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Who creates value in a user innovation community? A case study of MyStarbucksIdea.com

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Abstract

Purpose – Successful open innovation requires that many ideas be posted by a number of users and that the posted ideas be evaluated to find ideas of high quality. As such, successful open innovation community would have inherently information overload problem. The purpose of this paper is to mitigate the information problem by identifying potential idea launchers, so that they can pay attention to their ideas.

Design/methodology/approach – This research chose MyStarbucksIdea.com as a target innovation community where users freely share their ideas and comments. We extracted basic features from idea, comment and user information and added further features obtained from sentiment analysis on ideas and comments. Those features are used to develop classification models to identify potential idea launchers, using data mining techniques such as artificial neural network, decision tree and Bayesian network.

Findings – The results show that the number of ideas posted and the number of comments posted are the most significant among the features. And most of comment-related sentiment features found to be meaningful, while most of idea-related sentiment features are not in the prediction of idea launchers. In addition, this study show classification rules for the identification of potential idea launchers.

Originality/value – This study dealt with information overload problem in an open innovation context. A large volume of textual customer contents from an innovation community were examined and classification models to mitigate the problem were proposed using sentiment analysis and data mining techniques. Experimental results show that the proposed classification models can help the firm identify potential idea launchers for its efficient business innovation.

Keywords Sentiment analysis, Open innovation, User innovation, Data mining, MyStarbucksIdea.com

Paper type Research paper

Introduction

In 2008, Starbucks started to provide “Splash sticks” to the customers to minimize coffee splashes. Customers were very satisfied with this fresh item because of its superior convenience compared to a sticker which had been used to cover lid openings (for the same purpose). This stick was originated not from an internal expert, but from a typical customer, who posted his idea about the item on Starbucks’ innovation community, MyStarbucksIdea.com. Including this idea, Starbucks has been gathering valuable ideas directly from its customers through the community. And these ideas have contributed to innovating Starbucks.

The success of Starbucks’ user innovation strategy supports the argument of Prahalad and Ramaswamy (2004) that customers can be a unique source of knowledge which is critical for the new product or service development and cannot be attained

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from other sources. Jaworski and Kohli (1993) also mentioned that it was the customers that could provide information about their needs for firms' innovation. Thus, customer engagement can lead to more novel product ideas which will bring bigger value to the firms (Kristensson *et al.*, 2004).

In light of this, firms are recommended to take more open approaches such as establishing user innovation communities. Chesbrough (2003) emphasized that organizations should combine internal and external resources in today's boundary-free world to gain a competitive advantage that can lead to the successful innovation. Laursen and Salter (2006) advocate the extension of a firm's relationships to the external environment for its important role in enhancing the performance of the firm. Accordingly, firms across diverse industries such as retailing (e.g. Nike NIKEiD and Zappos about.zappos.com), high-tech (Cisco Support Community and Dell IdeaStorm), automotive (e.g. BMW M Power community) and healthcare (e.g. Philips NetForum Community) are promoting customer involvement to gather valuable knowledge for their innovations.

The creation of such valuable knowledge depends on the quantity and quality of the user interaction in the community (Mahr and Lievens, 2012), since users themselves are the main sources of the knowledge and the principal agents of the interaction. Therefore, successful open innovation requires both the participation of a number of users so that many ideas are posted by them and evaluation of the posted ideas to find ideas of high quality. As such, open innovation community has inherently information overload problem since the number of ideas and comments attached to them for their evaluation can be huge. Consequently, it is important to find users who provide innovative ideas, in order not to spend time in processing useless ideas. However, how to identify such users is limitedly known (Kristensson and Magnusson, 2010) and if we know the users, we may pay attention to the ideas of such users to find implementable ideas out of them.

With this motivation, this paper examined the whole user-generated contents from Starbucks' community, MyStarbucksIdea.com, with a focus on the characteristics of users. Our investigation of this community reveals that users are divided into two groups, i.e., a group of users whose ideas are adopted to be launched by Starbucks (launchers) vs the other group of users whose ideas have not been adopted (non-launchers) and that there exist clear differences between the two groups in generating knowledge. Although launchers are minorities, the quantity and the quality of their contribution to the community per person are significantly higher than those of non-launchers. Such phenomenon implies that the understanding the characteristics of idea launchers and utilizing them to find launchers can contribute to mitigating the information overload problem.

Thus, this study started with the following questions: what are the factors which differentiate the idea launchers from non-launchers; and how can we identify and predict potential idea launchers in advance? To answer these questions, various features of both users and their ideas were extracted to develop classification models for potential idea launchers using data mining techniques and sentiment analysis. The classification models can help companies predict potential idea launchers.

