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Pacific Asia Conference on Information Systems (PACIS)

Summer 6-27-2016

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Abstract

In recent years, the world incurs many social issue and environmental disaster, so charity giving is become popular. Nowadays, the crowdfunding also become popular and the charity usually use specific type of crowdfunding called Peer-to-Peer fundraising. Many donor relationship management software and solutions have appeared. But they rarely utilize power of social network and majority of them focus on the aspect of fundraiser not on the aspect of donors. In this research, we will propose a social supported recommendation mechanism for non-profit fundraising. We will examine the donor preference, relationship between donor and fundraiser, and the characteristic fundraising dynamics to enhance the success rate of fundraising project and satisfaction rate of the donor.

Keywords: charity, non-profit, social network, social fundraising, recommendation.

1 INTRODUCTION

In recent years, the world incurs many social issues, such as population aging, education inequality, and social stratification. In addition, climate change and anthropogenic impact on the environment are caused by environmental disaster. Hence, many people become a volunteer in order to help people who need to help. Nevertheless, one important problem of charity is finance. Fortunately, currently, they can raise fundraising campaign and use crowdfunding through Internet.

Crowdfunding is derived from crowdsourcing which utilize "power of crowd". Social fundraising is multi-tiered approach of crowdfunding and it is also called P2P (peer-to-peer) fundraising because a donor would create a fundraising page to support specific campaign approbated and feed revenue back to the original campaign. Hence, a fundraiser can pay more attention at their own supports (such as family, friends or community members). According to Blackbaud, a provider of non-profit software and services surveys (Blackbaud, 2016; Flannery & Harris, 2011), online channel is gradually becoming an important channel for young generation and also still growing.

There are many channels for charity fundraising. We can separate them into three types: offline channel (e.g. direct mail and hold offline campaign), online channel (e.g. mobile giving and social fundraising, a specific type of crowdfunding), and multichannel – mixing of online and offline channels.

Regarding charity fundraising, the studies found that donors would be influenced by social media, festival (Blackbaud, 2016), and their friends (Bhagat, Loeb, & Rovner, 2010). By the perspective of organization efficiency, donors often choose the non-profit organizations with cost-effectiveness and lower overhead rate (Baron & Szymanska, 2011; Ord, 2012). Moreover, the donor's decision has a pattern based on their behaviors (e.g. how often they give and the amount per giving) (Althoff & Leskovec, 2015; Song, Lee, Ko, & Lee, 2015). Notwithstanding, social fundraising approach is more suitable for charity and more efficient than general crowdfunding, those supporters do not have enough knowledge or experience with discovering donors. They usually broadcast campaign pages (or their fundraising page if they are created) to their social media (such as share to Facebook wall or tweet on Twitter) or use message directly (such as E-Mail or Facebook message). But it will cause communication fatigue and those messages are likely ignored. Hence, "How to support novice of fundraiser at social fundraising" is one important issue about social fundraising's efficiency. This research will design a social-based recommendation mechanism that fundraisers will receive the mostly likely list of donors based on their own social network and preference. In this paper, we will develop a recommendation mechanism considering about the relationship between donor and fundraiser, donor behavior, fundraising phase to enhance a donor's giving willingness and relationship with fundraiser.

This paper is arranged as follows: Section 2 discusses related works. We present our proposed mechanism in Section 3. In Section 4, we show our experiment design to test our mechanism. Finally, concludes this paper in Section 5.

2 RELATED WORK

2.1 Philanthropy fundraising

Nowadays, Internet and social media are become a part of our daily lives, hence, more and more people giving via online channel and also utilize power of social media to disseminate campaign information for philanthropy (Miller, 2009). "ALS Ice Bucket Challenge" is an excellent example to demonstrate how powerful of social media (Ni, Chan, Leung, Lau, & Pang, 2014; Townsend, 2014). In addition, there are many crowdfunding platform that allow using for nonprofits organization, social entrepreneurship (Lehner, 2013), personal causes likes: CrowdRise (for all philanthropy use, including personal), GlobalGiving (for grassroots charitable projects) and DonorsChoose.org (for educational

charities). Especially GlobalGiving, the platform raise over $217 million in fundraising at 165 countries and has over 521 thousand donors (GlobalGiving, 2016).

