Tracking the Dynamics in Crowdfunding

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ABSTRACT

Crowdfunding is an emerging Internet fundraising mechanism by raising monetary contributions from the crowd for projects or ventures. In these platforms, the dynamics, i.e., daily funding amount on *campaigns* and *perks* (backing options with rewards), are the most concerned issue for creators, backers and platforms. However, tracking the dynamics in crowdfunding is very challenging and still under-explored. To that end, in this paper, we present a focused study on this important problem. A special goal is to forecast the funding amount for a given campaign and its perks in the future days. Specifically, we formalize the dynamics in crowdfunding as a hierarchical time series, i.e., *campaign level* and *perk level*. Specific to each level, we develop a special regression by modeling the decision making process of the crowd (visitors and backing probability) and exploring various factors that impact the decision; on this basis, an enhanced switching regression is proposed at each level to address the heterogeneity of funding sequences. Further, we employ a revision matrix to combine the two-level base forecasts for the final forecasting. We conduct extensive experiments on a real-world crowdfunding data collected from Indiegogo.com. The experimental results clearly demonstrate the effectiveness of our approaches on tracking the dynamics in crowdfunding.

KEYWORDS

Crowdfunding, Dynamics, Hierarchical time series

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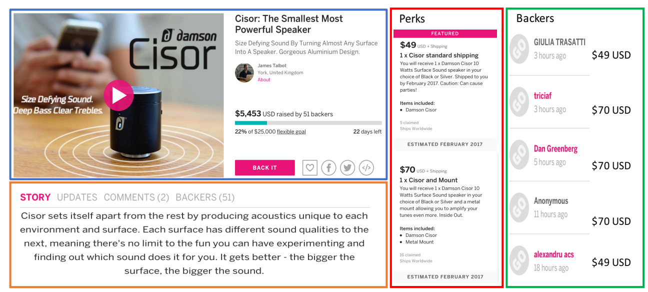


Figure 1: An example of raising-money campaign.

1 INTRODUCTION

Crowdfunding, as a particular form of crowdsourcing, is the practice of funding a project or venture by raising monetary contributions from a large number of people. Recent years have witnessed the rapid development of crowdfunding platforms, such as Kickstarter.com[1], Indiegogo.com[2]. In 2015, it was estimated by *Forbes* that over US $34 billion were raised worldwide in this way, compared with that the venture capital industry invests $30 billion on average each year [3].

As the most popular type of crowdfunding, reward-based platforms (e.g., Indiegogo.com) enable people to create projects for raising money they need, in return for "rewards" (often vowing future products). When an individual (or a team) wants to raise money on these platforms, she will create a *campaign* for her project. Figure 1 shows the snapshot for one raising-money campaign on Indiegogo.com. From the campaign page, we can see some basic properties of this campaign, e.g., *creator, goal, story* and also the dynamic funding progress, e.g., *funded/remaining amount, remaining days*. A campaign often sets several (e.g., 10) types of "rewards" (i.e., perks) with different prices, thus backers could make different monetary contributions by selecting different perks. The funding sequence is shown in the green rectangle of Figure 1, which is indeed a two-level time series, i.e., the dynamic of funding amount on perks and dynamic of summarized-funding amount on this campaign.

In the literature, there are a number of studies on crowdfunding [4, 27, 29]. Most of these existing works focus on predicting the campaign success, i.e., reaching the fixed funding goals or

[1]https://www.kickstarter.com
[2]https://www.indiegogo.com

not [22, 27, 29], with small-scale datasets. However, many platforms, such as Indiegogo.com, encourage the "flexible goal" instead of the "fixed goal" [10], where the success of a campaign is no longer a big concern of creators. In fact, for creators, backers and platform operators, they all want to understand and forecast the dynamics of campaigns and perks every day, rather than just predict the final funding results. Specifically, successful forecasting of the dynamics could benefit all three parties: (1) creators can update their campaigns and adjust the perk settings in time based on the dynamics; (2) backers can make better decisions according to the current popularities and future dynamics; (3) platform operators can provide better services, such as management and recommendation of campaigns based on the dynamics. Unfortunately, less effort has been made towards this goal. To this end, in this paper, we propose a focused study on tracking and forecasting the dynamics in crowdfunding in a holistic view. To the best of our knowledge, this is the first attempt in this area.

However, it is a very challenging task. First, there are hierarchical dynamics in longitudinal crowdfunding data, i.e., multiple time series of funding amount for a given campaign and its multiple perks. How to model the hierarchical dynamics is a nontrivial problem. Second, funding dynamics are potentially affected by the visiting crowd's decision making and various factors, such as social features, prices, and time. To track and forecast the dynamics, how to model the effects of these factors in the decision making of crowd is very challenging. At last, the dynamics vary a lot among different campaigns, perks, and even different funding phases. Thus, how to address such heterogeneity is also difficult.

To conduct this study, we first collect massive real-world crowdfunding data with detailed daily transaction information from Indiegogo.com [3]. After carefully exploring the data, we identify important factors that affect the decision making of crowd and the dynamics of crowdfunding, and construct useful features at both campaign and perk levels. To address the hierarchy of crowdfunding dynamics, we propose a two-layer framework for modeling the dynamics at both campaign and perk levels. Specific to each level, we first develop a single regression model to capture the impacts of various factors (e.g., financial features, social features, time) on the decision making of the crowd (i.e., visitors and backing probability). Further, to address the aforementioned heterogeneity of funding sequences, we propose an enhanced switching regression at each level. Then we employ a revision matrix to combine the two-level base forecasts in order to achieve an optimal final forecasting. Finally, we evaluate our approaches by conducting extensive experiments with our collected data. The experimental results clearly demonstrate the effectiveness of our proposed approaches for tracking and forecasting the dynamics in crowdfunding. Specifically, the contributions of this paper can be summarized as follows:

- We propose a focused study on tracking and forecasting the dynamics of crowdfunding at both campaign and perk levels using a unique dataset collected from Indiegogo.com.
- We develop a special regression at each level for dynamics in crowdfunding by modeling the funding process. Further, we introduce an enhanced switching regression to better handle the heterogeneity of dynamics among different campaigns, perks and different funding phases.
- We develop a novel two-layer framework that could capture the intrinsic relationship between campaign-level dynamics and perk-level dynamics, and employ a revision matrix to combine the base forecasts at two levels for achieving better final forecasting of dynamics.
- We conduct extensive experiments to validate the effectiveness of our method by comparing with several state-of-the-art methods, and report some interesting findings.

[3]The data is publicly available in http://home.ustc.edu.cn/%7Ezhhk/DataSets.html

2 RELATED WORK

The related work can be grouped into two categories, i.e., the work on crowdfunding and the studies on time series forecasting.

2.1 Crowdfunding

Since crowdfunding is a recently emerging market, many problems are still under-explored in the literature. In the past, some prior studies focused on an important issue: predicting the funding results, i.e., success or failure of a campaign, and identifying the influence factors [14, 22, 27]. For example, to predict the success or failure of campaigns and also estimate the time of success, [22] formulated the campaign success prediction as a survival analysis problem and applied the censored regression approach where one could perform regression in the presence of partial information. Lu et al. [27] inferred the impacts of social media on crowdfunding and found the social features could help predict the success rate of project. Mitra and Gilbert [28] explored the factors which lead to successfully funding a crowdfunding project. They found the language used in the project has surprisingly predictive power accounting for 58.56% of the variance around successful funding. Besides the studies of predicting final funding results, some researchers studied the fundraising dynamics for campaigns in their complete funding durations [19]. However, these studies are mainly from the statistical and empirical perspectives to understand the backers' behaviors, and are still lack of deep and quantitative explorations. In fact, creators, backers and platform operators all want to track the dynamics of both campaigns and perks every day, rather than just to predict their final funding results. Unfortunately, less effort has been made towards this goal.

