Money talks: A predictive model on crowdfunding success using project description

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Full Papers

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Abstract

Existing research of crowdfunding mainly focuses on the basic properties of the project such as category and goal, the information content of the project, however, is barely studied. By introducing Elaboration Likelihood Model into crowdfunding context and using a large dataset obtained from Kickstarter, a popular crowdfunding platform, we study the influence of project descriptions in terms of argument quality and source credibility, and investigate their impacts on funding success. We find information disclosed in project descriptions is associated with funding success. We also examine the practical impacts of project description by using a predictive model. Results show that our model can predict with an accuracy rate of 73% (71% in F-measure), which represents an improvement of 15 percentage points over the baseline model and 4 percentage points over the mainstream model. Overall, our results provide insights to researchers, project owners and backers to better study and use crowdfunding platforms.

Keywords

Crowdfunding, Kickstarter, Elaboration Likelihood Model, information content, persuasiveness

Introduction

In recent years, crowdfunding has emerged as a revolutionary financing model that allows small entrepreneurs to raise investment in the early stages of their projects, particularly those that would otherwise struggle to obtain capital (Kuppuswamy and Bayus 2013; Belleflamme et al. 2014). Today, there are 452 crowdfunding platforms across the world, which together channeled $1.47 billion in donations in 2011 alone (Kickstarter 2014). Popular crowdfunding platforms such as Kickstarter and IndieGoGo rely on existing web-based payment systems to facilitate the exchange of resources between owners (creators, entrepreneurs) and backers (supporters, investors)[1] (Gerber and Hui 2013). Having projects successfully funded is crucial to project owners, providing not only the initial funds but also access to valuable future

[1] In this paper, the terms owner, creator and entrepreneur are interchangeable, and the terms backer, supporter and investor are interchangeable, unless otherwise specified.

resources. The pass of the "pilot test" can reinforce project owners' confidence, gain exposure, help them connect to potential venture capitalists (VCs), and eventually turn their projects into entrepreneurial firms. Although existing studies in this area have identified a variety of factors that may directly or indirectly impact the funding success of a project, they mainly focus on basic project properties such as goal (the amount to be raised), duration (the period of days to raise fund), and category (the type of project) (Greenberg et al. 2013; Mollick 2014). The rich information embedded in the project descriptions, however, is often ignored.

Project description is an important communication channel between project owners and backers. We believe owners have a great propensity to use project descriptions strategically to promote their projects (products) and influence backers to contribute. On crowdfunding platforms, backers "pre-order" products before their existence, these products are "promised" to be delivered in a future day based on mutual trust. Backers have no control over the project development, and there is little external information such as customer reviews for backers to evaluate a product or an owner. The project description thus becomes one of the important information sources for backers to evaluate a project and make their funding decisions. On the other hand, there are very limited channels on crowdfunding platforms for project owners to communicate with potential backers regarding their projects. That is especially true before the project is launched. Given the fact that the number of crowdfunding projects is increasing dramatically in recent years, the competition for backers' attention is also becoming increasingly fierce (Mollick 2014). It highlights the importance for project owners to decide what and how information is presented in project descriptions. We believe studies on understanding the rich information contained in project descriptions can advance our knowledge regarding the micro-process of crowdfunding and how project descriptions can influence the funding success. To the best of our knowledge, there are few studies in this area.

This paper seeks to fill this gap by investigating the information content of project descriptions on the Kickstarter platform. Drawing on the theory of the Elaboration Likelihood Model (ELM), we study the influence of project description on crowdfunding success. Specifically, we operationalize the influence process using constructs such as argument quality and source credibility, which may affect backers' contribution decisions and the funding success of a project. Our results show that, when the information content of project description is considered, our model can predict funding success with an accuracy rate of 73% (or 71% in F-measure). It represents an improvement of roughly 15 percentage points over the baseline model based on informed guessing and 4 percentage points over the mainstream model based on basic project properties; both improvements are statistically and practically significant.