The philanthropy fundraising campaign generally use for attract new supporters, provide the opportunity to reveal the idea or mission of organization and even maintain the relationship of current supporters (Webber, 2004). If use social media to solicit potential donor, it would be more likely to trust the solicitor (Saxton & Wang, 2013). The studies shown that many nonprofits organization have not make the best use of Internet and social media due to not have enough resource (Waters, 2007; Waters, Burnett, Lamm, & Lucas, 2009).

2.2 Recommendation Systems

The major goal of recommendation systems is to recommend most suitable content (or thing) to a specific user. In general, those systems use historical data to model specific user's behavior and push most suitable thing to a specific user. The recommendation system can be classified to three types: content-based, collaborative filtering, and hybrid (combining content-based and collaborative filtering).

Content-based recommendation systems focus on analysing a specific user's historical data as user's preference. Before ranking the item, it performs "item representation" to get characteristics of an item. It uses those characteristics of the items to construct user's preference and ranking items by similarity of item. Finally, the system would generate the recommend list of item to user(Belkin & Croft, 1992; Pazzani & Billsus, 2007). But this approach has some drawbacks, such as difficulty to extract characteristics of content and challenge to find other target users' preference (over-specialization). Collaborative filtering recommendation systems focus on analysing the similarity between a target user and like-minded users. It used like-minded users to inference the target user's preference that is not presented (Nakamura & Abe, 1998). This approach has the drawbacks or limitations, such as rating sparsity, new item problem and new user problem. Hybrid approach makes predictions based on a weighted combination of the content-based and collaborative filtering recommendation (De Campos, Fernández-Luna, Huete, & Rueda-Morales, 2010).

2.3 Social Networks

The widespread use of the Internet and mobile platform has motivated the people popularly adopt social media such as Facebook or Twitter. A social network is a social media that everyone can use it to create, share and exchange their thinking through Internet. Hence, social network can disseminate information not only in small social circle but also a whole social network and results in a small world (Gurevitch, 1961). The first social network that we can identify is SixDegrees.com, named from six degrees of separation, in 1997(Ellison, 2007). After that, more and more successful social networking sites (e.g. LinkedIn, Facebook and Twitter) have shown up. Up to now, the social media is one of popular and important channels for many domains such as marketing, politics and philanthropy (Loader & Mercea, 2011; Nah & Saxton, 2012; Saravanakumar & SuganthaLakshmi, 2012). In social network structure, each person connects with other persons and turn into a huge graph that we can extract information, knowledge, intelligence which we have never discovered with social computing (Wang, Carley, Zeng, & Mao, 2007).

3 THE SYSTEM FRAMEWORK

We will develop a social-based non-profit fundraising recommendation mechanism that can discover donors with higher willingness and trustiness through social network and fundraising platform. We aim to improve efficiency of social fundraising, specially, in the discovery of donors. The processes of our proposed mechanism are described as follows and shown in Figure 1 and the framework shown in Figure 2: (1) First, our proposed mechanism allows a fundraiser to discover potential donors. They can query to our mechanism to satisfy their goals. (2) Second, we would do relationship analysis from a fundraiser's social media. We would analyze interaction of donor and fundraiser form social media.

Next, we also consider about closeness in social network. (3) Third, we perform preference analysis to compute donor's preference from social media and fundraising platform. (4) Fourth, we also consider about information of campaign page from the fundraising platform. In this step, our main objective is to discover campaign pages and let a fundraiser discover more suitable donors. In other words, this step can provide more interesting campaigns to a donor. (5) Finally, we would merge the above results with using appropriate weights and use Top-K to generate the list by ranking score of merged results. We would present a list of donors to a fundraiser and they can use it to solicit others who are in our list of recommendation.

Next section we will introduce major modules included in our framework. After those three module processed, we would merge results and produce a recommendation list to the fundraiser.