Besides the task of predicting success, a few studies have explored the other problems in crowdfunding or the similar service, e.g., P2P lending, from data mining perspectives, such as campaign recommendations [30], loan recommendations [36, 38], investor (backer) recommendations [2], market state modeling [37] and backing motivation classifications [26].

2.2 Time Series Forecasting

In the literature, time series forecasting has been widely studied [5, 6]. Models for time series forecasting have many forms and can describe different stochastic processes. For example, the autoregressive model [1, 8] and vector autoregression model [18] assume that the current value linearly depends on the previous values. However, conventional autoregressive models only include the response variables without exogenous variables. To address

Table 1: A Summary of data.

Entity	Amount
Campaign	14,143 (13,227 flexible, 916 fixed Campaigns)
Perk	83,450
Member	27,721 Creators (Belong to 14,137 Teams), 211,812 Backers
Contribution	1,862,097 Counts, $ 206,151,977 Amount
Comment	172,824 Comments, 68,189 Replies

the non-linear dependency of input variables and output variables, some other models were applied, such as support vector machine [7] and neural networks [33, 34]. In particular, with the development of deep learning in recent years, many studies found that the recurrent neural network (RNN) can provide satisfactory results for nonstationary time series forecasting [9, 13]. However, most of these methods work as a black box, and are lack of explanatory.

Indeed, developing a forecasting model could not only predict the funding amount but also interpret the decision making of the crowd and the factors impacting the decision, which is very needed for crowdfunding. Unfortunately, little effort has been made to track and forecast the dynamics of crowdfunding in this way.

3 PRELIMINARIES

In this section, we first introduce the working mechanism of Indiegogo.com, and also the collected dataset from this website. Then we introduce the constructed features from the data.

3.1 Indiegogo.com and Dataset

In crowdfunding services, there are generally three types of actors: the individual *creators* or teams who propose the *campaigns to* be funded for their ideas, the visiting individuals (i.e., potential *backers*) who look for campaigns to support, and a *platform* (e.g., Indiegogo.com) that brings these two parties together [12]. Based on the different types of rewards for backers, crowdfunding platforms can be mainly classified into four categories, i.e., *donation-based, reward-based, equity-based* and *lending-based* platforms [21]. As the most popular type, reward-based platforms follow a mode in which a backer's primary objective for funding is to gain a non-financial reward, i.e., *perk* in Indiegogo.com. Indiegogo.com also encourages the "flexible goal" instead of the "fixed goal" and "all-or-nothing" rule [10, 36, 37] for campaigns, which is very different from other common crowdfunding platforms, such as Kickstarter.com [2, 14, 22, 27, 30]. That is to say, for one flexible campaign, it is not necessary to raise a fixed amount of money in the declared durations in order to make this campaign effective. Even a less amount of fund (than the flexible goal) is collected eventually, the funding transaction of this campaign will still be effective. Also, one campaign can continue collecting fund after the flexible goal is reached or over time. In other words, for the flexible-goal campaigns in Indiegogo.com, the declared goals and durations are only for informational purposes.

Indiegogo data contains a variety of heterogeneous information about all entities as shown in Table 1. Entities of each type include various information in the form of unstructured data, such as image, video, and text, and structured data, such as geo-spatial, numerical, categorical, and ordinal data. From these entities, we can obtain the hierarchical dynamics (e.g., daily funding amount time series)

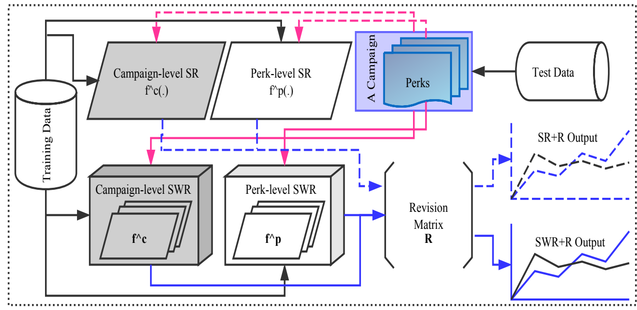


Figure 2: Overview of our solution.

for both campaigns and perks, and also construct various features including both static and time-varying ones.

3.2 Constructed Features

From this dataset, we construct 24 features for campaigns and 30 features for perks. A summary of them is shown in Table 2.

3.2.1 Campaign Features. The campaign features can be grouped into 4 categories, i.e., campaign profile, social media, perk summary and funding progress. The features of campaign profile and social media are extracted from campaign entities. The features of perk summary, i.e., *Perk Option, Claimed Num*, are extracted from the corresponding perk entities of a campaign. The features of funding progress and also *Available Num* are extracted from contribution entities, which are time-varying.

These features are very heterogeneous, including both numerical, categorical data and also text. For consistency, we represent all features as numerics or numerical vectors [25]. Specifically, for the categorical data with less than 10 dimensions, such as *Type, Owner Type, Currency*, and *Verification*, we adopt the **one-hot encoding** [36], i.e., converting a categorical variable with n categories into a n-dimensional binary vector, in which only the value in the corresponding category is set to one and the other values are set to zero. For the categorical data with more than 10 dimensions, such as *Category* and geo-spatial data, i.e., *Country, City*, we use the **count encoding**, i.e., replacing the variables by the respective count frequencies of the variables in the dataset. For text data, such as *Title, Story*, we adopt a **doc2vec** tool [20] to convert them into numerical vectors. Specifically, the numerical vector for *title* is 10-dimensional and the vector for *story* is 100-dimensional.

3.2.2 Perk Features. The perk features can be grouped into three categories, i.e., perk profile, funding progress and the features from its campaign. In particular, the funding dynamic of a perk is highly related to its campaign features. Thus, we also include the features of the corresponding campaign as a part of each perk's feature. We preprocess them in the same way as introduced for campaigns, except the perk description is represented by a 10-dimensional numerical vector.

4 PROBLEM AND METHOD OVERVIEW

In this section, we first introduce the problem of tracking the dynamics in crowdfunding, and then overview our proposed method. For better illustration, Table 3 lists the mathematical notations used in this paper.

Table 2: The description of features.

