WILL YOUR PROJECT GET THE GREEN LIGHT? PREDICTING THE SUCCESS OF CROWDFUNDING CAMPAIGNS

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Abstract

Capital is always essential for a business project over times. After emerging in 2000, crowdfunding gradually becomes one of the most popular fundraising resources. However, the mechanism of crowdfunding significantly differs from traditional capital-collecting approaches. As long as the amount of pledged money reaches the goal in time, the project succeeds, its initiator receives the funds, the platform gains the revenue, and its backers acquire rewards. Reaching the goal by deadline becomes an important issue. The goal of our study is to develop an effective technique for predicting whether a crowdfunding campaign will succeed or fail. On the basis of a dataset collected from Kickstarter, our empirical evaluation results suggest that our proposed technique significantly outperforms the benchmark method. In addition, with the use of time-dependent factors, the prediction accuracy improves from 72.89% at day 0 to 87.13% at the first day and eventually to 89.62% at day 7.

Keywords: Crowdfunding, Crowdfunding Outcome Prediction, Machine Learning, Social Interaction, Dynamic Features, Random Forest

1 INTRODUCTION

As far as venturers are concerned, capital is essential for them to initiate a project (Cassar 2004; Gompers et al. 2004). In the past, starters seldom have the opportunity to raise funds from others due to limited promotion channels (Cosh et al. 2009). Therefore, most people generally appeal to their parents and friends and barely rely on their own efforts. Being lack of sufficient funds or supports, many initiators fail to manage their projects from time to time. As the economy develops, there are some entrepreneurs, often called "angels," owning spare money and willing to provide aids to starters (Freear et al. 1995; Lerner 1998). In fact, a plan will not be accepted until the initiator elaborates a proposal to personally persuade these wealthy angels to involve. Such time-consuming, face-to-face contacts represent a serious obstacle to the progression of a project. Hardly was this phenomena gradually ameliorated until the Internet was booming since 1990s. Instead of those traditional fundraising approaches, there is an alternative by which whoever entertains an attractive idea is able to collect capital by means of the social power of crowds throughout the world on plentiful online platforms. This emerging concept, called "crowdfunding" and first implemented in the year 2000, has been growing rapidly all over the world and bringing abundant of plans to life (Belleflamme et al. 2014; Briggman 2014; Giudici et al. 2012).

In general, project creators (initiators) choose a minimum funding goal (for pedagogical purposes, we use "goal" and "threshold" interchangeably throughout the paper) and a deadline before launching a project on online crowdfunding platforms. During the campaign, which is specifically referred to as the whole fundraising process in this paper, the project can be seen by billions of users on the website. Those users who approve the idea are called the "backers" of the campaign if they are willing to pay pledge money to back up for it in the early stage, and usually receive relative rewards in return. The 2013 crowdfunding report by Massolution estimated that around $5.1 billion in transactions occurred globally in 2013.[1] The World Bank also stated the market potential for crowdfunding has been predicted to reach $96 billion in the next twenty-five years.[2] Seeing that crowdfunding becomes a trend, various projects have been sprung up on online platforms nowadays. Nonetheless, we find something interesting that even the central idea of two projects are highly similar to each other, they might end up with divergent results (i.e., one acquires a great amount of money, whereas another fails) possibly due to different ways of promotion their projects and different project descriptions. Prior studies indicate that the amount of fund raised is affected by certain significant factors (Mollick 2014). Although the amount of money exceeding the threshold reflects how much the initiator can receive, a more fundamental question project initiators concern is that whether their projects will succeed or not. It is crucial for project initiators to know factors possibly leading to different project results so that the initiators can better manage their projects during the campaign and improve their success rate. In response, it is essential to develop a prediction technique that can effectively predict the result of a crowdfunding campaign. Moreover, with this prediction technique, it is also desirable to highlight influential factors to the results of crowdfunding projects.

