MAANG? MANGA? Characterizing Spontaneous Ideation Contest on Social Media

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ABSTRACT

Social media is not only a place for people to communicate on a daily matter but also a virtual venue to transmit and exchange various ideas. Such ideas are known as the raw voices of potential consumers, which come from a wide range of people who may not participate in consumer surveys, and therefore their opinions may contain high value to companies. However, how users share their ideas on social media is still underexplored. This study investigates a spontaneous ideation contest about a generic term for new Big Tech companies, which occurred when Facebook changed its name to Meta. We constructed a comprehensive dataset of tweets containing candidates and examined how they were suggested, spread, and exchanged by social media users. Our findings indicate that different ideas are better on different metrics. The ranking of ideas was not decided immediately after the idea contest started. The first people to post ideas have smaller followers than those who post secondarily or who only share the idea. We also confirmed that replies accumulate unique ideas, but most of them are added in the first depth in reply trees. This study would promote the use of social media as a part of open innovation and co-creation processes in the industry.

CCS CONCEPTS

• Applied computing → Sociology; • Social and professional topics; • Information systems → World Wide Web;

KEYWORDS

social media, ideation contest, twitter, co-creation, open innovation

1 INTRODUCTION

Collecting novel ideas is critical for many organizations. As ideas are the source of innovation and success, organizations need to have a continuous flow of ideas [6]. With the increasing speed of information sharing about products, competition in business is intensifying every year, and thus there is an increasing demand for collecting ‘good’ ideas [5].

Industries and academia have been seeking for efficient methods to acquire good ideas. The efforts include studying the mechanisms of idea generation in individuals [9] and creating an organizational system that facilitates idea generation from employees [27]. Also, companies have started outsourcing their idea generation [12]. Incorporating external knowledge, such as open innovation [15] or co-creation [17], is expected to accelerate internal innovation and reduce the risk of product failure as it helps to involve potential customers in idea generation. Ideation contest is one of the leading choices to outsource ideas, which gathers participants and ask them open questions about new ideas. Companies such as Dell [3], IBM [21], and Starbucks [22] have succeeded in the ideation contest using crowdsourcing platforms [3] or corporate ideation platforms [11]. However, the problem with these platforms is that the number of participants is limited and sometimes biased [24].

The use of social media for ideation contests is gaining attention to supplement existing methods [24]. Social media is a place where a wide variety of ideas are posted and discussed on a daily basis [26], allowing companies to solicit ideas from a more expansive space [1] and gain ideas from the types of people who would otherwise be excluded [19]. Due to these properties, researchers have proposed the inclusion of social media information in the business innovation process [24] and demonstrated its benefits theoretically [4]. Nonetheless, there is little exploration about efficiently extracting ideas from social media [13].

This study focuses on ideation contests on social media, which we call spontaneous ideation contests, and characterizes their collective behaviors. Our analyses can facilitate ideation content on social media by 1) identifying the timing to acquire ideas on social media by knowing when these ideas get generated and mature, 2) knowing whom to usually follow for efficiently extracting ideas on social media by understanding the characteristics of the people...
who generate and spread ideas, and 3) learning how to secure a variety of ideas by analyzing how ideas accumulate in discussions. We choose the generic term of Big Tech companies as the case study. Big Tech companies were mainly referred to as FANG (Facebook, Amazon, Netflix, and Google) or FAANG (FANG + Apple) using their acronyms [10]. However, as Facebook changed its company name to Meta in October 2021, it triggered an ideation contest and sparked many ideas and discussions on social media about their new generic name. This case can be an exemplar of ideation contests because the name change of a big company such as Facebook is a phenomenal event and because an ideation contest about a name (i.e., naming contest [20]) is the most straightforward form of ideation contests [29]. For the analysis, we exhaustively collected posts on Twitter regarding the generic names of Big Tech and analyzed them based on the following RQs:

- RQ1: How are the dynamics of the spontaneous ideation contest?
- RQ2: How are ideas spread in the network of contest participants?
- RQ3: How are ideas exchanged among the participants?

As a result, we found 21 candidate acronyms of a new Big Tech name, and they have differences in which metric they are superior. The ideation contest started right after Facebook’s name change was announced, and the movement subsided in a few days. The first people to post ideas have fewer followers, while those with more followers post ideas secondary or share the first posts. We also confirmed that the replies accumulate unique ideas, which could reach up to the fourth depth in a reply tree.

Our contributions are as follows. This study is the first to focus on a spontaneous ideation contest in social media and characterize its process. We collect and publish ideation contest datasets on the Big Tech moniker in Facebook’s name change. This study would promote the use of social media as a part of open innovation and co-creation processes in the industry.