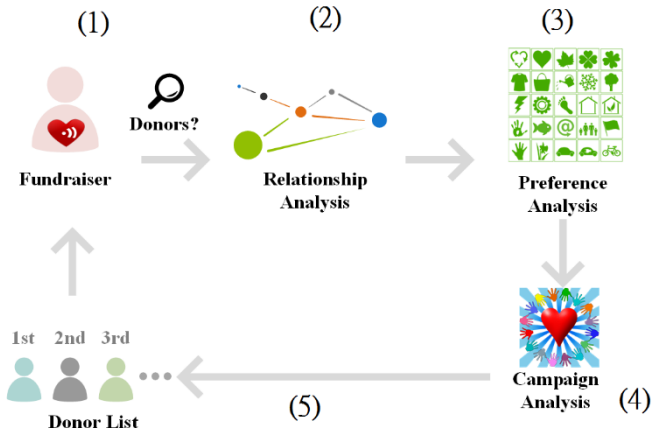

Figure 1. The processes of our proposed mechanism.

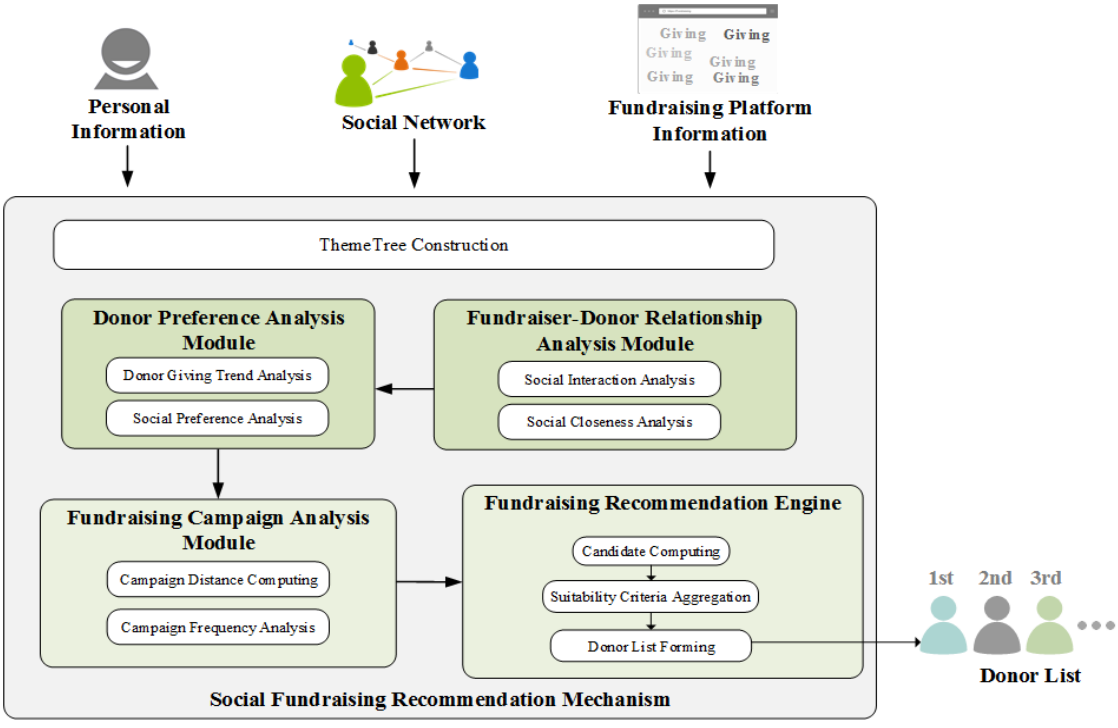

Figure 2. The framework of our proposed mechanism.

3.1 ThemeTree Construction

In this section, we must construct a ThemeTree in order to match user's preferences and campaign theme. The ThemeTree is a three-layers tree structure. The first layer is the root layer. The second layer is a theme names that are collected from a social fundraising platform. The third layer, leaf nodes, is the preference type that is classified from Facebook.

3.2 Fundraiser-Donor Relationship Module

In this module, we will analyze the relationship closeness between a donor and a fundraiser. The relationship between donor and fundraiser can be explained by a network graph. In this graph, vertex represents a person and edge represents the relationship between two people who have interaction with each other.