To avoid any ambiguity, here we explicitly define the term "result" mentioned formerly as the final state of a campaign. A project is considered a **successful** campaign if the prespecified threshold (i.e., goal) is met by or before the deadline whereas failed in opposite. Because the result of a campaign has only two outcomes: success and failure, we can simply regard our target prediction task as a binary classification problem. Our solution is mainly based on the machine learning approach rather than traditional regression methods. By incorporating an appropriate set of features (factors) and using salient supervised learning algorithms (Greenberg et al. 2013; Mollick 2014), we can predict the results of crowdfunding campaigns and figure out key factors affecting the success of crowdfunding

[1] Crowdsourcing (2013). "2013CF-THE CROWDFUNDING INDUSTRY REPORT" From http://research.crowdsourcing.org/2013cf-crowdfunding-industry-report

[2] World Bank (2013). "Crowdfunding's Potential for the Developing World" From https://openknowledge.worldbank.org/handle/10986/17626

campaigns. Our proposed technique adopts random forest (Breiman 2001) as the underlying learning algorithm, with the features from five categories: intrinsic characteristics, financial mechanism, content quality and sentiment, social interaction, and progression effect. Existing prediction methods predict the result of a crowdfunding campaign on the basis of the data collected when the project starts. These single-time-point prediction models often ignore time-dependent factors and thus limit their utilities in practice. In our proposed technique, because the values of some features in the social interaction and progression effect categories change as a crowdfunding campaign moves forward, we evaluate the time effect on the prediction effectiveness of our proposed technique (i.e., making predictions at different stages of campaigns).

As for the dataset, Kickstarter is chosen as our research target for empirically evaluating the effectiveness of our proposed technique, because Kickstarter is an iconic crowdfunding website. In 2014, Kickstarter had 3.3 million people and pledged more than half a billion dollars to bring 22,252 creative projects to life, implying Kickstarter is an influential crowdfunding website nowadays. Accordingly, Kickstarter is usually considered an experiment target in previous studies, and using Kickstarter makes our evaluation results reliable and trustworthy.

Our research makes the following contributions. For the crowdfunding research, we develop a more effective prediction technique by including a comprehensive set of features as the predictors. Because some features are time-dependent, our proposed technique can establish a series of classification models and make predictions at different stages of the campaign. From the practical perspective, the series of classification models can serve as valuable decision support tools for project initiators to assess possible results of their projects at different stages. If the predicted results are not favorable (i.e., failed state), project initiators can adjust their projects (e.g., by altering the values of some time-dependent variables) so that the success rates of these projects can improve. Moreover, for some highly creative projects, crowdfunding platforms can use our proposed technique to evaluate their possible results across various stages of these campaigns and help promote those that are likely to fail (e.g., placing these projects on the top of the list). Such intervention can help these creative projects succeed and eventually increase the attractiveness of the crowdfunding platforms.

The reminder of this paper is organized as follows: Section 2 reviews the literature relevant to our study. In Section 3, we detail the design of our proposed technique for predicting the success of crowdfunding campaigns. In Section 4, we report our empirical evaluation on the basis of a dataset collected from the most prestigious crowdfunding website, Kickstarter. Lastly, we conclude our paper with a summary in Section 5.

2 LITERATURE REVIEW

Crowdfunding, a process of crowd-sourced fundraising, is a new way to raise funds from crowd on the Internet within a given time duration. This novel fundraising method differs from traditional ones, so figuring out the key factors to success and applying them to the development of prediction model have been an important issue in the crowdfunding research.

2.1 Factors that Impact the Success of Crowdfunding Campaigns

In previous works, the factors affecting the success or failure of crowdfunding campaigns covered several categories, including intrinsic characteristics (e.g., project category such as art or technology, project initiator's location), financial mechanism, content quality and sentiment, and social interaction. In goal-setting campaigns, it has been widely discussed that how high the goal should be set, especially in reward-based crowdfunding (Wash 2013). For instance, a financially unrealistic goal may decline investors from backing the project. Besides, pledge methods impact not only the affordability for backers with specified money, but also the satisfaction from backers with the ratio of contribution to the project (Kuppuswamy et al. 2014). Therefore, financial mechanism is always a major dimension when analysing and predicting the success or failure of crowdfunding campaigns. Specifically, predictors in this category that have been considered in previous works include the goal and the number of pledge methods.