2 RELATED WORKS

2.1 Ideation Contest

Ideation contest is one of the co-creation activities of companies aiming at outsourcing ideas [12, 24]. There are some types of ideation contests in addition to naming contests, such as graphic design and creative writing contests [29]. Most of them have been firm-initiated ideation contests, in which a company solicits ideas through crowdsourcing or a corporate ideation platform, which are mainly financially incentivized [16]. As the analysis on corporate ideation platform, Bayus [3] analyzed their behavior and the quality of their ideas with respect to serial ideators and ideators with only one idea. Hossain and Islam [14] analyzed the growth process of the platform and the relationship between the total number of ideas and the number of viable ideas. In contrast, we analyze spontaneous ideation contests on social media, which have the advantage of obtaining various participants’ opinions with less bias than corporate ideation platforms [1, 19].

2.2 Idea Extraction from Social Media

Social media is rich in various kinds of ideas, and there is a strong demand for methods to use these ideas in corporate innovation. In fact, many companies attempt to use social media to enhance their innovation process in some forms [25], and idea creators such as fashion designers have been using social media frequently in recent years to encounter new inspiration [2, 28]. However, methods for systematically extracting ideas from social media are still under-explored. So far, the primary use of social media in the industry has been to look up related words or feedback for a specific product as marketing research [8], and there has been little study on the mechanism of how social media users generate ideas. As close studies, Carr et al. [7] searched for the related words of a product from social media, analyzed their volume, and confirmed the insights obtained through social media searches and found that social media information is helpful for designers. Our study advances this line of research and is the first empirical analysis of an ideation contest on social media.

3 DATA COLLECTION

To examine the process of the ideation contest, we look for the candidates of the new Big Tech name and collect tweets about them.

| Idea   | Tweet | RT  | Like | Reply | QT  |
|--------|-------|-----|------|-------|-----|
| MAANG  | 807   | 0.64| 5.87 | 0.99  | 0.20|
| MANGA  | 709   | 1.51| 10.41| 0.87  | 0.21|
| MANG   | 152   | 1.03| 5.52 | 0.95  | 0.38|
| MAANAA | 103   | 0.67| 7.65 | 0.58  | 0.19|
| MAMAA  | 98    | 0.62| 2.05 | 0.56  | 0.21|
| MAGMA  | 48    | 0.88| 12.35| 2.13  | 0.31|
| GAMMA  | 41    | 0.39| 4.90 | 1.32  | 0.10|
| MAGA   | 41    | 1.73| 33.54| 2.02  | 0.54|
| TAANG  | 18    | 0.06| 1.61 | 0.44  | 0.06|
| MAGNA  | 15    | 0.00| 1.13 | 0.40  | 0.07|
| MAAMA  | 9     | 0.33| 8.11 | 1.56  | 0.11|
| MAMATA | 9     | 9.89| 83.78| 6.44  | 1.78|
| MAMA   | 7     | 0.43| 4.29 | 0.57  | 0.14|
| MAMANG | 5     | 0.00| 1.20 | 0.20  | 0.00|
| AMAMA  | 4     | 0.00| 0.50 | 0.25  | 0.00|
| MAANAM | 3     | 0.33| 8.00 | 0.33  | 0.33|

Table 1: The idea candidates and their statistics. The statistics include the number of posts containing (Tweet), retweet (RTs), like, reply, and quote retweets (QTs). The metrics except for Tweet indicate the average values per tweet.

3.1 Finding Candidates

We firstly collect tweets to identify candidate acronyms. We use the Twitter Academic API1 to obtain tweets containing “FANG” or “FAANG”, which have been common names for Big Tech [10] from 28 Oct 2021 to 30 Nov 2021, one month window after Facebook’s

1https://developer.twitter.com/en/products/twitter-api/academic-research
name change. The API is case-insensitive in search. As a result, we
obtained 53,975 English tweets without retweets (RTs). From this
dataset, we extract the 150 most co-occurred words with “FANG” or
“FAANG” based on Jaccard coefficient [23], and conduct a manual
examination to extract a set of candidate acronyms of the new
Big Tech companies. As a result, we obtained 21 candidate ideas
(shown in Table 1). We note that omit those candidates with one
tweet, which are MAMSANG, TMAANG, MAANAT, MANATAM,
MATANTA, from the Table 1.