Literature review

User innovation community and information overload problem

User innovation communities can be defined as "distributed groups of individuals having an interest in solving a general problem and/or developing a new solution supported by computer mediated communication" (Dahlander and Wallin, 2006, p. 1246). Although user innovation community is not a new phenomenon (Franke and Shah, 2003; Von Hippel, 1988), the increase in digitalization and decrease in the cost of communication have brought the recent rapid growth in the number of online communities for user innovation (Mahr and Lievens, 2012). In user innovation communities, individuals not only interact with firms but also interact among themselves. They talk about their experience related to the products or services, raise questions, suggest possible solutions to the raised questions, and further elaborate or evaluate them. These user interactions play important roles in innovation development by providing complementary knowledge and skills (Von Hippel, 2005; Rowley *et al.*, 2007).

User innovation communities run for a limited time or unlimitedly. The former has the form of a one-time contest or multi-stage tournament (Terwiesch and Xu, 2008; Terwiesch and Ulrich, 2009). In such communities running for a limited time, the winner is selected with his or her best idea after the contest. What determines the effectiveness of problem solving (Jeppesen and Lakhani 2010; Boudreau *et al.*, 2011) and what attracts ideators to contribute to the contest (Yang *et al.*, 2009) have been among the research questions in innovation contest area. On the other hand, the latter demands ongoing idea generation from its users. Some firms like Dell or Starbucks ask their community members to continuously share ideas for innovation. This type of user innovation community is an emerging trend among firms as more and more firms are considering such ongoing user innovation communities as useful tools and strategic assets to innovate themselves continuously. In these user innovation communities, self-motivated members repeatedly share what they want firms to do or communicate their ideas with other members after undergoing product or service experiences (Füller, 2010; McAlexander *et al.*, 2002; McWilliam, 2000).

In general, more and more ideas from various individuals increase diversity of innovation resource and are likely to result in more options for firm to take. Thus, increase in the number of individuals participating in a user innovation community is a key factor for the success of the community. From the very success, however, the community can face a critical problem ironically: huge amounts of information to be processed can raise information overload problem. This problem can ruin the effectiveness and efficiency of user innovation.

Information overload has long been an issue among the previous studies in business area for the expandable nature of information. Cohen and Levinthal (1990) mention about the challenge of absorptive capacity which means firms' ability to identify and adapt new knowledge into the current business. Maes (1994) proposes an approach which can help to reduce information overload by building agents. As Web 2.0 has become pervasive, information overload is among the actively discussed issues especially in online review context. With a large amount of actual text collected from online review communities, prior studies extracted various features to develop classification models to predict review helpfulness or box office success (Ghose and Ipeirotis, 2011; Ngo-Ye and Sinha, 2014; Pang *et al.*, 2002). They proposed automatic or semi-automatic method to tackle the problem of information overload. In user innovation area, many researchers also pointed out the serious consequences which information overload problem could bring about (Desouza *et al.*, 2008; Di Gangi and Wasko, 2009; Di Gangi *et al.*, 2010; Turoff *et al.*, 2004; Franke and Piller, 2004; Frey and Lüthje, 2011; Pilz and Gewald, 2013; Sie *et al.*, 2011), however, the previous studies have not discussed or covered the information overload problem sufficiently, and they did not propose a practical method to mitigate the problem.

Evaluating ideas to select implementable ideas is an important, but daunting task which requires a substantial amount of time. Without an effective and efficient method to utilize and analyze the huge number of collected ideas, potentially promising ideas can become useless. Thus, this study proposes a system aiming at mitigating the information overload problem in a user innovation community. Our system recommends potential idea launchers based on their ideas' adoptability by a firm so that they can pay attention to their ideas. Our approach is supported by prior studies which emphasize the importance of right users by arguing that if a firm does not attract such users who can provide valuable ideas, user innovation will fail obviously (Piller and Walcher, 2006) and thus, identification of active users who are enthusiastic in submitting implementable ideas is critical (Martínez-Torres, 2012).

Sentiment analysis

Opinions play a central role in almost every human behavior. Our thoughts and activities are, to a substantial degree, influenced by how others experience and evaluate the world. That is the reason why we often refer to opinions of others when making decisions. Such tendency is seen among organizations as well as individuals. Firms want to know customer opinions about their products and services to find rooms for improvements. And customers seek what other customers think about a product before purchasing it.