The description of a campaign, covering the content quality and sentiment, can impact the perception of viewers. Content quality somehow stands for the extent of the initiator's effort and preparedness of the campaign (Chen et al. 2009). Content quality can be estimated by the numbers of photos, words, and videos, the number of spelling errors (Mollick 2014), and the score of Flesch-Kincaid grade level (Greenberg et al. 2013), corresponding to the richness, correctness and readability of the content. On the other hand, the sentiment of the description of a campaign reflects the general attitude (positive or negative) of the initiator. Such attitude expressed in the description of the campaign can also influence the perception of readers.

After the campaign is created, subsequent actions of initiators performed on crowdfunding platform may also affect the final state (success or failure) of their projects. With the proliferation of social media and interactions in Web 2.0 environments, researches on Internet-based services such as crowdfunding or group buying gradually regard social information as a crucial research target (Burtch et al. 2013; Lu et al. 2014; Shane et al. 2002). Social interaction can be any kind of connections or communications occurring among users. In our case, FAQs or comments can be categorized as one kind of social interactions between project initiators and potential backers. Meanwhile, social media provides more insights into the campaign, including the size of social network of founder as the source of "friends and family" money (Agrawal et al. 2013; Mollick 2014), and the number of links to different social media and shares; these imply the popularity and spreadability of the project.

2.2 Learning Methods Employed

On the basis of the features factors discussed above, most of prior studies use logistic regression in statistics to construct prediction models (Mollick 2014). Some works take into account of geography or project category issues and accordingly build multiple regression models according to different population or project categories (Briggman 2014; Mollick 2014). Although machine learning methods cannot provide statistical explanation and test between the factors considered (i.e., independent variables) and the crowdfunding campaign results (dependent variable), their computational approach does not involve rigid statistical assumptions and generally can result in more effective prediction. Greenberg et al. (2013) employ random forest, a classification algorithm in machine learning, to predict the success or failure of a crowdfunding campaign, with an average accuracy of 65%. However, their model neglects time-dependent factors, such as the number of Facebook shares, the completeness of the project. In response, in addition to static features, we include these time-dependent factors as dynamic features into our proposed prediction technique and thus can make more effective predictions as the campaigns move forward.

3 OUR PROPOSED TECHNIQUE

In this section, we detail the design of our proposed technique for predicting the success of crowdfunding campaigns shown in Figure 1. By treating the target prediction task as a binary classification problem and considering time-dependent factors, our proposed technique produces a series of classification models for different stages (time points) of crowdfunding campaigns. To extract features for the target prediction task, the content of each preclassified campaign (i.e., training instance) including the pledge history and description is handled by currency standardization and preprocessing on missing values first. Subsequently, the features adopted by our proposed technique are classified into five categories: intrinsic characteristics, financial mechanism, content quality and sentiment, social interaction, and progression effect. The first three categories contain all static features because their values do not change over time. Considering that the campaign proceeds over time, we deliberately separate from the other categories the last category, which consists of a dynamic feature, whose value is time-dependent. Furthermore, different from other categories, social interaction is a rather special one, because it is a mixture of static and dynamic features. To concretely illustrate the meaning and procedure of the proposed technique, we define the notations of some variables in Table 1.