Feature level	Category	Feature Type	Feature	Description
Campaign Feature	Campaign Profile	Static	Title	Title of the campaign
			Story	Detailed description of the campaign in text
			Team Size	Number of members in the crowdfunding team
			Type	Flexible or fixed goal
			Duration	Declared funding duration of the campaign
			Goal	Amount the campaign wants to fund
			Country	Country of the creator
			City	City of the creator
			Category	Category of the campaign, such as Technology, Education
			Owner Type	Purpose of the campaign, such as business, individual, non-profit
			Currency	Currency for paying the perks, such USD
	Social or Media		Image Num	Number of images provided by the campaign
			Video Num	Number of videos provided by the campaign
			Social Exposure	Number of exposure places, e.g.,Facebook, Twitter, Youtube, website
			Friend Num	Number of friends of funding team in Facebook
			Verification	Whether the campaign was verified in Facebook
	Perk Summary		Perk Option	Number of perk options
			Claimed Num	Total claimed number of perks
		Time-varying	Available Num	Total available number of perks
	Funding Progress		Backer Num	Number of backers who has contributed to the campaign
			Funded Amount	Amount the campaign has collected
			Funded Percentage	Percentage the campaign has funded
			Comment Num	Number of comments the campaign received
			Reply Num	Number of replies the creator has made
Perk Feature	Perk Profile	Static	Description	Short description of the perk
			Featured	Whether this perk is recommended by the campaign
			Price	Unit price of the perk
			Claimed Num	Claimed number of the perk
	Funding progress	Time-varying	Sales Num	Number of perks have sold
			Available Num	Available number of the perk
	Campaign	-	Campaign Features	All the features of the campaign which this perk belongs to

Table 3: Mathematical notations.

Symbol	Size	Description
$\boldsymbol{Y^c}(\boldsymbol{Y^p})$	$I(K) \times T$	Daily funding amount matrix for I campaigns (K perks), T funding days;
$\boldsymbol{B}$	$I \times T$	Daily backer number matrix for I campaigns;
$\boldsymbol{\mathcal{X}^c}(\boldsymbol{\mathcal{X}^p})$	$I(K) \times T \times M^c(M^p)$	Campaign (perk) covariant/feature tensor, $M^c(M^p)$ is the length of covariant/feature vector;
$\boldsymbol{\mathcal{Z}^p}$	$K \times T \times J$	Unobservable cluster tensor for perks, J is the cluster number of perk sequences;
$f^p(.)(f^c(.))$	1	Base forecasts in SR for perks (campaigns);
$\boldsymbol{f^p}(\boldsymbol{f^c})$	$J(J') \times 1$	Base forecasts in SWR for perks (campaigns), $\boldsymbol{f^p} = \{f_j^p(.) \mid j \in \{1, \ldots, J\}\}$, $\boldsymbol{f^c} = \{f_{j'}^c(.) \mid j' \in \{1, \ldots, J'\}\}$;
$\boldsymbol{R_i}$	$(K_i + 1)^2$	Revision matrix for campaign $\boldsymbol{i}$ and its K_i perks.

4.1 Problem Statement

For I campaigns with T funding days[4], we have the daily funding amount time series $\boldsymbol{Y^c} = (\boldsymbol{Y^c}(i,t))_{I\times T}$, backer number time series $\boldsymbol{B} = (\boldsymbol{B}(i,t))_{I\times T}$, and the campaign features $\boldsymbol{\mathcal{X}^c} = ((\boldsymbol{\mathcal{X}^c}(i,t))_{I\times T}$. K_i represents the number of perks of i-th campaign, and $k_i \in \{1, ..., K_i\}$ represents the k_i-th perk of this campaign. For all the K ($K = \sum_{i=1}^{I} K_i$) perks, we also have their daily funding amount time series $\boldsymbol{Y^p} = (\boldsymbol{Y^p}(k,t))_{K\times T}$, and perk features $\boldsymbol{\mathcal{X}^p} = (\boldsymbol{\mathcal{X}^p}(k,t))_{K\times T}$. Each $\boldsymbol{Y^c}(i,t)$ or $\boldsymbol{Y^p}(k,t)$ represents the funding amount of i-th campaign or k-th perk at its t-th funding day.

Our goal is to learn a model $\mathbb{F}(.)$ which can be used to forecast the daily funding amount, i.e., $\boldsymbol{Y^c}(i, t+h), \boldsymbol{Y^p}(k_i, t+h)$, for i-th campaign and its perks in next h days, when given their funding amount sequences, i.e., $\boldsymbol{Y^c}(i, \boldsymbol{\tau})$, $\boldsymbol{B}(i, \boldsymbol{\tau})$ in previous τ days before t and their current features $\boldsymbol{\mathcal{X}^c}(i,t)$ and $\boldsymbol{\mathcal{X}^p}(k_i, t)$, where $\boldsymbol{\tau}$ represents $(t - \tau : t)$. Please note that, we do not use the previous-days series of funding amount and backer number on perks, i.e., $\boldsymbol{Y^p}$, $\boldsymbol{B^p}$, as the input variables even though they are available in our data. The reason is that the time series of funding amount and backer number on perks are sparser compared with those on campaigns. More importantly, according to the crowdfunding mechanism, all the backers of perks come from their campaign visitors. The rationality will be demonstrated in the experiments. Formally, the task can be formulated as:

$$\left\{\begin{array}{c} \widehat{\boldsymbol{Y^c}}(i, t+h) \\ \widehat{\boldsymbol{Y^p}}(1, t+h) \\ \ldots \\ \widehat{\boldsymbol{Y^p}}(K_i, t+h) \end{array}\right\} = \mathbb{F}(\boldsymbol{Y^c}(i, \boldsymbol{\tau}), \boldsymbol{B}(i, \boldsymbol{\tau}), \boldsymbol{\mathcal{X}^c}(i,t), \boldsymbol{\mathcal{X}^p}(k_i, t)) + \boldsymbol{\epsilon},$$

[4]For better presentation in matrix, we use a notation T to represent the funding days for all campaigns though their durations may be different.

where $k_i \in \{1, ..., K_i\}$ and $\boldsymbol{\epsilon}$ is the error vector. To forecast the time series in next h days, we first focus on predicting the values at current day t and the estimations in following days $t + h$ can also be derived by taking the current estimations as input variables.

4.2 Method Overview

Since the dynamics in crowdfunding are two-level time series, we propose a hierarchical model $\mathbb{F}(.)$ for fully considering the characteristics of hierarchy and making full use of the available information. Specifically, $\mathbb{F}(.)$ contains the campaign-level base forecasts (i.e., $f^c(.)$, $\boldsymbol{f^c}$), the perk-level base forecasts (i.e., $f^p(.)$ or $\boldsymbol{f^p}$), and a combination of them using a revision matrix $\boldsymbol{R}$. Figure 2 shows the overview of our method. Specifically, we first independently learn the base forecasts for campaigns (gray shapes) and perks (white shapes). At each level, we propose two kinds of structures for the base forecasts, i.e., **S**ingle **R**egression (denoted as SR, $f^c(.)$ and $f^p(.)$) and **SW**itching **R**egression (denoted as SWR, $\boldsymbol{f^c}$ and $\boldsymbol{f^p}$) based on the understanding of decision making of the crowd (visitors and backing probability) and assumptions on funding sequences. Then for a target campaign (purple) and its perks (blue), we use a revision matrix to get the final results by combining the estimations of these two-level forecasts.

5 STRUCTURES OF BASE FORECASTS

In this section, we define the structures of base forecasts: the single regression model, i.e., $f^c(.)$ and $f^p(.)$, and the switching regression model, i.e., $\boldsymbol{f^c}$ and $\boldsymbol{f^p}$. Specifically, we define the structures of base forecasts by exploring the mechanism of crowdfunding and modeling the decision making of "crowd". The two-level base forecasts have the similar forms. Thus, we detail the structures of perk-level base forecasts, and then directly give the structures of campaign-level base forecasts.