$Interaction(p_i, p_k)$ is the degree of common social activities between donor p_i and fundraiser p_k. We consider four types of activities from social media, if matching following conditions: (1) Comment: if they both write comment at the same post. (2) Like: if they both give likes to the same thing. (3) Tag: if they both be tagged in the same place or photo. (4) Pages: if they are all interested in the same pages.

$$Interaction(p_i, p_k) = Comment(p_i, p_k) * Like(p_i, p_k) * Tag(p_i, p_k) * Pages(p_i, p_k) \quad (1)$$

We would use Jaccard similarity coefficient to compute $Comment(p_i, p_k)$, $Like(p_i, p_k)$, $Tag(p_i, p_k)$ and $Pages(p_i, p_k)$ as shown in equation (2).

For example, donor p_i has nine comments and fundraiser p_k has six comments, and they have four common comments, so we can know $Comment(p_i, p_k) = Jaccard\left(Comment_{p_i}, Comment_{p_i}\right) = \frac{4+1}{9+6-4} = 0.45$.

$$Jaccard(A, B) = \frac{|A \cap B| + 1}{|A \cup B|} = \frac{|A \cap B| + 1}{|A| + |B| - |A \cap B|} \quad (2)$$

Next, we use the concept of closeness centrality to compute $Closeness(p_i)$ as equation (3). If the donor p_i connect to mode other people in social network, he/she can affect more people, in other words, he/she can more easy to connect with the fundraiser and influence his/her friends. $shortestPath(p_i, p_j)$ represents the shortest path between person i and j.

$$Closeness(p_i) = \frac{(N-1)}{\sum_{j=0}^{N} shortestPath(p_i, p_j)} \quad (3)$$

$$Where\ N\ is\ number\ of\ person\ in\ a\ social\ network\ and\ i \neq j$$

3.3 Donor Preference Analysis Module

In this module, we would want to know a donor's preference from the social fundraising platform and social media. We would analyze the decision trend of the donor and then predict their actual action of giving on the social fundraising platform. We also compute related data about user preference from social media.

The $GivingTrend(d_i, theme)$ represents preference of donor d_i in a specific $theme$, such as environment or education, in the social fundraising platform.

$$GivingTrend(d_i, theme) = Interactive(d_i, theme) * ThemePreference(d_i, theme) \quad (4)$$

The equation (5) can compute the value of $ctive(d_i, theme)$. The $ShareTimes(d_i, theme)$ means the times of donor d_i share specific $theme$. Similarly, $commentTimes(d_i, theme)$ means the times

of the comments donor d_i wrote at this $theme$. For example, donor d_i shared 3 times fundraising campaign page about "education", then the $ShareTimes(d_i, education)$ is 3. Likewise, $commentTimes(d_i, Environment) = 5$, if donor d_i wrote 5 times comment about environment at fundraising campaign page.

$$Interactive(d_i, theme) = ShareTimes(d_i, theme) + commentTimes(d_i, theme) \quad (5)$$

As just mentioned, we also compute the actual action of giving shown as equation (6) by the following kinds of giving data: (1) $GivingTimes(d_i, theme)$ represents the times that donor d_i donated to campaign. (2) $TotalGivingTimes(d_i)$ represents times that donor d_i donates to campaign for all time. (3) $donationAmount(d_i, theme)$ is the amount of donor d_i donation. (4) $TotalDonationAmount(d_i$r) represents the total amount of donor d_i's donation. In other words, $ThemePreference(d_i, theme)$ represents the percentage of donor d_i 's donation in a specific $theme$ and the value range is limited in the period between 0 and 1. If this value is lager, it means donor d_i more prefer in the specified $theme$.

$$ThemePreference(d_i, theme) = \frac{GivingTimes(d_i, theme) * donationAmount(d_i, theme)}{TotalGivingTimes(d_i) * TotalDonationAmount(d_i)}. \quad (6)$$

$SocialPreference(d_i, theme)$ represents the preference of donor d_i. We consider the following social media activities: (1) Check-in: it records Location-Based Service (LBS) data, such as location, time and what his/her does. (2) Like: user can use it to show they like someone's opinion. We use it to understand their preference. (3)Pages: On Facebook, everything can become to pages and we can use it to know what a user likes or is interesting in. (4) Comment: user can write the comment on social media.