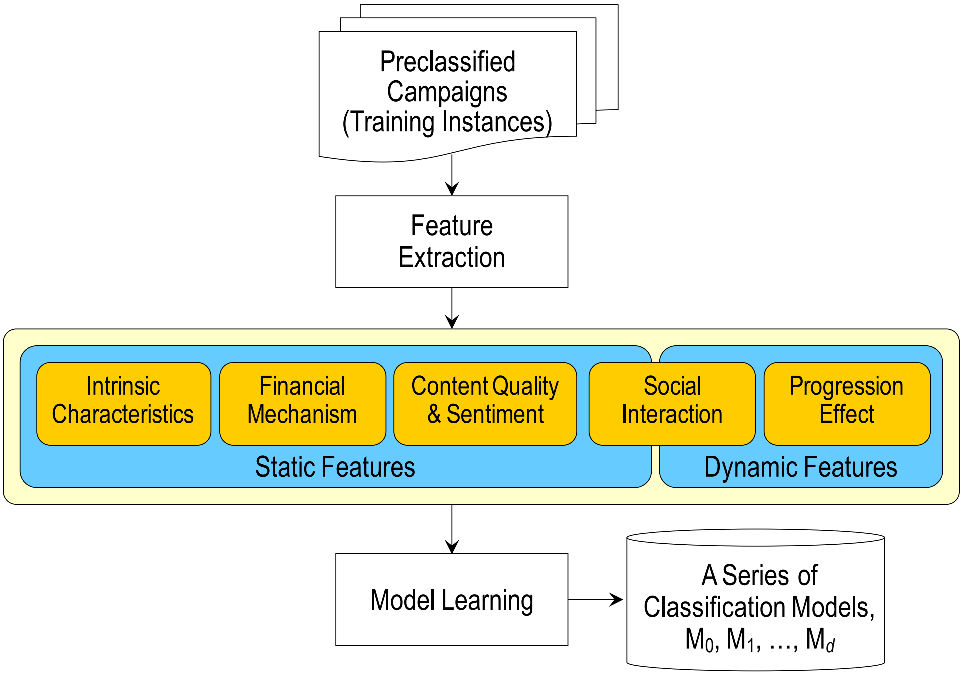

Figure 1. Process of Our Proposed Technique for Predicting the Success of Crowdfunding Campaigns

Notation	Description
f_i	ith feature
M_j	Classification model constructed for jth stage (i.e., in this study, day j after crowdfunding projects are initiated)
T_s	Basic time unit, the time slot between two consecutive stages (i.e., in this study, one day)
T_d	Latest stage examined (if T_d = 7 days, the number of classification models constructed will be $T_d + 1$)

Table 1. Notations of Variables

Noted that the classification model at each time point (stage) is a distinctive one. Generally, the crowdfunding platforms use a day as a time unit to set the length of project duration and hence we regard one day for T_s. For choosing a reasonable value for T_d, we set seven days for T_d. Thus, we will construct eight models, ranging from M_0, M_1, …, M_6, to M_7, where M_j is the classification model constructed for the jth day after crowdfunding projects are initiated. In other words, the first classification model M_0 is trained with campaigns whose static features are extracted at the beginning of the projects, but dynamic features are excluded. The second classification model, M_1, is similarly trained with campaigns whose static features' values remain the same as those for M_0 and the values for dynamic features are extracted at the end of first day of the campaigns. The classification model for M_j is similarly constructed. For each single campaign, the values for the static features stay identical from M_0 to M_d, whereas the values of dynamic features evolve over time. Besides, any campaign that succeeds or fails before T_d is excluded from subsequent classification models. In general, the number of campaigns for training for each classification model decreases over time. In the next subsections, we will detail the process as well as the design of our proposed technique (as Figure 1 shows).

3.1 Feature Extraction

Since Kickstarter has become a worldwide crowdfunding website, the currency values differ from one campaign to the other. To make sure the value of each campaign equivalently evaluated on the same basis, we convert every currency-related attribute to the universally accepted unit, US dollar, according to the long-term 180 days foreign exchange rate of Bank of Taiwan on Dec. 30, 2014. After standardizing currency and removing campaigns with missing values, we can start to extract the values of the features for each campaign.

AUD→USD	CAD→USD	EUR→USD	GBP→USD	NZD→USD	USD
0.80315	0.85608	1.21850	1.55193	0.76554	1

Table 2. Foreign Exchange Rate of Bank of Taiwan on Dec. 30, 2014

To make a classification model more accurately, what features to incorporate is always an important issue (Dash 1997). Many crowdfunding platforms are available on the Internet. Without losing the generality, the set of features considered in our proposed technique are applicable to most of crowdfunding platforms. In the following, we explain and illustrate our features in each of the five categories.