In this sense, sentiment analysis is considered a useful method for firms to extract knowledge from enormous amount of customer opinions, because sentiment analysis makes it possible to analyze opinions and sentiments in a formal or informal text in an automatic way (Thelwall *et al.*, 2011). There are many jargons used to mean similar tasks, e.g., sentiment analysis, opinion mining, subjectivity analysis, emotion analysis, etc. However, they are all under the umbrella of sentiment analysis or opinion mining. Traditionally, sentiment analyses are focussed on searching for entities and classifying their sentimental orientations depending on positivity or negativity (Lerner and Keltner, 2000; Zhuang *et al.*, 2006). Sentiment analysis has been mainly applied to review texts such as movie or product reviews (Pang *et al.*, 2002; Whitelaw *et al.*, 2005; Zhuang *et al.*, 2006; Tang *et al.*, 2009). More recently, sentiment analysis is widely adopted in social web analysis (Agarwal *et al.*, 2011; Kouloumpis *et al.*, 2011; Kucuktunc *et al.*, 2012; Tumasjan *et al.*, 2010). The results from these studies suggest the usefulness and effectiveness of sentiment analysis in identifying sentiment orientation of textual contents.

There exist two types of approach to conducting sentiment analysis, i.e., machine-learning approach and lexicon-based approach. The former extracts features from texts and then trains a selected classifier with a human-coded corpus. The features can include not only words, but also bigrams, trigrams or part-of-speech tagged words (Pang and Lee, 2008). This machine-learning method is normally domain specific, while the latter is a domain-independent approach which utilizing a pre-defined set of terms with known sentiment orientation. Such a set includes General Inquirer lexicon (Stone *et al.*, 1966), the *LIWC Dictionary* (Pennebaker *et al.*, 2003), WordNet-Affect (Strapparava and Valitutti, 2004) or SentiWordNet (Baccianella *et al.*, 2010). In addition, a list of specific words, emoticon lists and semantic rules to deal with negation are used to supplement the lexicon method (Neviarouskaya *et al.*, 2007; Taboada *et al.*, 2011).

In this research, we believe that sentiment-related information in customer ideas and comments can be significant in classifying each user into idea launcher or not, thereby mitigating the information overload problem. Previous studies in user innovation domain have analyzed only a limited amount of data in a manual way, while we analyze the whole textual data from the target data set in an automated way based on lexicon-based sentiment analysis using SentiWordNet.

Research context

In this paper, Starbucks is examined. The company is widely considered as a leading company in the effective use of open innovation community and is rated as a top in the aspect of social engagement among 100 leading brands. Starbucks tightly aligns its strategy with the exploitation of social media from brand definition and promotion to execution through service delivery.

Starbucks established MyStarbucksIea.com in March 2008, searching for a way to talk to and listen to the customers directly. As of February 2014, more than 200,000 users had participated in the user interactions and over 170,000 opinions had been posted on the community.

The process of idea generation in the community can be explained as below.

Register: any customer can register on the community to become a community member.

Share: a customer can post whatever he/she wants to share as his/her own idea. Starbucks provides 15 idea categories such as coffee and espresso drinks, food, and atmosphere and locations. Each idea must belong to one of the categories. This categorization occurs when a user posts an idea.

Vote: customers can vote to promote their preferred ideas or to demote non-preferred ones. Each idea has idea points that increase or decrease depending on customers' promotion or demotion, respectively. This voting system is a user-quantified idea evaluation, and the points represent how many customers agree to an idea, positively or negatively.

Discuss: customers can also put comments on any ideas to discuss them with others in more detail. Through the discussion, the initial idea is evaluated and developed further.

See: through the voting and discussion, some promising ideas go into the internal review process. The review process is open to the customers, so that they can see the current status of each idea, that is, whether it is under review, reviewed, coming soon (to be launched) or launched. Since Starbucks launched the community, over 300 ideas have been implemented.

Table I shows some examples of ideas and related information posted on the community. In the first example, a user posted an idea, asking for a gluten-free food option. The idea attained 16,800 points, i.e., 1,680 users promoted the idea. The idea finally was adopted and launched by Starbucks. The second idea asking for the combination of cheese burgers and Frapuccinos did not attract the support of other users. As such, it was reviewed and rejected finally. The third idea which is under review already got big idea points from other users, while the fourth one has been launched even though it has only 184 supporters. Note that ideas are mostly written colloquially and they include ideator's sentiments.

