stress, imposter syndrome, cut throat, overwhelming times, challenges adjusting