3.1.1 Intrinsic Characteristics

Intrinsic characteristics consist of a campaign's basic profile and its founder's background. The campaign's basic profile includes the category of the campaign, the location where the campaign is initiated and the currency used (where the founder lives). The popularity of project category and preference of currency for the crowd may affect the result of the campaign. However, the initiating location of the campaign may not have an impact on the result of the campaign. Thus, we do not consider the initiating location of the campaign as a feature in this study. On the other hand, the founder's background likely influences the trust of potential backers to the campaign. Specifically, in our study, we take the following founder's background into consideration: the number of Facebook friends of the founder, and the number of projects created and backed by the founder. Table 3 lists all features that we include in the category of intrinsic characteristics.

Features	**Type**	**Value Domain**
Project category of the campaign (f_1)	Static	Nominal data ranging from 1 to 15
Number of Facebook friends of the founder (f_2)	Static	Non-negative integer
Number of projects backed by the founder (f_3)	Static	Non-negative integer
Number of projects created by the founder (f_4)	Static	Non-negative integer
Currency (f_5)	Static	Nominal data ranging from 1 to 6

Table 3. Features in the Category of Intrinsic Characteristics

3.1.2 Financial Mechanism

Financial mechanism, made up with money-related items that a project initiator can manipulate, influences how much a project possibly can get and is especially important for business projects. For a crowdfunding project, the founder determines its goal and pledge methods. In addition to the number of pledge methods, the diversity of pledge methods designed for each crowdfunding project may also differ for different campaigns. Therefore, the pledge methods are further analysed to extract the maximal pledge price, minimum pledge price, average pledge price, and standard deviation of pledge prices as additional features in the category of financial mechanism. Table 4 lists all features that we consider for this category.

Features	Type	Value Domain
Goal (f_6)	Static	Positive integer (normalized into US dollars)
Number of pledge methods (f_7)	Static	Non-negative integer
Maximal pledge price (f_8)	Static	Non-negative float
Minimal pledge price (f_9)	Static	Non-negative float
Average pledge price (f_{10})	Static	Non-negative float
Standard deviation of pledge price (f_{11})	Static	Non-negative float

Table 4. Features in the Category of Financial Mechanism

3.1.3 Content Quality and Sentiment

Content quality and sentiment indicate how deliberately the founder designs or handles the introductory page of a project. If a founder adequately utilizes multimedia for and write fluently the introductory page, people can undoubtedly understand the conveyed idea, approve it, and are more likely to become its backers. Besides, the quality of content also affects the perception of potential backers about the founder's effort. In this study, we capture three aspects of the content quality of the introductory page of a project, including richness (i.e., the number of photos, videos, and words), correctness, and readability. The correctness of the introductory page is measured, in a reverse manner, by the number of spelling errors. To measure the readability of the introductory page of a campaign, we employ the Flesch-Kincaid grade level, which produces the readability score that specifies the education level (grade) the target audience needs for reading the article. Finally, the sentiment of content conveyed by the founder may affect the perception of readers and even more the decision of backing. Table 5 lists all features that we consider for the category of content quality and sentiment.

Features	Type	Value Domain
Number of photos (f_{12})	Static	Non-negative integer
Number of videos (f_{13})	Static	Non-negative integer
Number of words (f_{14})	Static	Non-negative integer
Number of spelling errors (f_{15})	Static	Non-negative integer
Flesch-Kincaid Grade Level (f_{16})	Static	Float ranging from 0 to 100
Sentiment score of description (f_{17})	Static	Nominal data, where positive, neutral, and negative are denoted by 1, 0, and -1

Table 5. Features in the Category of Content Quality and Sentiment

3.1.4 Social Interaction

Social interaction, viewed as the interactions between initiators and users/backers, includes the number of comments left by (potential) backers, number of project updates, number of social words in the description (counted by a text-analysing tool called LIWC, Linguistic Inquiry and Word Count), whether the project is connected with Facebook, number of Facebook shares, and number of FAQs. These features represent the level of interactions between the initiator and potential backers, and the extent of popularity and spreadability of the campaign in public. Moreover, social interaction is also a sign, which indicates the initiator's elaboration on this campaign. If a project initiator makes efforts to promote his/her project and clarify all questions that potential backers have, this initiator is thought to be conscientious, trustworthy and reliable. As a result, this project is likely to attract more backers to join in. Table 6 lists all features that we include in the category of social interaction. Evidently, the top two features are static features, whereas the remaining features are dynamic features. In addition, at day 0, these dynamic features do not exist and thus are excluded from M_0.