In our experiment, we selected Facebook as our experiment platform of social media, because Facebook is more suitable for the non-profit field (Hong, Hu, & Burtch, 2015). Hence, we can classify those four activities from Facebook, fortunately, Facebook already classified those activities and we used it to match our ThemeTree. Thus we can use it to infer user's preference. For example, suppose the donor gave "Like" to the pages working for child education, we can infer his/her will concern about child education.

$$\begin{aligned} &SocialPreference(d_i, theme) \\ &\quad = CheckIn_{theme}(d_i) + Like_{theme}(d_i) + Pages_{theme}(d_i) \\ &\quad + Comment_{theme}(d_i) \end{aligned} \quad (7)$$

3.4 Fundraising Campaign Analysis Module

In this module, we would focus on characteristic of campaign and use it to identify importance of campaign. We use two factor of campaign to compute their importance, goals of campaign, and frequency of update campaign.

First, the distance of goals of campaign may influence motivation of investment or donation. $CampaignDistance(c)$ represents current percentage of campaign c is raised. $CampaignRaised(c)$ is amount of already raised at campaign c. $CampaignGoal(c)$ represents the amount of setting goals of campaign c. We can know 1 means their goals are reached; 0 means nobody donates to this campaign; if the value is greater than 1, it means their goals are reached and the platform allows they continue to fundraise. Setting goals of campaign is not enforced on some fundraising platforms, such as CrowdRise. If the goal of campaign is reached, some platform would allow continuity of the campaign, such as GlobalGiving.

$$CampaignDistance(c) = \begin{cases} 1, & if\ not\ set\ goal \\ \dfrac{CampaignRaised(c)}{CampaignGoal(c)}, & if\ set\ goal \end{cases} \quad (8)$$

Crowdfunding heavily relies on relationship between a creator and a backer, charity fundraising have no exception. We already analyze relationship between donors and fundraisers in above modules. In crowdfunding platform, progress report of fundraiser is another way to facilitate donor motivation. Generally speaking, main objective of progress report is to inform donor the current status of campaign. However, it can also become a way of promoting or soliciting donor. Each platform has different implementation, but we can capture their update time in order to compute the frequency of update campaign.

$CampaignFrequency(c)$ represents how often the campaign is updated. N_{Update} represents the number of record of update. $Time_{oldest}$ is the oldest time of record of update, $Time_{newest}$ is the newest time of record of update.

$$CampaignFrequency(c) = \begin{cases} 0, & if\ N_{Update} \leq 1 \\ \dfrac{N_{Update}}{Time_{oldest} - Time_{newest}}, & if \text{ if } N_{Update} > 1 \end{cases} \quad (9)$$

If value of $CampaignFrequency(c)$ is greater, it means this project is more active and fundraiser is more willing to pay attention in this campaign.

Next, we will examine importance of a campaign. The early days of crowdfunding project are the most importance period, and it may determine a project's success or not. Social fundraising also have this characteristic, so we use $CampaignImportance(c)$ to represent the value of importance of campaign c.

$$CampaignImportance(c) = \frac{CampaignFrequency(c)}{CampaignTime(c) + 1} \quad (10)$$

3.5 Fundraising Recommendation Engine

In this section, we would generate a list of recommended candidates by using multiple-criteria decision analysis (MCDA) to evaluate above result of modules. After performing MCDA, we can produce the list of recommended fundraisers. The fundraiser will receive a list consists of two information components: (1) campaign information: (2) list of candidate donors. Campaign information contains basic campaign information as: campaign name, amount of campaign raised, time of campaign elapsed, and importance of campaign. The list of candidate donors, provides, donor name, donor photo at social media, relationship between fundraiser, donor preference, and contact information:

4 EXPERIMENTS

Our experiment will be performed by following the four stages:
(1) Build the experiment environment

In this stage, we build web-based service for our experiment. As we mentioned previously, we use PHP as our major back-end program language and, generally, it run on Apache server, which is the most famous HTTP server in the world. Thus, we can build our service in Linux operating system and it can make our service more stable.