This paper is organized as follow. We first review literature related to the determinants of crowdfunding success and Elaboration Likelihood Model. We then introduce our measures to quantify the influence of project description followed by a description of our dataset. After that, we present and discuss our empirical results. Finally, we provide conclusions and discuss opportunities for future research.

Background and Literature Review

Although crowdfunding is a relatively new phenomenon, existing research has greatly advanced our understanding on this viable method of funding new ventures. Researchers have identified a variety of factors that may directly or indirectly impact the funding success of a project. Some researchers find that project properties, such as category, goal, and duration, are associated with funding successes. Others show that the existence of images or videos in project introduction is associated with funding success (Greenberg et al. 2013; Mollick 2014). Studies have also shown that a project owner's social influence, proxied by the numbers of friends on social networks such as Facebook, has an impact on funding success (Mollick 2014). Furthermore, researchers find that there is a strong geographic component to the nature of projects, with founders are more likely to propose projects that reflect the underlying cultural products of their geographic areas (such as country music in Nashville, Tennessee) (Agrawal et al. 2014; Mollick 2014). They suggest that the nature of the population in which founders operate is related to funding success (Kuppuswamy and Bayus 2013; Li and Duan 2014). These determinants have been incorporated by researchers to predict the funding success of projects, in the hope to provide guidance for maximizing the funding success (Greenberg et al. 2013)[2]. Although existing research on determinants and prediction of funding success contribute

[2] There is also research studying the dynamics after a project is launched, however, it is out of the scope of this paper.

greatly to our understanding of crowdfunding, few studies have been focused on the information content of the textual description of projects. However, studies have shown that descriptions are important for people to evaluate quality, novel, and creative ideas (Dean et al. 2006).

In order to increase their funding success, we believe project owners have a propensity to strategically use project descriptions as a marketing tool to influence potential backers' contribution decisions. One theoretical perspective that can advance our understanding of the influence process on backers' contribution decisions is the Elaboration Likelihood Model (ELM). ELM posits that attitude change among users may be caused by two "routes" of influence, the central route and the peripheral route, which differ in the amount of thoughtful information processing or "elaboration" demanded of individual users (Petty and Cacioppo 1986; Bhattacherjee and Sanford 2006). In the context of crowdfunding, the central route requires backers to think critically about information disclosed in project descriptions and scrutinizes the relative merits prior to making contribution decisions. The peripheral route, on the other hand, involves less cognitive effort, where backers rely on cues such as past experience of the project owners, rather than on the quality of arguments, to make their decisions.

ELM has been widely used in empirical research in social psychology, marketing and consumer research literature (Lien 2001; Bhattacherjee and Sanford 2006; Fan et al. 2013; Cheng and Loi 2014; Ho and Bodoff 2014). As we discussed above, on crowdfunding platform, project backers act as consumers and "pre-order" the product promised to be delivered on a future day. Because of the limited communication channels, the project description is one of the few tools project owners can use to promote their projects and influence backers to contribute. There are only a few studies that have examined the information content of project descriptions. These studies, however, either use a case study approach relying on small samples (Ordanini et al. 2011) or simply include phrases as predicting variables (Mitra and Gilbert 2014), thus lack the theoretical supports and fail to capture valuable informational features contained in the project description. While there may be additional theories on influence, ELM appears to be well suited to our exploration of the influence of project description within the crowdfunding context, which until now has largely eluded existing literature. We aim to narrow this gap in crowdfunding research.

Methodology and Data

Operationalization of Constructs

Following existing ELM literature (Petty and Cacioppo 1986; Bhattacherjee and Sanford 2006; Li 2013), the central and peripheral routes are operationalized in this study using the argument quality and source credibility constructs, respectively. Argument quality refers to the perceived quality of information content based on the message content only (Bailey and Pearson 1983; Rabjohn et al. 2008). Basing on the work by Wang and Strong (1996) and Wang et al. (2011) and considering that we focus only on the one-way communication (through project description) from project owners to backers, we identify 3 argument quality dimensions (amount of data, ease of understanding, and objectivity) that are content-based and can be automatically extracted using text mining techniques[3]. Following previous literature, we measure the amount of data by using the number of words in the project description (Wang et al. 2011; Zhou et al. 2014), the ease of understanding by calculating the Gunning fog index (hereafter Fog index) of the project description (Li 2008; Wang et al. 2011), and objectivity by using the ratio of positive and negative words in the project description (Wang et al. 2011).