Features	Type	Value Domain
Number of social words (f_{18})	Static	Non-negative integer
Facebook connection (f_{19})	Static	Nominal data in form of binary: 1 and 0
Number of updates (f_{20})	Dynamic	Non-negative integer
Number of comments (f_{21})	Dynamic	Non-negative integer
Number of Facebook shares (f_{22})	Dynamic	Non-negative integer
Number of FAQs (f_{23})	Dynamic	Non-negative integer

Table 6. Features in the Category of Social Interaction

3.1.5 Progression Effect

Progression effect contains only a distinctive feature called completeness, which dynamically keeps track of the amount of money raised on each single day. As with other dynamic features, the completeness feature is excluded from the feature set for M_0 (i.e., at day 0). For day 1 to day 7 (i.e., $1 \leq t \leq 7$), the formula for the completeness feature is as follows:

$$f_{24} = Completeness_t = \frac{Amount\ of\ Money\ Currently\ Raised_t}{Goal(Expected\ Amount\ of\ Money)} \times 100\%, \text{for } t \in \mathbb{Z} \cap [1, 7]$$

Campaign's completeness normally increases as time goes by. Although the completeness of a campaign can exceed 100%, in our study, when a campaign succeeds (i.e., its completeness reaches 100%), this campaign will be removed from subsequent classification models. Therefore, the progression of all campaigns in our dataset will not be over 100%. The main supporting reason that makes us to consider this feature is as follows: In a crowdfunding environment, the bandwagon effect is commonly observed, because many people just behave collectively without a considerable thought. This phenomenon is somehow similar to the additive effect. Especially for crowdfunding, other incentives, including the inner satisfaction of contribution to campaigns and rewards in exchange of pledges, lead backers to support campaigns with a higher completeness rate. For instance, a user tends to support a campaign whose completeness is 80% instead of another one with the completeness of only 10%, because the former has a much higher chance to succeed. That is why we believe that the progression (i.e., completeness) of a campaign has an effect on the result of the campaign.

3.2 Model Learning

Once the values of all features for each preclassified campaign (i.e., training instance) has been extracted, the next step is to construct a series of classification models, one for each stage of the campaigns (i.e., day 0 to day 7 in this study), with the corresponding static and dynamic features. In this study, we adopt random forest as the underlying supervised learning algorithm when building the series of classification models.

4 EMPIRICAL EVALUATION AND RESULTS

4.1 Dataset

As described previously, we collect our dataset from Kickstarter. The data, including pledge history and campaign's content, are from Kickspy (a website collecting data from Kickstarter) as well as from Kickstarter directly. The statistics of our dataset are summarized in Table 7. 45.84% of the campaigns succeeded before their deadline. The number of campaigns for each day is shown in Table 8. As shown, the numbers of successful and failed campaigns are at a comparable level across the seven days; making the comparisons of prediction effectiveness across different days more practical.

Period	April 1, 2014 to April 30, 2014
Number of campaigns	4,121
Number of successful campaigns	1,889
Number of failed campaigns	2,232
Average number of backers	139.7
Average goal (converted to US dollars)	54,305
Average number of comments	19.62
Average number of pledge methods	9.82

Table 7. Statistics of Our Dataset for Evaluation Purposes

	T_0	T_1	T_2	T_3	T_4	T_5	T_6	T_7
Total number of campaigns	4,121	4,009	3,926	3,893	3,847	3,801	3,764	3,710
Successful campaigns	1,889	1,777	1,695	1,663	1,620	1,574	1,539	1,487
Failed campaigns	2,232	2,232	2,231	2,230	2,227	2,227	2,225	2,223