Proposed method

Overall process

First of all, whole textual data from a user innovation community, MyStarbucksIdea.com were collected and stored them into a database. After preprocessing, various features from the data set, which are related to idea, comment or to user were extracted. Then, to extract additional features, sentiment analysis was conducted. With expanded

Date	Idea content	Idea point	Idea status
April 1, 2008	"Offer a gluten-free food option. Many people suffer from this and there is virtually nothing to eat at Starbucks due to gluten"	16,800	Launched
July 10, 2010	"Combine the two best things ever: cheesburgers and Frappuccinos!"	−390	Reviewed
November 13, 2010	"Soy is highly allergenic and really not healthy in large quantities. Many people (actually probably most) also cannot tolerate cow's milk. Please offer rice, almond, or coconut milk, since you don't allow people to bring in their own milk alternatives. This has kept me out of Starbucks for years"	30,580	Under review
May 7, 2011	"I love that you guys offer reusable cups for cold drinks, but the majority of the time I order talls, and I recently realized that if I order a tall in a grande cup, they have to measure it out in a plastic tall cup and waste a cup anyway. This bothers me a lot. I don't want to be wasteful, but I also don't want to have to buy a grande every time I order. You guys should follow through with the green initiative that you tout and make reusable cups in all sizes. I'm sure a lot of people go in with grande reusable cups, order a tall, and don't even realize that a tall cup is still being wasted; this is unfair to people trying to be environmentally conscious. Please consider making a 12-oz. tall reusable cold cup tumbler"	1,840	Launched

Table I. Examples of popular ideas in MyStarbucksIdea.com

features, feature selection was performed. Finally, a model for idea launcher identification was proposed. Figure 1 depicts the overall process of our approach. The process will be explained in more detail later.

Data collection and preprocessing

From December 10, 2012 through December 16, 2012 (one week), textual data related to 89,093 ideas, 175,412 comments added on those ideas and 124,743 users who posted an idea or a comment, was collected using a web crawler. It includes various information

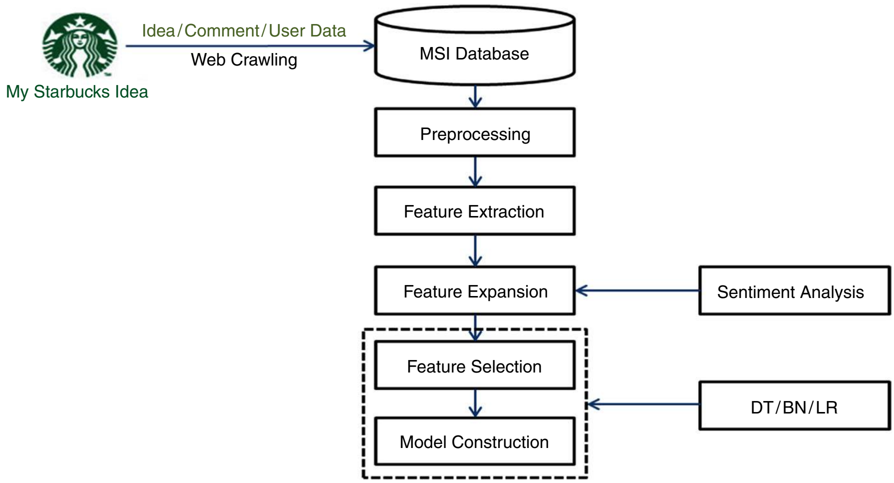

Figure 1. Overall process of analysis

such as idea contents, idea point, idea status, the number of comments for each idea, comment contents, user profile and the number of idea/comment each user posted, etc.

In the preprocessing, ideas and comments with missing values, duplicated ones, or those written in non-English characters were discarded. Ideas consisting of less than five words were also excluded. As a result, the final data set consists of 83,657 examples each of which includes data about idea, ideator and comment.

Target feature investigation

The ideators were divided into two groups, i.e., idea launchers and non-launchers. It was found that there are significant differences between the two groups in terms of the quantity and the quality of idea/comment generation. As shown in Table II, the number of ideas and the number of comments generated per user of idea launchers are much bigger than those of idea non-launchers. Since our data set is un-balanced, as is shown in the table, under-sampling was conducted first to make the data set balanced. Speaking more specifically, only 319 ideas are launched ones among the 83,657 ideas. As such, 319 ideas were randomly selected from unlaunched ideas. As a consequence, the data set consists of 638 ideas. To minimize the influence of random sampling of 319 ideas out of 83,338 unlaunched ideas, ten such data sets were made.

Extraction of basic features

Various features which might possibly be influential on user behaviors from idea, comment and user information were extracted and stored in tables in our data set. Seven features were extracted such as idea point (idea point attained from other users), idea length (the number of words in an idea), the number of comments (the number of comments on an idea), the number of ideas posted (the number of ideas a user posted), the number of comments posted (the number of comments a user posted), personal information disclosure (whether or not a user disclose his/her personal information) and post-registration period (period in month from registration of a user to idea submission).

Extraction of expanded features

User-generated contents like ideas and comments naturally contain sentiment information including evaluations or opinions. By analyzing such sentiment information, sentiment-related features like subjective-objective polarity and positive-negative polarity of both comments and ideas are extracted to be added more to the set of basic features for building classification models.