Source credibility, on the other hand, indicates a message recipient's perception on the credibility and authority of the information source reflecting nothing about the information content Chaiken (1980). While different proposals on the underlying dimensions of source credibility have been discussed in various studies, two dimensions, competence, and trustworthiness, have consistently emerged (Sussman and Siegal 2003). In the context of our study, the social connections between project backers and owners[4] are unknown to us. Backers' trust on owners is mainly based on their competence. Since competence-based

[3] We only consider the textual information in the project description.

[4] We do not consider the personal connection between backers and owners outside the crowdfunding platform.

source credibility refers to past experience or expertise (Wang et al. 2011), we measure the overall source credibility by using the number of projects backed and the number of projects created by the owner in the past.

Data and Predictive Model

We collect real crowdfunding data from Kickstart.com to carry out our empirical analysis. Founded in 2009, Kickstarter has become one of the largest and most popular crowdfunding platforms around the world. Our data sample covers all the projects from 2009 to November 2014. We exclude those funding projects that are still ongoing. In addition, we exclude projects that are canceled or pending. They are not treated as failed projects because we do not have information regarding the underlying reasons why they are in such a status. In addition, we follow previous study and remove those projects with a funding goal below $100 (1982 projects) or above $1,000,000 (294 projects), because these extremely small or large projects may have different features from the majority of projects (Mollick 2014). We also remove those projects with less than 100 words in their descriptions, because, upon inspection, they are either incomplete or represent non-serious efforts to raise funds. Our final data sample consists of 154,561 projects across all 15 funding categories.

Because each project can be classified as either a success (meeting the funding goal when the campaign is completed) or a failure (not meeting the funding goal when the campaign is completed), we build a logistic regression model to study the influence of project descriptions on the success of a funding project. Our model is shown below.

$$Logit(Success) = \beta_0 + \beta_1 numWords + \beta_2 fog + \beta_3 objectivity + \beta_4 numBacked + \beta_5 numCreated + \beta_6 otherControls + \mathcal{E}$$

In addition to our independent variables, we add control variables for other major predictors of funding success identified by previous research, such as project category, goal and duration (Greenberg et al. 2013; Mollick 2014). All variables used in this study are described in Table 1.

Type	Construct	Variable	Description
Newly Introduced Variables	Argument Quality	numWords	The number of words contained in a project description.
		fog	Readability of project description, measured by the Gunning Fog Index.
		objectivity	The ratio of positive and negative words in a project description.
	Source Credibility	NumCreated	The number of projects previously created by the owner
		NumBacked	The number of projects previously backed by the owner
Previously Identified Variables	Control Variables	Goal	Project goal, the amount an owner seeks to raise.
		Duration	The number of days for which a project accepts funds.
		FBConnected	Whether project owner has a Facebook page for the project.
		FBF	The number of Facebook friends a project owner has.
		HasImage	Whether a project includes an image on the project page
		HasVideo	Whether a project includes a video clip on the project page.
		NumRewards	The number of pledge levels
		Year	The year when a project is launched.
		Category	The funding category of a project.

Table 1. Variable Description

Empirical Results

In order to evaluate the practical impact of our newly identified variables on the prediction performance, we compare the prediction performance of our predictive model to two baseline models. The first baseline model is built based on informed guessing. In this model, we classify each project as "success" or "failure" simply according to the overall probability of funding success. For example, if 40% projects are successfully funded, the overall probability of funding success is 40%. Therefore, each project will be classified as "success" with a probability of 40% and to "failure" with a probability of 60%. Then we calculate the prediction performance by comparing projects' assigned status values (i.e., success or failure) with their true status values. The second baseline model is called the mainstream model, which is a logit regression model only including all the control variables identified in previous studies.