5.1 Single Regression Model, $f^p(.), f^c(.)$

In SR, we suppose the funding amount time series of campaigns or perks can be modeled by a single model. Specifically, at perk level, SR has the form of $f^p(.)$. In fact, SR can explore the previous-days funding dynamics and also capture the impacts of time-varying covariants (perk features) and time by an inbuilt parametric Hazard function [11, 23].

Different from other conventional time series problems, crowdfunding is a financial service in which a complete funding activity contains two processes, i.e., *user visiting* and *visitor backing*. That is, a campaign may obtain more contributions if it can attract frequent visits. Also, not all the visitors will contribute her visiting campaigns. A visitor of campaign i will contribute to this campaign only if her evaluation on this campaign is higher than a threshold. If so, this visitor will back this campaign by selecting a perk based on her evaluation and comparison of perks. Therefore, in $f^p(.)$, we try to model the funding process by two components, i.e., *current visitors*, and *backing probability of selecting a perk*.

5.1.1 Modeling Visitors.

We assume the current visitors of a campaign come from two ways: *infected by previous backers*, and *the spontaneous visitors*. The visitors of a perk are essentially the current visitors on its campaign, because all users first access campaigns rather than perks.

Infected Visitors. The intrinsic objective of crowdfunding is to attract massive contributions from the "crowd", thus the propagation is crucial for a campaign. Crowdfunding mechanism encourages the backers to share their backed campaigns to their friends via virtual social relations, e.g., Facebook, Twitter, or real-life relations, and indeed, backers are also willing to do that. What's more, researchers have found that the prior fundings on a campaign have great effects on its dynamics in the following durations [32]. Thus, previous backers influence the current and following propagation of a specific campaign and also its current underlying visitors. Specifically, we model the infected visitors PU_t^i at current time t by the propagation of the backers in previous τ days on campaign i as:

$$PU_t^i = (\boldsymbol{\alpha^p})^T \cdot \boldsymbol{B}(i, \boldsymbol{\tau}), \tag{1}$$

where $\boldsymbol{\alpha^p}$ is the coefficient vector to weight the propagation influences of backers in previous τ days.

Spontaneous Visitors. Besides the visitors infected by the propagation of previous-days backers, there are also some spontaneous visitors arriving at any funding days of a campaign. The spontaneously arriving visitors may be attracted by the properties of a campaign. Specifically, we suppose that the spontaneous visitors on campaign i at time t, SU_t^i, follow a *Poisson* distribution [23] as follows:

$$Pois(SU_t^i = m|\lambda_i) = \frac{\exp(-\lambda_i)\lambda_i}{m!}, \tag{2}$$

where λ_i is the parameter for mean visiting in a unit time. As described above, to capture the impacts of time-varying covariants of perks, we allow parameter λ_i to be a function of the time-varying campaign covariants $\boldsymbol{X^c}(i, t)$ [23]:

$$\lambda_i = (\boldsymbol{\xi^p})^T \cdot \boldsymbol{X^c}(i, t), \tag{3}$$

where $\boldsymbol{\xi^p}$ is the coefficient vector to weight the covariants. Thus, the spontaneous visitors of a campaign SU_t^i can be computed as:

$$\mathbf{E}(SU_t^i) = \int_0^\infty Pois(SU_t^i)\, d(SU_t^i) = \lambda_i. \tag{4}$$

In summary, we can infer the underlying visitors U_t^i of campaign i at time t by:

$$U_t^i = \mathbf{E}(PU_t^i + SU_t^i) = (\boldsymbol{\alpha^p})^T \cdot \boldsymbol{B}(i, \boldsymbol{\tau}) + (\boldsymbol{\xi^p})^T \cdot \boldsymbol{X^c}(i, t). \tag{5}$$

After modeling the current visitors of one campaign, in the following, we will introduce the second factor which influences the funding dynamics, i.e., backing probability of selecting a perk.

5.1.2 Backing Probability of Selecting a Perk: $g(.)$.

In this study, we explore the Hazard model [11, 23] to approximate the backing probability of crowd, i.e, $g(t, \boldsymbol{x})$, where $\boldsymbol{x}$ is the abbreviation of $\boldsymbol{X^p}(k_i, t)$. Hazard function is widely-used in COX of survival analysis, which is the instantaneous rate of occurrence of the event. Specifically, we explore the density function, i.e., $g(t, \boldsymbol{x})$, for the probability of event. In our study, the event refers to the backing behavior [23]. The reason for exploring proportional Hazard to approximate the backing probability is that Hazard can reflect the impacts of both time and features on event which are all important in the dynamics of crowdfunding. In survival analysis, the probability density function can be derived from the definition of Hazard model $h(t)$:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \le Tb \le t + \Delta t | Tb \ge t)}{\Delta t} = \frac{g(t)}{1 - G(t)} = \frac{g(t)}{S(t)},$$

where Tb is the random variable which represents the time until the event occurs, i.e., backing the campaign by selecting a specific perk, and $g(t), G(t)$, $S(t)$ are respectively the probability density function, cumulative distribution function and survivor function of Tb. Specific to perk k_i of campaign i at time t, Hazard function has the following form:

$$h(t|\boldsymbol{x}) = h_0(t) \exp((\boldsymbol{\beta^p})^T \cdot \boldsymbol{\mathcal{X}^p}(k_i, t)), \tag{6}$$

where $h_0(t)$ is a baseline function, which is perk independent and a function of time. Hazard function can capture the impacts of both time and time-varying covariants by the baseline function and the risk proportion. A campaign and its perks share a same $h_0(t)$ function since they conform a same funding timeline. Term $\exp((\boldsymbol{\beta^p})^T \boldsymbol{\mathcal{X}^p}(k_i, t))$ is the proportional risk associated with the covariates. The baseline function is arbitrary nonnegative perk-independent of time for parameter functions. In our study, we adopt a Gompertz distribution form [17, 31]:

$$h_0(t) = \exp(\gamma_0 + \gamma_1 t). \tag{7}$$

After defining the form of proportional Hazard model $h(t)$, the density function, i.e., $g(t, \boldsymbol{x})$, can be derived. The details of derivation are shown in Appendix A. In summary, we can get the form of the base forecast, i.e., $f^p(.)$, as follows.

$$\begin{aligned}\widehat{\boldsymbol{Y^p}}(k_i, t) &= f^p(\boldsymbol{B}(i, \boldsymbol{\tau}), \boldsymbol{\mathcal{X}^c}(i, t), \boldsymbol{\mathcal{X}^p}(k_i, t)|\Theta^p) + \epsilon_t^p \\ &= p_{k_i}((\boldsymbol{\alpha^p})^T \boldsymbol{B}(i, \boldsymbol{\tau}) + (\xi^p)^T \boldsymbol{\mathcal{X}^c}(i, t)) g(t|\boldsymbol{\mathcal{X}^p}(k_i, t)) + \epsilon_t^p,\end{aligned}$$

where p_{k_i} is the unit price of perk k_i, $\Theta^p = (\boldsymbol{\alpha^p}, \boldsymbol{\xi^p}, \boldsymbol{\beta^p}, \boldsymbol{\gamma})$. Parameters Θ^p can be learned by maximum likelihood estimation or equally least square when the error follows Gaussian distribution:

$$\begin{aligned}\mathcal{L}(\Theta^p) = \arg\min_{\Theta^p} \frac{1}{2} \sum_{i=1}^{I} \sum_{k_i=1}^{K_i} \sum_{t=\tau}^{T} (\boldsymbol{Y^p}(k_i, t) - \widehat{\boldsymbol{Y^p}}(k_i, t))^2 \\ + \lambda^p ||\Theta^p||_2,\end{aligned} \tag{8}$$

where λ^p is a regularization parameter and $||.||_2$ denotes the $L2$ norm, which is used to avoid overfitting.