A lexical resource, SentiWordNet, was used to measure positivity, negativity, polarity and subjectivity scores of each idea and each comment. SentiWordNet contains about 207,000 word-sense pairs or 117,660 sets of synonyms called synsets with sentiment and subjectivity information for each word for classification (Esuli and Sebastiani, 2006). Table III shows a part of the sentiment lexicon which is built based on SentiWordNet in this study. Scores in the table represent the degree of positivity, negativity and subjectivity (ranging from 0 to 1) and polarity (ranging from −1 to 1).

Table II.
Idea/comment productivity between idea launchers and idea no launchers

Group	No. of users	No. of ideas generated Total	No. of ideas generated per user	No. of comments generated Total	No. of comments generated per user
Idea launchers	319	655	2.053	1,839	5.764
Idea no launchers	63,407	83,002	1.309	51,960	0.819

Positivity and negativity of a word obtained from SentiWordNet is the degree of positive and negative sentiment the word represents, respectively. Polarity of a word is calculated by subtracting the negativity from the positivity of the word. Thus, polarity represents the overall sentimental orientation (Whitelaw *et al.*, 2005). Subjectivity of a word refers to the extent of sentiment whether or not it is negative and/or positive and is obtained by adding the positivity and the negativity of the word (Esuli and Sebastiani, 2006).

We identified sentiment words in each idea and each comment, and obtained the four scores of those words using Table III. Using these information, we calculate sentiment values of each idea and comment as follows. For example, in a given idea, "It will be good if I can have a soymilk option. Old customers like me will be satisfied with it," the words, good and satisfied are identified as sentiment words. Positivity of each idea is the sum of all those of sentiment words in the idea. We normalize the score with the word count of the idea. Thus, the positivity of the exemplar idea is calculated by summation of positivity of good and satisfied and division by word count of the idea, i.e. $(0.75 + 0.7)/20 = 0.0725$. Negativity, polarity and subjectivity of each idea and comment are calculated similarly.

Since most comments are short, instead of calculating subjectivity of comments, we calculate the standard deviation of the polarity of comments to see how the idea corresponding to the comments is controversial, i.e. whether or not there exists a sharp division between those who like the idea and those who dislike it.

In summary, eight new features are expanded to include positivity, negativity, polarity and subjectivity of ideas each user posted and positivity, negativity, polarity and variation of sentiment of comments each user posted to an idea. In total, 15 features are listed in Table IV, including both seven basic features (extracted from ideas, comments and users) and eight expanded features (obtained from sentiment analysis).

Classification model construction

Models for the classification of idea launchers were built with the 15 features using artificial neural network and decision tree (DT) and Bayesian Network algorithms implemented in Weka 3.6.10.

Prior to building the classification models, we evaluated 15 features using a χ^2-test algorithm to examine the influence of features on our target feature. With the backward elimination wrapper approach to feature selection, we selected features. More specifically speaking, 45 experiments in total (15 experiments with three techniques, respectively) were conducted to find the best classification model and the best set of attributes used to build the model. We evaluated and compared their classification results obtained from tenfold cross-validation. The same process is applied to each of the ten data sets, respectively. We used hit ratio as an evaluation measure for classification accuracy.

Word	Positivity	Negativity	Polarity	Subjectivity
Good	0.75	0.05	0.7	0.8
Satisfied	0.7	0	0.7	0.7
Vague	0.3	0.325	−0.025	−0.625
Surprising	0.625	0.2	0.425	0.825
Sorry	0.125	0.5	−0.375	0.625

Table III. A part of sentiment lexicon

Features	Description
Idea point	Idea point attained from other users
Idea length	The number of words in an idea
The number of comments	The number of comments on an idea
The number of ideas posted	The number of ideas a user posted
The number of comments posted	The number of comments a user posted
Personal information disclosure	Whether or not a user disclose his/her personal information
Post-pegistration period	Period in month from registration time of a user till idea generation time
Idea positivity	Total positivity score of an idea
Idea negativity	Total negativity score of an idea
Idea polarity	Polarity score of an idea
Idea subjectivity	Total subjectivity score of an idea
Comment variation	Standard deviation of polarity scores of comments on an idea
Comment positivity	Total positivity score of comments on an idea
Comment negativity	Total negativity score of comments on an idea
Comment polarity	Polarity score of comments on an idea

Table IV.
Feature description

Experimental results

The results of feature selection of each data set are shown in Table V. In the prediction of idea launchers, significant features are found to be similar across the data sets. Among the features, the number of ideas posted and the number of comments posted are the most meaningful, when considering their significance. Most of comment-related sentiment features (comment variation, comment positivity and comment polarity) are generally significant, while idea-related sentiment features except idea positivity, are not. Descriptivity of an idea (idea length) is found to be not significant in predicting idea launchers. Personal information disclosure and post-registration period are not influential, either.