For each predictive model, we employ N-fold cross validation test (with N set as 3, 5 and 10) to evaluate the prediction performance. The N-fold cross validation test has been widely used to validate the performance of classification (Bengio and Grandvalet 2004; Li 2010). For each N, our data sample is randomly divided into N parts, N experiments are then performed, with N-1 parts used as training data for the predictive model to classify the remaining part. The average prediction performance is reported for the given N. Following the previous research, we use the F-measure to evaluate the prediction performance, which considers both prediction accuracy and recall accuracy and thus provides a balanced performance evaluation (Ferri et al. 2009; Sokolova and Lapalme 2009; Powers 2011). Our results of N-fold cross validation test are reported in Table 2.

N	Baseline	Mainstream	Proposed model
3	57.12	66.45	70.43
5	58.18	67.13	71.01
10	58.03	67.22	71.17

Table 2. N-Fold Cross-Validation Tests (F-Measure)

The results show that our proposed model achieves the highest F-measure, with the average F-measure around 71%. The average F-measure of the mainstream model is around 67%, and baseline model around 58%. The differences among these three models are statistically significant. Considering that the mainstream model only beats the baseline model by 9 percentage points (58% to 67%), the 4 additional percentage points (67% to 71%) increase in performance by our proposed model is fair significant, representing 44% of the improvement over informed guessing. These results together show that our newly introduced variables have significant practical impacts on the funding success of projects. The results clearly show evidence on the influence of project descriptions on funding success.

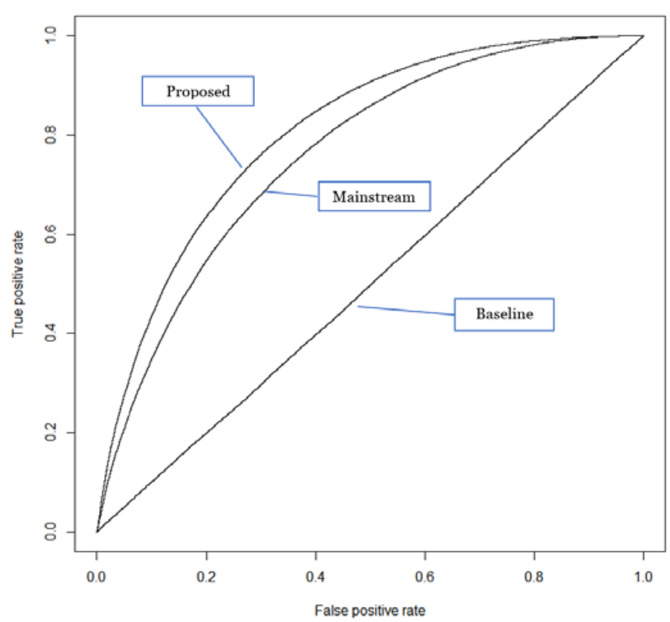

Figure 1. The ROC Curves of Baseline, Mainstream and Proposed Models

In order to better compare our results with those reported by previous studies, we replace the F-measure with the overall accuracy measure. We observe a similar pattern among those three predictive models. The un-tabulated results show that the mainstream model has an accuracy rate of 69%, which is comparable to what is achieved by Greenberg et al. (2013). Our proposed model have an accuracy rate of 73% (achieved at cutoff=0.47), which is roughly 15 percentage points improvement over the baseline model and 4 percentage points improvement over the mainstream model. These results again corroborate our finding that information disclosed in project description have practical impacts on funding success.

Both accuracy and F-measure are designed for the overall performance of predictive models. But sometimes we need more specific information to make the funding decision. This is especially true when we evaluate prediction performance from the perspective of backers (or VCs). Because of the limited time and resource, backers may not be interested in the overall success rate. Instead, they care more about whether projects predicted as success will truly be successfully funded. In another word, they want a predictive model that has high true positive rate and low false positive rate (and the model should have the ability to rank the projects based on their probability of success). By using ROC (Receiver Operating Characteristic) curve (Fawcett 2006), we investigate whether our proposed model has improved performance compared to the baseline model and the mainstream model. The results are illustrated in Figure 1.