Now, we have given the specific structure of $f^p(.)$. Similarly, we define the structure of base forecast $f^c(.)$ for campaign level as:

$$\begin{aligned}\widehat{\boldsymbol{Y^c}}(i, t) &= f^c(\boldsymbol{Y^c}(i, \boldsymbol{\tau}), \boldsymbol{\mathcal{X}^c}(i, t)|\Theta^c) + \epsilon_t^c \\ &= ((\boldsymbol{\alpha^c})^T \boldsymbol{Y^c}(i, \boldsymbol{\tau}) + (\xi^c)^T \boldsymbol{\mathcal{X}^c}(i, t)) g(t|\boldsymbol{\mathcal{X}^c}(i, t)) + \epsilon_t^c.\end{aligned}$$

Please note that, in the campaign-level modeling, there is not a declared price for each campaign. Thus, for consistency, we use the funding amount observation $\boldsymbol{Y^c}(i, \boldsymbol{\tau})$ rather than the backer number observation $\boldsymbol{B}(i, \boldsymbol{\tau})$ in $f^c(.)$.

5.2 Switching Regression Model

According to our observations, different campaigns and perks have great heterogeneities, and even for one campaign or perk, its funding dynamic at different funding phases may vary a lot. Thus, training a single model, i.e., $f^c(.)$ or $f^p(.)$ is inadequate. Also, some studies have found that the time series have the clustering characteristics, that is, the sequences in the same cluster have the similar growth pattern [24]. Thus, in this subsection, we introduce an enhanced switching regression model, i.e., SWR, based on a more reasonable assumption, i.e., funding amount sequences of campaigns and perks respectively form different clusters in which sequences have different dynamic patterns. We also take the perk-level base forecasts $\boldsymbol{f^p} = \{f_j^p(.)|j \in \{1, ..., J\}\}$ as examples to introduce SWR, where $f_j^p(.)$ is the base forecast for j-th perk sequence cluster and J is the number of clusters. $f_j^p(.)$ has the similar form with $f^p(.)$ in SR, but each $f_j^p(.)$ has its own parameters.

Besides the observable variables, i.e., $\boldsymbol{Y^c}, \boldsymbol{Y^p}, \boldsymbol{B}, \boldsymbol{\mathcal{X}^c}, \boldsymbol{\mathcal{X}^p}$, in $\boldsymbol{f^p}$, we also assume there are some unobservable cluster indicator variables, such that $\boldsymbol{\mathcal{Z}^p} = (\boldsymbol{\mathcal{Z}^p}(k, t))_{K \times T}$, where $\boldsymbol{\mathcal{Z}^p}(k_i, t))$ can be abbreviated as $\boldsymbol{z}$ and $\boldsymbol{z} = (z_1, ..., z_J)$. Specifically, $z_j \in \{0, 1\}$ and $|\boldsymbol{z}| = 1$, where $z_j = 1$ means the funding amount sequence $(\boldsymbol{Y^p}(k_i, \boldsymbol{\tau}), \boldsymbol{Y^p}(k_i, t))$ of k_i-th perk at time slice t belongs to the j-th sequence cluster of perks, and vice versa. That is to say, a funding sequence at a given specific time only belongs to one specific cluster. Please note that, the clustering object is sequence segments rather than complete funding sequences of perks so that a perk may belong to different clusters in different time slices. Thus, for perk k_i at time t, we have:

$$\widehat{\boldsymbol{Y^p}}(k_i, t) = \prod_{j=1}^{J} f_j^p(\boldsymbol{B}(i, \boldsymbol{\tau}), \boldsymbol{\mathcal{X}^c}(i, t), \boldsymbol{\mathcal{X}^p}(k_i, t)|\Theta_j^p)^{z_j} + \epsilon_t^p, \tag{9}$$

where Θ_j^p are the parameters learned from the sequence segments in j-th cluster. Similarly, we can also get the campaign-level base forecasts $\boldsymbol{f^c}$.

6 MODEL LEARNING AND FORECAST

In this section, we first detail the learning process for $\boldsymbol{f^p}$, in the same way, $f^p(.), f^c(.), \boldsymbol{f^c}$ can also be learned. Then, for a given target campaign and its perks, we propose to revise the forecasts by an optimization combination of the two-level base forecasts for the final forecasting.

6.1 Learning Base Forecasts in SWR

Because $\boldsymbol{\mathcal{Z}^p}$ in $\boldsymbol{f^p}$ is unobservable, we can learn Θ_j^p and cluster the sequence segments simultaneously by an EM-process. Since the clusters are hard restraint, we can achieve learning through two steps, i.e., estimating the cluster variables $\boldsymbol{\mathcal{Z}^p}$, optimizing the parameters Θ_j^p with current $\boldsymbol{\mathcal{Z}^p}$.

Estimating $\boldsymbol{\mathcal{Z}^p}$. Donate $\Theta_j^p(\boldsymbol{o})$ as the parameters in o-th iteration. In each iteration, we estimate $\boldsymbol{\mathcal{Z}^p}$, i.e., let each $z_j = 1$ iff:

$$j = \arg\min_{j'=1}^{J} |\boldsymbol{Y^p}(k_i, t) - f_{j'}^p(.|\Theta_{j'}^p(\boldsymbol{o}))|. \tag{10}$$

Optimizing $\Theta_j^{\boldsymbol{p}}$. After estimating $\mathcal{Z}^{\boldsymbol{p}}$, we optimize the current parameters $\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})$. In each iteration, the loss function $\mathcal{L}(\Theta_j^{\boldsymbol{p}}(\boldsymbol{o}))$ is defined as:

$$\mathcal{L}(\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})) = \arg\min_{\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})} \frac{1}{2}\sum_{i=1}^{I}\sum_{k_i=1}^{K_i}\sum_{t=\tau}^{T}\sum_{j=1}^{J} z_j(Y^{\boldsymbol{p}}(k_i,t) - \widehat{Y^{\boldsymbol{p}}}(k_i,t))^2 + \lambda_j^p ||\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})||_2. \tag{11}$$