3.2 Collecting tweets about candidates
We use the Twitter API again to search for tweets containing those
21 candidates over the same period. As a result, we retrieved 3.55
million English tweets, excluding RTs. However, we found that
many of the candidates had homonyms (e.g., MAMA for a music
award, MAGA for a political slogan). Therefore, we narrowed down
the tweets to those that contain (FANG or FAANG) AND (any one
or more of the candidate words) to match the context of this study.
We checked all the tweets manually and excluded four tweets that
had nothing to do with the context of Big Tech. As a result, we
retrieved 1,903 tweets (Idea tweets) excluding RTs, of which 1,545
were regular tweets that were neither replies nor quote retweets
(QTs). We then collected 1,801 replies, 766 QTs, and 1,617 RTs of
those 1,903 tweets.

3.3 Types of ideas and their statistics
The candidates, the frequency of tweets containing them, and vari-
ows metrics are shown in Table 1. All the candidates are acronyms
consisting of A, G, M, N, S, and T. We judged the company names
indicated by these letters to be the following ten companies by
observing the tweets: Apple, Amazon, Alphabet, Google, Microsoft,
Meta, Netflix, Salesforce, Tesla, Twitter. Here, Google and Alphabet
refer to the same company; hence even if A and G are mixed in
one word, it does not mean that it refers to Google and Alphabet si-
multaneously. Interestingly, various companies are proposed other
than the original FAANG companies.

In terms of the number of tweets, MAANG and MANGA are
the two most frequently mentioned ideas. MAANG is clearly the
replacement of F with M in FAANG, indicating that the most direct
idea is the one that comes to mind of the people the most. Next,
MANGA is a term that refers to Japanese comics² and we suppose
that its popularity is due to the fun nature of its connotation. MANG,
which is also thought to be a direct replacement for FANG, is the
third most popular idea, presumably because FAANG has been
used more than FANG. In fact, out of the 1,903 Idea tweets, 1,766
contained FAANG, while FANG was included in only 141 tweets.

For the other metrics, ideas with a larger number of posts do not
necessarily outperform. In terms of RTs and like, which indicate
the engagement of other users, MAANG is not at the top, but MANGA,
MAGA, and MAMATA have the highest numbers. The same is true
for reply and QT, with MAGMA, MAGA, and MAMATA having the
highest numbers.

Note that we observed tweets that listed multiple ideas in a
single tweet. Of the 1,903 Idea tweets, 135 (8.73%) tweets contained
multiple ideas. As for the number of ideas in the 135 tweets, the
max is 7, the minimum is 2, the mean is 2.12, and the median is 2.

4 RQ1: HOW ARE THE DYNAMICS OF THE
SPONTANEOUS IDEATION CONTEST?
To investigate how ideation contests rise and converge, and to un-
derstand whether the dynamics vary from idea to idea, we analyze
the time series of the volume of tweets containing ideas. Figure 1 vi-
sualizes the hourly volume of tweets containing the top 5 ideas and
the hourly volume of RTs of those tweets. The period is one week,
starting from the day before the Facebook name change. We can see
that all the ideas emerge at almost the same time. This indicates that
the ideation contest started right after the announcement of the
name change. After that, the number of ideas gradually converged
to zero, with convergence and excitement repeating several times.
By October 31, three days after the announcement, the contest is
almost over. When we look at the number of tweets, it is hard to
judge which is dominant between MAANG and MANGA at the
start, and the gap is gradually opening up: thus, it would be better
to wait a day before making a judgment on which idea is dominant
in this case. Also, in terms of RTs, MANGA is overwhelmingly
large initially, but in line with MANGA’s gradual dominance in
the number of tweets, MANGA has been overtaken by MAANG in
hourly RTs at the third peak.

5 RQ2: HOW ARE IDEAS SPREAD IN THE
NETWORK OF CONTEST PARTICIPANTS?
To investigate how and where ideas generate and diffuse, we create
a network of users who propose and spread ideas. We obtained
the followers of (1) the authors of Idea tweets and (2) those who
share (by RT or QT) the Idea tweets. First, we examine whether
the authors of Idea tweets had seen other Idea tweets before they
posted Idea tweets. To this aim, we put the Idea tweets and the RTs
of Idea tweets in chronological order. For each Idea tweet, we check
whether the followers of the idea tweets’ authors have tweeted or
shared the ideas. Then, we label the author as Primary if they
have not seen any idea tweets beforehand, and Secondary if their
followees have already tweeted or shared the ideas. If an author
is given both labels, the Primary label gets priority. Among the
1,903 Idea tweets, the number of Primary tweets was 1,161, and the
number of Secondary tweets was 742. We can see that the majority
is coming up with ideas on their own.

²https://en.wikipedia.org/wiki/Manga
To see how they connect, we create a follower network. The max connected component of the network is 79.2% of all users who conduct the Idea tweet or retweet to them. We can see that the majority are connected to each other and form a single island. On the other hand, the rest of the users, except for the max connected component, consisted of almost independent users with less than 3 components.