	Data sets									
Features	1	2	3	4	5	6	7	8	9	10
Idea point	○	○	○	–	○	○	–	○	○	○
Idea length	–	–	–	–	–	–	–	–	–	○
The number of comments	○	–	–	○	–	○	–	○	○	–
The number of ideas posted	○	○	○	○	○	○	○	○	○	○
The number of comments posted	○	○	○	○	○	○	○	○	○	○
Personal information disclosure	–	–	–	–	–	–	–	–	–	–
Post-registration period	–	–	–	–	–	–	–	–	–	–
Idea positivity	○	○	○	○	–	○	○	–	○	○
Idea negativity	–	–	–	○	–	–	–	–	–	○
Idea polarity	–	–	–	–	–	–	–	–	–	–
Idea subjectivity	–	–	–	–	–	–	–	–	–	–
Comment variation	○	○	○	○	○	–	○	–	○	○
Comment positivity	○	○	○	–	○	○	○	○	–	○
Comment negativity	○	–	–	–	○	○	–	–	–	–
Comment polarity	○	–	○	○	–	–	○	○	–	–

Table V.
Results of feature selection

Figure 2 and Table VI show classification models from data sets 1, 5 and 7, respectively, since the data sets were used to build models of top-three accuracy. Across our data sets including the three data sets, DT model was found to outperform the other two models in general. The highest average accuracy of the DT models from ten data sets is 75.67 percent.

Figure 3 shows the DT for idea launchers from data set 1 and Table VII represents the classification rules extracted from the DT. Each leaf node (represented by a person

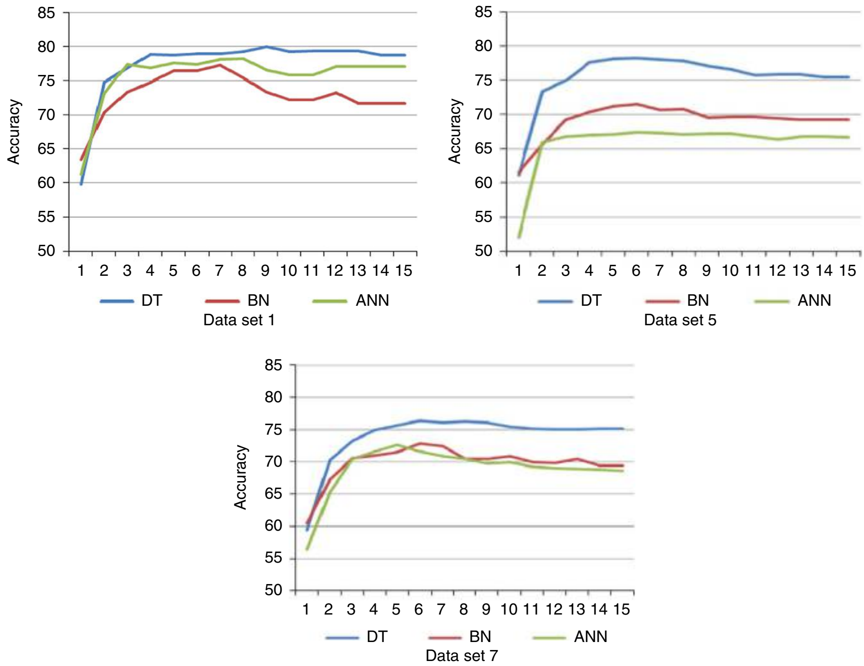

Figure 2.
Hit ratio of classification models for idea launchers

Table VI.
Accuracy comparisons among classification models for idea launchers

	Data set 1			Data set 5			Data set 7		
No. of features	DT	BN	ANN	DT	BN	ANN	DT	BN	ANN
1	59.75	63.33	61.2	61.1	61.5	52.04	59.4	60.4	56.43
2	74.76	70.33	73.2	73.4	65.7	66	70.2	67.2	65.2
3	76.82	73.33	77.3	74.9	69.15	66.82	73.3	70.5	70.4
4	78.8	74.7	76.8	77.65	70.33	67.02	74.9	70.94	71.63
5	78.7	76.4	77.5	78.1	71.2	67.15	75.65	71.45	72.6
6	78.9	76.4	77.33	78.25	71.45	67.45	*76.35*	72.84	71.6
7	78.9	77.2	78	*78.04*	70.64	67.33	76.1	72.41	70.84
8	79.2	75.33	78.1	77.83	70.77	67.12	76.24	69.42	70.48
9	*79.91*	73.33	76.5	77.1	69.5	67.2	76.06	70.44	69.7
10	79.2	72.2	75.7	76.54	69.65	67.25	75.4	70.86	69.94
11	79.33	72.2	75.7	75.8	69.65	66.84	75.14	69.92	69.18
12	79.33	73.3	77.05	75.84	69.42	66.34	75	69.81	69
13	79.33	71.67	77.05	75.84	69.15	66.75	75.02	70.4	68.89
14	78.67	71.67	77.02	75.42	69.24	66.75	75.14	69.45	68.76
15	78.67	71.67	77.02	75.42	69.24	66.7	75.14	69.45	68.55