As shown in Figure 1, comparing to the mainstream model, our proposed model has a ROC curve which is more convex toward upper-left. This indicates that the proposed model has a higher true positive rate and a lower false positive rate, which is more useful for backers to make their funding decisions.

Conclusions and Discussions

The success of crowdfunding warrants its importance of research, we expect an increasing use of crowdfunding in future venture investment. By using a large dataset obtained from Kickstarter, a popular crowdfunding platform, we examine the information content of project description and measure its influence based on the Elaboration Likelihood Model. We provide evidence that information disclosed in project descriptions is related to funding success, we then test its practical impacts through newly introduced measures by using a predictive model of funding success. Our results show that the proposed model can predict funding success with an accuracy rate of 73% (or 71% in F-measure), which represents an improvement of roughly 15 percentage points over the baseline model based on informed guessing and 4 percentage points improvement over the mainstream model based on basic project properties.

This paper contributes to the crowdfunding literature in several ways. First, to the best of our knowledge, this study is among the first to study crowdfunding with a focus on information content disclosed in textual project descriptions. Second, this paper is also among the first to introduce communication theory (i.e., the Elaboration Likelihood Model) into the crowdfunding context. Using a text mining approach, we measure the influence of project descriptions and investigate its impacts on funding success. Third, the results reported in this paper highlights the importance of project descriptions and provide insights for project owners to increase their funding success through higher argument quality and source credibility. Fourth, existing predictive models usually employ overall accuracy to measure performance (Etter et al. 2013; Greenberg et al. 2013; Mitra and Gilbert 2014). From the perspective of backers, our proposed model is evaluated using a more balanced performance measure (i.e., F-measure and ROC curve) to better serve backers to make funding decisions. Taken together, our results provide meaning insights to researchers, project owners, and backers to better understand funding success and failure on crowdfunding platforms.

This study is subject to several limitations. First, we conduct our studies merely base on one crowdfunding platform. Although Kickstarter is recognized as a successful and popular crowdfunding platform, it is just one of the many platforms. It differs with other platforms from a variety of aspects. Second, we mainly consider the communication between owners and backers through the crowdfunding platform (within-platform activities). There are many channels of "offline" communication and interactions between owners and backers (off-platform activities), which are also critical to funding success. Third, we limit our study to the information content of project description before project launch. The information content of project updates and comments after project launch are also important to funding success.

This study also provides valuable opportunities for future research. First, some of the limitations can be addressed in our future research. For example, most of current research only focuses on one type of crowdfunding platform (or model), future research can compare different crowdfunding platforms and gain more insights. This study can also be extended to the stage after the project is launched and provide real-time monitoring and suggestions to increase funding success for project owners. Second, we only focus on basic textual features, future studies can examine more advanced features such as linguistic structures or employ more advanced methodologies such as topic modeling. Third, with the fast growing of crowdfunding projects, it is becoming increasingly difficult for a project owner to attract enough backers and for a backer to choose a suitable project. Future research can work on bringing the two types of participants closer by identifying potential backers to owners or recommending potential projects to backers. Fourth, the main purpose of this study is to highlight the important influence of project description on funding success. In order to further improve the prediction performance, however, future research can use other classification algorithms such as Support Vector Machine (SVM), which provide better model calibration. Fifth, most current research assumes that the backers are ordinary individuals. However, the Venture Capitalists (VCs) can also use the platform to identify potential projects. And the pass of the JOBS Act (Jumpstart Our Business Startups Act) in April of 2012 has paved the way for equity crowdfunding (Barnett 2014). The involvement of VCs may affect how owners and backers play this game. And the current practice of VCs may also be impacted profoundly. However, we know little about these issues. We encourage future research to explore these areas and advance our knowledge regarding crowdfunding.

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