For optimizing the above function, we adopt the alternating least squares (ALS) [39]. ALS is a popular optimization method with accurate parameter estimation and fast convergence rate, which computes each parameter by fixing the other parameters when minimizing the object function. Specifically, the updating rules for some representative parameters in $\mathcal{L}(\Theta_j^{\boldsymbol{p}}(\boldsymbol{o}))$ are as follows:

$$\boldsymbol{\alpha}_j^{\boldsymbol{p}}(\boldsymbol{o}) \leftarrow \boldsymbol{\alpha}_j^{\boldsymbol{p}}(\boldsymbol{o}) - \eta_\alpha \frac{\partial \mathcal{L}}{\partial \boldsymbol{\alpha}_j^{\boldsymbol{p}}(\boldsymbol{o})}, \quad \boldsymbol{\xi}_j^{\boldsymbol{p}}(\boldsymbol{o}) \leftarrow \boldsymbol{\xi}_j^{\boldsymbol{p}}(\boldsymbol{o}) - \eta_\xi \frac{\partial \mathcal{L}}{\partial \boldsymbol{\xi}_j^{\boldsymbol{p}}(\boldsymbol{o})},$$
$$\boldsymbol{\gamma}(\boldsymbol{o}) \leftarrow \boldsymbol{\gamma}(\boldsymbol{o}) - \eta_\gamma \frac{\partial \mathcal{L}}{\partial \boldsymbol{\gamma}(\boldsymbol{o})}, \quad \boldsymbol{\beta}_j^{\boldsymbol{p}}(\boldsymbol{o}) \leftarrow \boldsymbol{\beta}_j^{\boldsymbol{p}}(\boldsymbol{o}) - \eta_\beta \frac{\partial \mathcal{L}}{\partial \boldsymbol{\beta}_j^{\boldsymbol{p}}(\boldsymbol{o})},$$

where $\Theta_j^{\boldsymbol{p}}(\boldsymbol{o}) = (\boldsymbol{\alpha}_j^{\boldsymbol{p}}(\boldsymbol{o}), \boldsymbol{\xi}_j^{\boldsymbol{p}}(\boldsymbol{o}), \boldsymbol{\gamma}(\boldsymbol{o}), \boldsymbol{\beta}_j^{\boldsymbol{p}}(\boldsymbol{o}))$ are the parameters in o-th iteration, and $\boldsymbol{\eta} = (\eta_\alpha, \eta_\xi, \eta_\gamma, \eta_\beta)$ are the learning rates. The details of gradients are given in Appendix B. Repeat these two steps until convergence.

6.2 Revise Forecasts by Optimal Combination

We have learned the campaign-level and perk-level base forecasts, i.e., $\boldsymbol{f^c}$ and $\boldsymbol{f^p}$, respectively. Next we introduce how to get the final forecasting for given target campaign i and its K_i perks by combining the independent estimations of the two-level base forecasts.

In the literature, researchers have proposed some combination strategies, such as "bottom-up" and "top-down" strategies for hierarchical time series data [15]. Specifically, bottom-up strategies attempt to produce forecasts at the lowest level and aggregate them to the upper levels of the hierarchy, while top-down methods produce forecast at the top level and then disaggregate to the lower levels using proportions. These two types of strategies are not suitable for the problem in crowdfunding, because processing base forecasts at lower (perk) level suffers the sparsity while processing base forecasts at campaign level will not consider the relations of perks in a same campaign. To this end, we propose to produce independent forecasts at both campaign and perk levels, and then use a revision matrix to get the final estimations. The proof of optimality of this combination strategy can be found in [15, 16].

Specifically, we denote $(\widehat{Y^c}(i,t), \widehat{Y^p}(1,t), ..., \widehat{Y^p}(K_i,t))^T$ as $\widehat{Y}(i,t)$ which represent the estimations for target campaign i and its perks at t by the base forecasts. $\widetilde{Y}(i,t)$ are the final estimations for them after the revision. That is,

$$\widetilde{Y}(i,t) = \boldsymbol{R_i}\widehat{Y}(i,t), \tag{12}$$

where $\boldsymbol{R_i}$ is the revision matrix for campaign i and its perks which can provide an optimal combination of the independent estimations of base forecasts. Specifically, $\boldsymbol{R_i}$ has the following form:

$$\boldsymbol{R_i} = \frac{1}{K_i+1}\begin{pmatrix} K_i & 1 & 1 & \cdots & \cdots & 1 \\ 1 & K_i & \text{-}1 & \text{-}1 & \cdots & \text{-}1 \\ 1 & \text{-}1 & K_i & \text{-}1 & \cdots & \text{-}1 \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ 1 & \text{-}1 & \cdots & \text{-}1 & K_i & \text{-}1 \\ 1 & \text{-}1 & \cdots & \cdots & \text{-}1 & K_i \end{pmatrix}.$$

Thus, the final estimations for campaign i and perk k_i are:

$$\widetilde{Y^c}(i,t) = \frac{1}{K_i+1}(K_i\widehat{Y^c}(i,t) + \sum_{k_i=1}^{K_i}\widehat{Y^p}(k_i,t)),$$
$$\widetilde{Y^p}(k_i,t) = \frac{1}{K_i+1}(\widehat{Y^c}(i,t) - \sum_{k_i'}\widehat{Y^p}(k_i',t) + K_i\widehat{Y^p}(k_i,t)),$$

where $k_i' = \{1, ..., k_{i-1}, k_{i+1}, ..., K_i\}$ represent the other perks of the target campaign except current perk k_i. We can see that, the matrix revises the final estimations by considering both perk-perk and perks-campaign relations. The revision optimizes the final estimations especially when the individual base forecasting for target campaign or perk performs bad. We will empirically examine that in the experiments.

7 EXPERIMENT

In this section, we construct experiments with the collected dataset to evaluate the performances of our approaches.

7.1 Experimental Setup

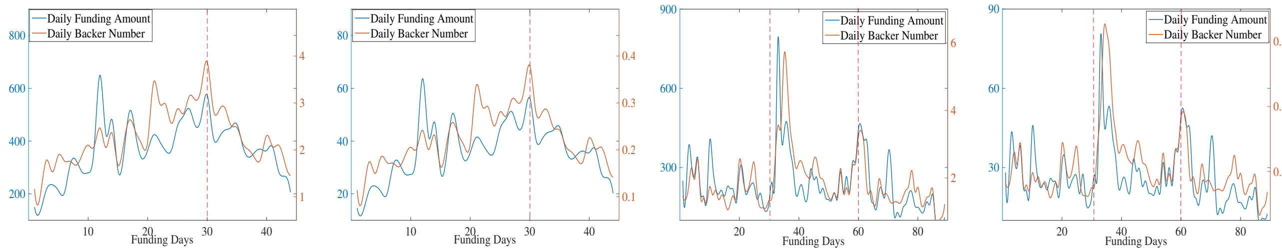
We partition the dataset into subsets based on the declared funding durations of campaigns and construct experiments mainly on two subsets whose durations are 30 and 60 days. Specifically, for 30-days campaigns and perks, we construct observations and features in their duration (30 days) and the following 15 days after that. Similarly, for 60-days campaigns and perks, we construct observations and features in their durations (60 days) and the following 30 days. For each subset, we partition the data into a training set and a test set, i.e., we randomly select 20% elements from $\boldsymbol{Y^c}$ as the test set. Consequently, the other variables in the corresponding places, e.g., $\boldsymbol{B}, \boldsymbol{\mathcal{X}^c}, \boldsymbol{\mathcal{X}^p}$, will also be selected. The remaining elements are used for training. We process each subset five times in this way. The reported results are averaged over five-round tests. Table 4 shows one-round data partitioning.

Table 4: Data partitioning.

Sub_sets	#Training Sequences		#Test Sequences	
	Campaign	Perk	Campaign	Perk
30_days	8,000	88,663	2,000	23,204
60_days	8,000	93,986	2,000	22,984

7.1.1 Comparison Methods. We compare the following methods on forecasting the dynamics, i.e., daily funding amount, for campaigns and perks.