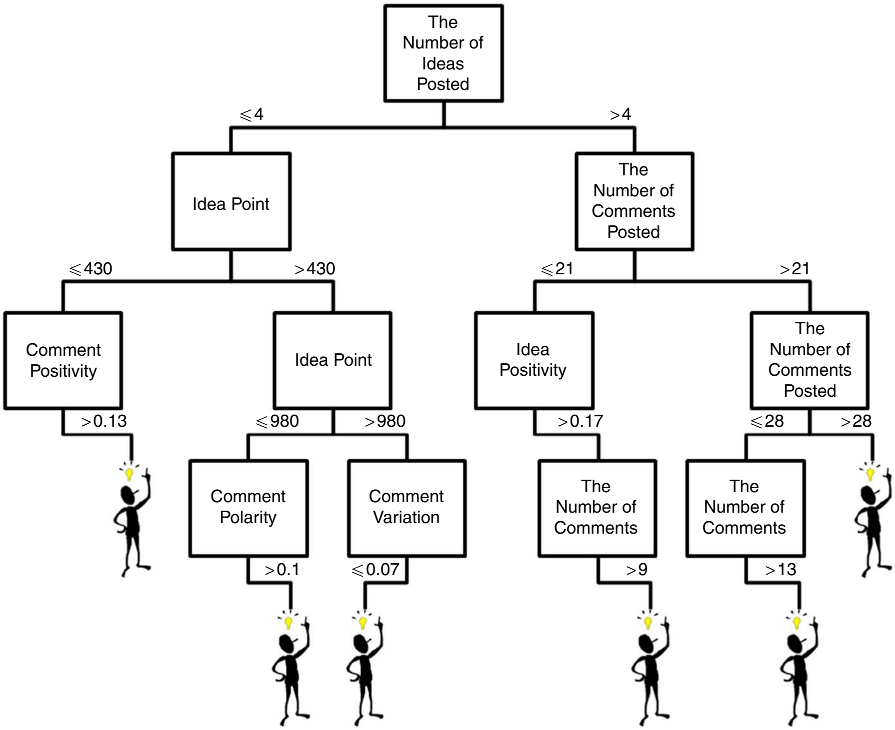

Figure 3. Decision tree for idea launchers (data set 1)

Table VII. Classification rule examples for idea launchers

No.	Rule description
1	The number of idea posted ⩽ 4 and idea point ⩽ 430 and comment positivity > 0.13 →launcher
2	The number of idea posted ⩽ 4 and idea point > 430 and idea point ⩽ 980 and comment polarity > 0.1→launcher
3	The number of idea posted ⩽ 4 and idea point > 430 and idea point > 980 and comment variation ⩽ 0.07→launcher
4	The number of idea posted > 4 and idea positivity > 0.17 and the number of comments > 9→launcher
5	The number of idea posted > 4 and the number of comments posted ⩽ 28 and the number of comments > 13→launcher
6	The number of idea posted > 4 and the number of comments posted > 28 →launcher

in the tree) becomes a rule for classifying an idea launcher. For example, rule one in Table VII reads that when a user's the number of idea posted is no more than four, idea point is no exceeds 430 and comment positivity is higher than 0.13, such user will probably be an idea launcher. Another rule (rule 6 in Table VII) shows that when a user's the number of idea posted exceeds four and the number of comments posted is more than 28, such user is likely to become an idea launcher. In our target community, it takes less than two weeks on average for an idea to get more than 28 comments or to get 980 points. As such, within two weeks after posting an idea, we can apply our rules to the idea to predict whether or not, the ideator who posted the idea will likely to become idea launcher.