Table 8. Number of Campaigns for Each Day

4.2 Evaluation Results

In this section, we organize our experiments into two parts. The first one is to evaluate the effectiveness of our proposed technique with a benchmark model and assess the predicting power of each category of features, whereas the second one is the effectiveness attained by our proposed technique at different stages (from day 0 to day 7) of campaigns (i.e., involving only static features for day 0 and using both static and dynamic features for day 1 to day 7). We choose Greenberg et al.'s model (2013) as our performance benchmark and define the features used by Greenberg et al. as F_G, which includes f_1, f_2, f_6, f_7, f_{13}, f_{14}, f_{16}, f_{17}, and f_{19}. These features cover a part of the intrinsic characteristics, financial mechanism, content quality and sentiment, and social interaction categories. In the meanwhile, we exclude three features from the original study, because the duration feature is not well defined and two features about twitter's information do not show on Kickstarter anymore. In this study, we employ a 3-fold cross validation to evaluate the effectiveness of our proposed technique. Furthermore, to obtain a reliable performance estimate, we conduct the 3-fold cross validation 100 times and the overall effectiveness of a technique examined is the average over the 100 trials.

4.2.1 Comparative Evaluation Results

In this experiment, we exclude the feature of progression effect and use the values at the end of a campaign's lifetime for the social influence features along with all static features in the intrinsic characteristics, financial mechanism, and content quality and sentiment categories to build classification models. We first compare the effectiveness of our proposed technique with that of the benchmark method, i.e., the model by Greenberg et al. (2013). As Table 9 illustrates, our proposed technique achieves an accuracy of 84.67%, whereas the accuracy attained by the benchmark method is 69.88%. The statistical test (Demšar 2006) suggests that our proposed technique significantly outperforms the benchmark method in accuracy. The difference between the two methods is mainly on social interaction features. It is evident that the campaigns with more numbers of Facebook shares, comments and FAQs are more popular and more likely to succeed. Therefore, these features are discriminative for the two outcomes (success or failure). To further understand the importance of the features in each category, we adopt the same evaluation procedure on each of four categories. The respective accuracies and *t*-tests are shown in Table 9. The classification model with all features utilizes the prediction ability from the four categories and therefore outperforms the others. Besides, we find that the accuracy of the model with social interaction features can reach 75.37% and outperforms the model with the features from other category. Although content quality and sentiment features seems to be less relevant (with the lowest accuracy), it also improve the accuracy by 4.4% as compared to the baseline (54.1%), which classifies all campaigns into the majority outcome (i.e., failure). Although the success of campaign is due to the combination of merits in the four categories, for limited time and resources, project initiators should put emphases on or even manipulate social interaction, intrinsic characteristics, financial mechanism, and then content quality and sentiment to make their projects more appealing and increase their chance of being successful.

	Accuracy	Paired-Samples T-test on Accuracy				
		Greenberg et al., 2013	Intrinsic characteristics only	Financial mechanism only	Content quality and sentiment only	Social interaction only
All features	84.67%	304.5***[1]	380.9***	368.6***	500.8***	245.0***
Greenberg et al., 2013	69.88%	---	82.2***	85.5***	193.2***	-107.6***
Intrinsic characteristics only	65.05%	---	---	8.3***	98.1***	-189.4***
Financial mechanism only	64.49%	---	---	---	88.3***	-181.0***
Content quality and sentiment only	58.56%	---	---	---	---	-306.0***
Social interaction only	75.37%	---	---	---	---	---

[1.] 304.5 denotes the t-value between the accuracy of "all features" vs. that of Greenberg et al. (2013). ***: $p < .001$.

Table 9. Average Accuracy of Different Feature Sets and Paired-Samples T-test on Accuracy

4.2.2 Prediction Effectiveness at Different Stages

In this experiment, we analyze the effectiveness attained by our proposed technique at different stages (from day 0 to day 7) of campaigns. Specifically, if we attempt to predict the outcome of a campaign at day 0, the classification model essentially involves only static features. For day 1 to day 7, we use both static and dynamic features (including the feature of progression effect) to construct corresponding classification models. Table 10 shows the prediction effectiveness across different stages. At day 0, our proposed technique involving only static features can attain an overall accuracy of 72.89%, which is also greater than that of Greenberg et al.'s model (i.e., 69.88%; please see Table 9). As we have additional information about dynamic features, the prediction accuracy can improve considerably. For example, if we make predictions at day 1 rather than at day 0, the prediction accuracy improves substantially by 14.24% (i.e., from 72.89% to 87.13%). As we delay predictions by one more day (i.e., at day 2), we can enjoy an accuracy improvement by 0.90% (as compared to that of day 1). After day 2, the prediction accuracy remains comparable or improves slightly at most. We observe similar trends with other performance measures (i.e., precision, recall, and F1 for each outcome).