- **Switching Regression with Revision (SWR+R)**: training switching regression models (i.e., $\boldsymbol{f^c}, \boldsymbol{f^p}$) for campaigns and perks independently and then using the revision matrix to combine them for the final results. Empirically, the cluster numbers for campaigns and perks are respectively set as 4 and 8.



(a) Campaign_30days (b) Perk_30days (c) Campaign_60days (d) Perk_60days

Figure 3: Funding series display.

- **Switching Regression (SWR)**: training switching regression models (i.e., $\boldsymbol{f^c}$**,** $\boldsymbol{f^p}$) for campaigns and perks independently. The settings of SWR are the same as those in SWR+R.
- **Single Regression with Revision (SR+R)**: training single regression models (i.e., $f^c(.)$, $f^p(.)$) for campaigns and perks independently and then using the revision matrix to combine them for the final results.
- **Single Regression (SR)**: training single regression models (i.e., $f^c(.)$, $f^p(.)$) for campaigns and perks.
- **Random Forest (RF)**: training random forest regressions for campaigns and perks, in which the input variables are the same as those in SR and SWR.
- **Autoregressive Model (AR)**: training autoregressive models [1, 8] for campaigns and perks using the daily funding observations.
- **Average (AVE)**: using the averages of funding amount in previous τ days to predict the current funding. In these methods, the parameters τ are all set as 5.

7.1.2 Evaluation Metrics. To evaluate the forecasting performances, here we select two widely-used metrics, i.e., the *Root Mean Squared Error* (RMSE) [34] and *Mean Relative Squared Error* (MRSE) [8] for evaluation. Specifically, their definitions are:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}}, \quad MRSE = \frac{1}{N}\sum_{i=1}^{N}(\frac{\hat{y}_i}{y_i} - 1)^2,$$

where N is the number of predictions, y_i is the i-th real observation value and $\hat{y}_i$ is the corresponding estimated value.

7.2 Experimental Results

We first plot the funding time series and analyze the characteristics, and then report the forecasting results.

7.2.1 Funding Series Analysis. We mainly have two types of time series observations, *daily contributions* (backer numbers), and *daily funding amount* for both campaigns and perks. The funding time series of campaigns and perks are shown in Figure 3. From these figures, we can see that: 1) the adjacent daily funding amount is highly correlated, so that we exploit the variables in previous days (e.g., $\boldsymbol{Y^c}(i, \boldsymbol{\tau})$ and $\boldsymbol{B}(i, \boldsymbol{\tau})$) in our approaches; 2) the series of both campaigns and perks at different funding time have different dynamic patterns, e.g., 30-days campaigns and perks have observable peaks at the end of their declared durations, 60-days campaigns and perks have observable peaks at both the end and middle of their durations. Besides, in the start-up days, the funding amount is relatively small and grows slowly, while after the declared durations, the funding time series decays over time. These inspire us to explore the time effect (i.e., $h_0(t)$) and cluster the time series at the granularity of sequence segments rather than the complete series of campaigns and perks.

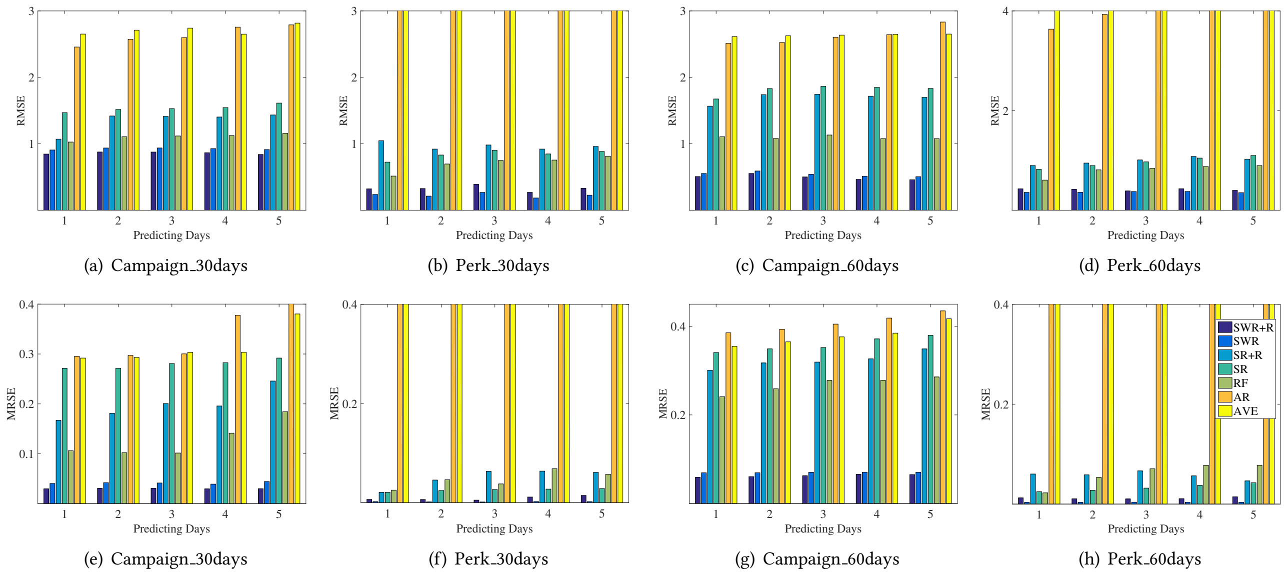
Table 5: The running time (seconds).

Methods	SWR+R	SWR	SR+R	SR	RF	AR	AVE
Training	1,860	1,860	254	254	1.52	9.69	-
Test	0.73	0.18	0.59	0.12	0.25	0.09	0.05

7.2.2 Efficiency Results. Table 5 records the running time (seconds) of different methods for training and test on all the constructed datasets. We can see that our models need more time than others for training. However, in tests, our two-level base forecasts, i.e., SWR and SR, run faster than RF.

7.2.3 Forecasting Performances. For better training and forecasting, we scaled the time series variables using ln(.) function, i.e., $\boldsymbol{Y^c}(i, t) = \ln(\boldsymbol{Y^c}(i, t) + 1)$. Figure 4 shows the forecasting performances with respect to the predicting days, i.e., h. Overall, our methods, i.e., SWR+R, SWR, SR+R, SR and the ensemble method, i.e., RF, perform significantly better than AR and AVE which lose the predicting abilities with the accumulation of errors over time. Second, in the campaign-level tests, SWR+R performs best; while in the perk-level tests, SWR performs best. The possible reason is that the base forecasts SWR (also SR) predict more accurately for perks, i.e., perk-level base forecasts work better than campaign-level ones (the perk instances for training are much more than campaigns'), so that, after revising, the performances on campaigns become better while performances on perks turn to a little worse. Even so, clearly, both SWR+R and SWR have the satisfactory performances compared with other methods, e.g., the values of RMSE or MRSE are reduced by more than 50% in most cases. Third, from the comparisons of SR and SWR, we can see the effectiveness of clustering for funding sequences. Finally, our methods perform much better for perks while AR and AVE have worse results for perks. That is because the time series of perks are much sparser and more unstable so that it is more difficult to predict for AR and AVE in which only the response variables are taken into consideration. Differently, our models explore the relations of perks and campaigns so that they work well for perks.