Discussion

Building a user innovation community is an emerging trend among firms across diverse industries because of its possible benefits including acquisition of valuable ideas from customers directly. Prior studies have mainly shown their interest in what kind of ideas should be adopted (Di Gangi and Wasko, 2009; Lee *et al.*, 2014) or what are the motivation of users in their idea generation (Hossain, 2012; Stahlbrost and Bergvall-Kareborn, 2011). However, few studies have paid attention to the relation between the characteristics of idea source, (i.e. users) and their contribution to firm innovation. In this study, we analyzed a data set from a user innovation community of a firm focussing on the question, "what kind of ideators contribute to innovation of the firm by generating implementable ideas?"

According to the results of our study, three insights emerged. First, potential idea launchers in the target community are the users who are active in posting ideas (which is indicated by the number of ideas posted in the research) and commenting on other users' ideas (which is indicated by the number of comments posted). This result provides a contrast to the finding of prior studies, cognitive fixation which explains the tendency of people to fixate on the features of previous ideas, leading to thoughts that are less innovative (Smith *et al.*,1993; Marsh *et al.*, 1996). We may interpret this contrast as follows: users in our context, does not fixate their thoughts in an idea generation or discussion process, but rather, they learn and gain understanding about innovation requirements such as feasibility, appropriability or compatibility of their ideas. Consequently, these users might gain competence in making implementable ideas through the process of generating ideas and commenting on ideas.

Second, sentiments which a user expresses within an idea, are mostly insignificant except for positivity (which is indicated by idea positivity) when predicting whether or not the user is likely to become an idea launcher. Existing studies addressed negative bias which means that negative opinions are likely to be given more weight due to their distinctiveness and novelty than positive ones (Anderson, 1971; Boucher and Osgood, 1969; Fiske, 1980). In our community context, we can expect that a user who tends to post ideas containing negative words might be attentive to due to his/her ideas' distinctiveness and novelty. Accordingly, such user is probable to become an idea launcher. However, the result shows that potential idea launchers in our community are inclined to describe their ideas with a positive sentimental orientation when posting ideas. Namely, there exists a positive bias instead of a negative bias in the community. We think that potential idea launchers are strongly motivated to contribute in firm's innovation process and they have constructive and positive attitude toward the firm. Thus, they seem to show the positive bias. Also, their positively biased ideas seem to be evaluated as more adoptable to the firm. This tendency may reflect the characteristics of open innovation community which aims to seeking progressive and constructive ideas for firm innovation.

Third, we found most of comment-related sentiment information is significant in our community in predicting potential idea launchers. This finding implies that the comments from peer users can provide clues to determine whether or not the idea generator is promising. In this sense, the firm is recommended to promote users to comment on ideas more actively aiming to collect more sentiment information earlier. Such recommendation is much more meaningful in other user innovation communities like Threadless in which idea adoption is determined completely by peer review (Ogawa and Piller, 2006).

In addition, the findings from our experiments have several implications. First, using the classification models we built, the firm can attempt to find potential idea launchers and encourage them to be more active in posting innovative ideas for the better management and performance of the community. Second, sentiment-related features from user-generated contents should be considered when implementing the idea launcher recommendation system to achieve better accuracy. Third, sentiment analysis can be a useful tool in tackling the possible challenges in user innovation communities where there exists a large amount of textual data containing user sentiment. Lastly, it will be helpful for the practitioners in open innovation domain to build classification models which are similar to our models for more effective and efficient management of their communities.

Conclusion

Considering the fact that idea launchers have contributed to enhancing the quantity and quality of innovation significantly more than non-launchers in our target community, the prediction of idea launchers is distinctly useful for the better management of user innovation communities. In that sense, the contribution of our study can be summarized as follows: first, we teased out various features which are not only basic features collected directly from the community, but also expanded features extracted from the results of sentiment analysis. In this process, we quantified sentiments which are contained in each idea and comment, such as positivity/negativity, subjectivity/objectivity and opinion variation. Second, we developed many classification models for the identification of potential idea launcher to select the best model out of them. The classification models we proposed show high accuracy in predicting potential idea launchers. Finally, we suggested the classification rules derived from the classification models. The rules can be utilized to identify users who are likely to contribute to the firm innovation in advance. This approach can help mitigating the information overload problem which user innovation communities possibly have.

This study has some limitations. First, the data used in our study were acquired from a coffee brand user innovation community. The characteristics of this domain may affect the results. Thus, a future study could elaborate our findings in user innovation communities of other firms from various industries, which may contribute to finding a better way of managing customers. Second, the number of samples used in our experiment after balancing was relatively small because there were only small numbers of ideas which were accepted by the company. If we conduct the same experiment after more samples are available, we may improve the reliability of the results.

For future research, we will analyze other open innovation communities. We plan to compare the results with that from MyStarbucksIdea.com to examine differences and similarities, and to find a way of managing customers' ideas more effectively and efficiently.

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