	Successful Campaigns			Failed Campaigns			
Stage	**Precision**	**Recall**	**F1**	**Precision**	**Recall**	**F1**	**Accuracy**
T_0	70.44%	70.41%	70.43%	74.97%	75.00%	74.98%	72.89%
T_1	84.21%	87.34%	85.75%	89.61%	86.96%	88.27%	87.13%
T_2	85.02%	87.73%	86.35%	90.45%	88.26%	89.34%	88.03%
T_3	85.27%	87.73%	86.48%	90.65%	88.70%	89.66%	88.29%
T_4	85.11%	88.58%	86.81%	91.44%	88.73%	90.06%	88.67%
T_5	85.91%	87.93%	86.91%	91.32%	89.81%	90.56%	89.03%
T_6	86.69%	88.43%	87.55%	91.89%	90.61%	91.24%	89.72%
T_7	86.20%	88.23%	87.21%	92.00%	90.55%	91.27%	89.62%

Table 10. Performance Evaluation of Classification Models Constructed at Different Stages

After campaigns initiate, the values of dynamic features in social interaction and progression effect start to increase. These values reveal the extent of how popular the campaign is, which is helpful for discriminating successful and failed campaigns. Our experiment highlights that the utility of dynamic features has significant impact on prediction effectiveness only on the first two days (especially, from day 0 to day 1). To increase the chances of success, project initiators should pay attention to enhancing the values of the dynamic features on the first one or two days after their projects initiate. When crowdfunding service providers or backers want to estimate the likely outcome of a campaign, they can wait and see the responses from the crowd and the interactions between the project initiator and the crowd (i.e., by observing those dynamic features) on the first one or two days after the project is launched. By striking the balance between timeliness and accuracy, they can predict the result of the campaign at the first day rather than at the beginning.

5 CONCLUSION AND FUTURE RESEARCH DIRECTIONS

To summarize, this study follows the data mining approach to propose a technique to predict the outcomes (success or failure) of crowdfunding campaigns. Specifically, we formulate this target prediction task as a binary classification problem and develop features (predictors) pertaining to five categories: intrinsic characteristics, financial mechanism, content quality and sentiment, social interaction, and progression effect. Our proposed technique adopts random forest as the underlying learning algorithm. On the basis of a dataset collected from Kickstarter, our empirical evaluation results show that our proposed technique outperforms the benchmark method (Greenberg et al. 2013). Furthermore, the evaluation results also suggest that the features in social interaction category are having the highest predicting power. Finally, our time effect experiment shows that the inclusion of dynamic features can improve prediction effectiveness. Specifically, the utility of dynamic features has significant impact on prediction effectiveness on the first two days (especially, from day 0 to day 1).

Some future research directions are summarized in the following. First, in our current study, we only concentrate on predicting whether a crowdfunding campaign will succeed or fail. It, however, is also important to estimate how far a possibly failed campaign is to reach its goal (i.e., its completion rate), because crowdfunding service providers can focus on and prompt those campaigns that are predicted to be failed but not too far from its goal. As a result, a two-stage prediction structure should be developed in the future. That is, the first stage is to predict whether a crowdfunding campaign will succeed or fail (i.e., our current study does) and, given a set of possibly failed campaigns, the second stage is to predict their completion rates (a future research direction). Second, we only employ random forest as the underlying learning algorithm in our current study. The adoption of other machine learning algorithms (e.g., decision tree induction, support vector machines) and evaluate their resultant effectiveness will have practical values and represent an interesting future research direction. Third, we should attempt to develop additional features to further improve prediction effectiveness of our proposed technique. For example, in our current study, we only extract a limited number of features (e.g., number of words, sentiment score, number of social words) from the content of campaigns (i.e., their introductory pages). With the help of text analysis techniques, additional content features can be developed and incorporate into our proposed technique for possible effectiveness improvement.

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