7.2.4 Parameter Effects. We also test the effects of the common parameter, i.e., τ, of the corresponding methods. We report the



(a) Campaign_30days (b) Perk_30days (c) Campaign_60days (d) Perk_60days

(e) Campaign_30days (f) Perk_30days (g) Campaign_60days (h) Perk_60days

Figure 4: Forecasting performances.

results when forecasting the dynamics only in next one days in Figure 5. In most cases, all methods will achieve better results, i.e., smaller RMSE and MRSE, as τ becomes larger. Please note that, in all cases, our model, i.e., SWR, has the best performances. The comparison results between SR, SWR, RF, AR and AVE clearly demonstrate the robustness of SWR and also the importance of our constructed features on tracking and forecasting the dynamics of funding time series in crowdfunding.

8 CONCLUSION

In this paper, we presented a focused study on tracking and forecasting the dynamics in crowdfunding in a holistic view. For constructing this study, we first collected massive real-world crowdfunding data with detailed daily transaction information from Indiegogo.com and generated various features at both campaign and perk levels. We then formalized the problem as the prediction with hierarchical time series and proposed a two-layer solution framework. Specifically, for both campaign and perk levels, we developed two regression models, i.e., SR and SWR, by exploring the decision making of crowd and the clustering characteristic of funding sequences. For a given target campaign and perks, we employed a revision matrix to combine the independent estimations of two-level base forecasts. Finally the experimental results on our collected data clearly demonstrated the effectiveness of our solutions, especially SWR and the combination.

In the future, we will test other combination strategies for the two-level base forecasts, e.g., bottom-up strategies, which produces forecasts at the perk level and aggregates them to the campaigns.

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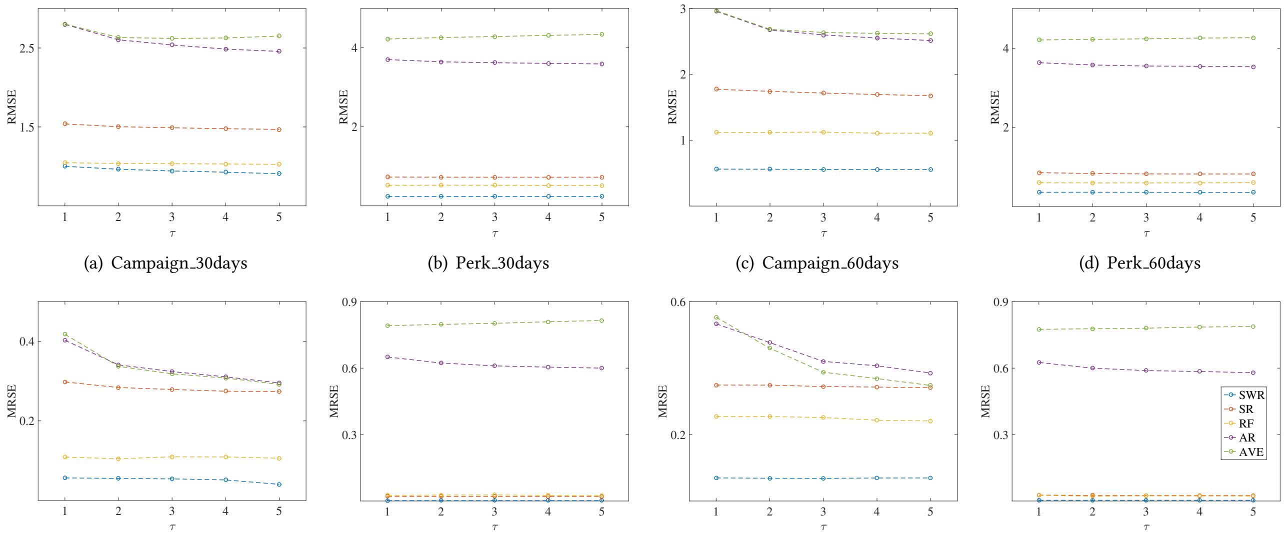

(a) Campaign_30days (b) Perk_30days (c) Campaign_60days (d) Perk_60days

(e) Campaign_30days (f) Perk_30days (g) Campaign_60days (h) Perk_60days

Figure 5: Effects of parameter τ.

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Appendix A. Derivation for $g(.)$ From the definition of proportional Hazard model, we have: $g(t|\boldsymbol{x}) = h(t|\boldsymbol{x})S(t|\boldsymbol{x})$; also, from [23, 35], we know: $S(t|\boldsymbol{x}) = \exp(-\int_0^t h(t_x|\boldsymbol{x})\, d(t_x))$; thus, $g(t|\boldsymbol{x}) = h_0(t)\exp((\boldsymbol{\beta^p})^T \boldsymbol{X^p}(k_i,t))\exp((-\int_0^t h(t_x|\boldsymbol{x})\, d(t_x))$.

Appendix B. Gradients for parameters in $f_j^p(.)$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\alpha}_j^{\boldsymbol{p}}(\boldsymbol{o})} = -\sum_{i=1}^{I}\sum_{k_i=1}^{K_i}\sum_{t=\tau}^{T}\sum_{j=1}^{J} AB(i,\boldsymbol{\tau})C + \frac{\lambda_j^p \boldsymbol{\alpha}_j^{\boldsymbol{p}}(\boldsymbol{o})}{||\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})||_2},$$

$$\frac{\partial \mathcal{L}}{\partial \xi_j^{\boldsymbol{p}}(\boldsymbol{o})} = -\sum_{i=1}^{I}\sum_{k_i=1}^{K_i}\sum_{t=\tau}^{T}\sum_{j=1}^{J} A\boldsymbol{X^c}(i,t)C + \frac{\lambda_j^p \xi_j^{\boldsymbol{p}}(\boldsymbol{o})}{||\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})||_2},$$

$$\frac{\partial \mathcal{L}}{\partial \gamma_0(o)} = -\sum_{i=1}^{I}\sum_{k_i=1}^{K_i}\sum_{t=\tau}^{T}\sum_{j=1}^{J} ACDE + \frac{\lambda_j^p \gamma_0(o)}{||\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})||_2},$$

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\beta}_j^{\boldsymbol{p}}(\boldsymbol{o})} = -\sum_{i=1}^{I}\sum_{k_i=1}^{K_i}\sum_{t=\tau}^{T}\sum_{j=1}^{J} ACDE\boldsymbol{x} + \frac{\lambda_j^p \boldsymbol{\beta}_j^{\boldsymbol{p}}(\boldsymbol{o})}{||\Theta_j^{\boldsymbol{p}}(\boldsymbol{o})||_2};$$

where

$$A = z_j(Y^{\boldsymbol{p}}(k_i,t) - \widehat{Y^{\boldsymbol{p}}}(k_i,t))p_{k_i},$$

$$C = \exp(\gamma_0 + \gamma_1 t + (\boldsymbol{\beta^p})^T\boldsymbol{x} - \frac{1}{\gamma_1}\exp(\gamma_0 + (\boldsymbol{\beta^p})^T\boldsymbol{x})(\exp(\gamma_1 t) - 1)),$$

$$E = 1 - \frac{1}{\gamma_1}\exp(\gamma_0 + (\boldsymbol{\beta^p})^T\boldsymbol{x})(\exp(\gamma_1 t) - 1),$$

$$D = (\boldsymbol{\alpha^p})^T B(i,\boldsymbol{\tau}) + (\xi^{\boldsymbol{p}})^T \boldsymbol{X^c}(i,t).$$