Figure 2: Follower network of accounts who proposed and shared ideas. Blue, orange and green nodes indicate the accounts who proposed ideas first (Primary), proposed ideas secondarily (Secondary), and just shared ideas (Spreader), respectively. The size of nodes aligns with the log value of their follower counts. An edge indicates their follower relationships.

Figure 2 shows the max connected component. The nodes are colored in three different ways: Primary (blue), Secondary (orange), and Spreader (green). Here, Spreader means the users who just share the Idea tweets by RT or QT. All edges are colored in gray. The size of the nodes is aligned with the log value of follower counts of accounts. The shape of the network is formed by the ForceAtlas2 algorithm [18], and the closer the nodes are, the more neighboring they are in terms of a follow-follower relationship. We can see that there is no oligopoly of followers within the max connected component by a few accounts. In addition, the Primary accounts (blue) are scattered and not located closely with each other, indicating that the source of ideas is scattered. When we look at the follower counts, those with the largest number of followers seem to be Primary or Secondary. Here, we create a box plot comparing the follower counts of the three types of nodes in Figure 3. Secondary has the largest number of followers on average, followed by Spreader and Primary, and the differences are all significant ($p < 0.0001$ with Mann-Whitney test with Bonferroni correction). In other words, it can be seen that the ideas of Primary with fewer followers are picked up by Secondary and Spreader with more followers.

Figure 3: Boxplot of follower counts for accounts of Primary, Secondary, and Spreader. The stars indicate the significant differences with Mann-Whitney test with Bonferroni correction ($****: p < 0.0001$).

6 RQ3: HOW ARE IDEAS EXCHANGED AMONG THE PARTICIPANTS?

We assume Ideation contests on social media can be the place of ‘idea exchanges’ through discussions. Therefore, we construct reply trees to analyze how ideas are exchanged and how discussions generate ideas. To construct reply trees, we collect all the replies rooted to the 1,545 regular tweets by using the conversation_id in the Twitter API. As a result, we obtained 2,013 replies. The number of regular tweets that received replies is 397 (25.7%) out of 1,545. The number of direct replies to the regular tweets varies, ranging from 64 at the maximum to 1 at the minimum, 3.83 at the mean, and one at the median, indicating that some regular tweets received an extremely large number of replies. Then, we connect the collected replies to form reply trees. Starting from the 397 regular tweets that received replies, treating a connected chain to the end of replies as one pattern, we form a total of 1,520 patterns of reply trees, including branches from the same crotch. The maximum length of a reply tree was 10, the minimum 2, the mean 2.41, and the median 2.

We investigate how the ideas get accumulated in these reply trees. We traced the reply tree from the root and counted how many unique ideas existed in each reply in the tree. As a result, among the 1,520 reply trees, we found 348 trees accumulate new ideas at some point of replies. Of these, new ideas are added in the first reply in 315 (90.5%) trees. At the maximum, a new idea was added at a reply depth of 4.

Figure 4 summarizes the relationship between the depth of replies and the number of ideas. The x-axis indicates the depth of replies when the last unique idea was added and the y-axis indicates the number of ideas stacked at that time. The size of the circles reflects the number of ideas in the reply tree when the last unique idea is added in the reply trees. The lines show the pattern of idea growth in reply trees: the thicker the line, the more ideas are added in the pattern. We can see that most of the ideas are proposed in replies with a depth of less than two and ideas of less than three. On the other hand, we can see that in some cases, more than four ideas are proposed from the beginning, and ideas were added for the first time in reply trees with depths of more than three.

https://developer.twitter.com/en/docs/twitter-api/conversation-id
We also confirmed that replies accumulate unique ideas, but most were the most proposed, did not necessarily replace the original ideas. Future research would include the comparison of new ideas from the ideation contest, but we have not examined how well it accounts for ideas to take account the context by a machine learning model for example, a more precise analysis would be possible.

Analyzing other cases can indeed be considered as future research. First of all, other examples of spontaneous ideation contests would also be the subject. Since only the FAANG case was analyzed this time, it is hoped that by analyzing other cases, we can learn the characteristics of ideation contests that are more generalized. In addition, non-spontaneous ideation contests can be considered for future research. For example, knowing how to ask social media users for ideas leads to more efficient idea extraction and will be useful for companies to create innovations.

7.3 Ethical Consideration

We did not take personal names into account in the analysis, nor did we publish them in the paper. When we publish the data, we follow Twitter’s guidelines and publish only the id of the tweet.

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