After our web-based service developed, we invite the users who are willing to join our experiment through sharing the link of our web-based service on Facebook. We also allow users to disseminate our web-based service to their friends in order to further propagate our service. Since Facebook's privacy policy, we must have the authorization from the users by Facebook Graph API. Hence, when users first time use our service, we prompt the dialog and ask users to permit our service can access personal information and we will store theirs access token in our system and use it to gather related information for our system.

We also ask users to fill the weight questionnaire, if a user never fills it. The weight questionnaire includes user preference, user relationship, and campaign context. Our interface chose slider instead of range of value (such 1 to 7, bigger means more important), because slider is more visualization than value and more accurate. After the user fill out the questionnaire, we use result of questionnaire to calculate the TOPSIS weighted normalized decision matrix.

(2) Develop the campaign information

Before executing the recommendation system, we must have campaign information. Hence, we provide interface for users who want to create a campaign in our service, and we those data are listed as follows: (1) campaign name (2) campaign theme (3) campaign period (start and end time) (4) campaign goal (5) campaign raised (6) existing campaign donor list (7) campaign story/content (8) campaign progress reports including update time and its content, such as message of thanks for donate. It is remarkable to existing campaign donor list field. This field can input donor's Facebook ID or profile page link (we use placeholder to guide our user to fill this field), we will process into Facebook ID in order to normalize and calculate it in our system.

(3) Execute recommendation system

In this stage, we have enough users (fundraisers and donors) and campaigns in our service. Hence we guide our users to execute the recommendation system. We perform recommendation system. Since our system provides two types of users, fundraisers and donors and can be exchangeable by the user type, we would provide two results based on types of users. A fundraiser want to discover donors to donate theirs campaigns, so we response the list of donors for a fundraiser. On the other hand, a donor wants to discover campaigns which he/she is interested or willing to donate, thus we reply the list of campaigns.

(4) Evaluate recommendation system

After users finish our service, we would ask users to fill the evaluation questionnaire out in order to know user's experience. Finally, we will use SPSS and Excel to evaluate our experiments.

Our experiments need to create a website for executing and evaluating our proposed mechanism. At front-end, we used HTML5, CSS3 and JavaScript as our major program languages and we would use AngularJS, jQuery libraries and also use Google Visualization API to display our recommendation list. Hence, we can provide users higher responsibility and more flexibility for developing the website. At back-end, we use PHP, MariaDB and Facebook Graph API. Thus, we can collect social data from Facebook and it cannot make our system too complex. Finally, we use analytical software IBM SPSS and Microsoft Office Excel to evaluate and draw experiment results.

We collect user's information, we must have authorization from theirs agree via Facebook Graph API. After we have authorization of users, we start to collect user's information in the past 12 months. Finally, we collected 4735 posts, 2093 check-ins, 9910 tags, 154592 likes, 15084 comments and 23773 fan pages liked. The experiment participants have 117 users and each user average have 466 friends.

We measure our proposed recommendation mechanism by feedback questionnaire. The questionnaire has a scale of scores is 1 to 5 (greater means more positive rating) and we ask users to answer the following question: How much do you want to donate to this campaign?

First, we provide the fundraiser the link that can contact with the donor via Facebook. Next, a fundraiser can choose donors to solicit. Finally, we ask those solicited donors to fill the questionnaire out.

We compare following approaches: (1) Random (2) DP+FC (Donor Preference Analysis and Fundraising Campaign Analysis) (3) FDR+FC (Fundraiser-Donor Relationship Analysis and Fundraising Campaign Analysis) (4) DP+FDR (Donor Preference Analysis and Fundraiser-Donor Relationship Analysis) (5) DP+FDR+FC (Donor Preference Analysis, Fundraiser-Donor Relationship Analysis and Fundraising Campaign Analysis).

We show the result of users' donation willingness score. All values are average scores from each approach. We know the random approach has a lower score than other approaches and DP+FDR+FC approach has the highest score.

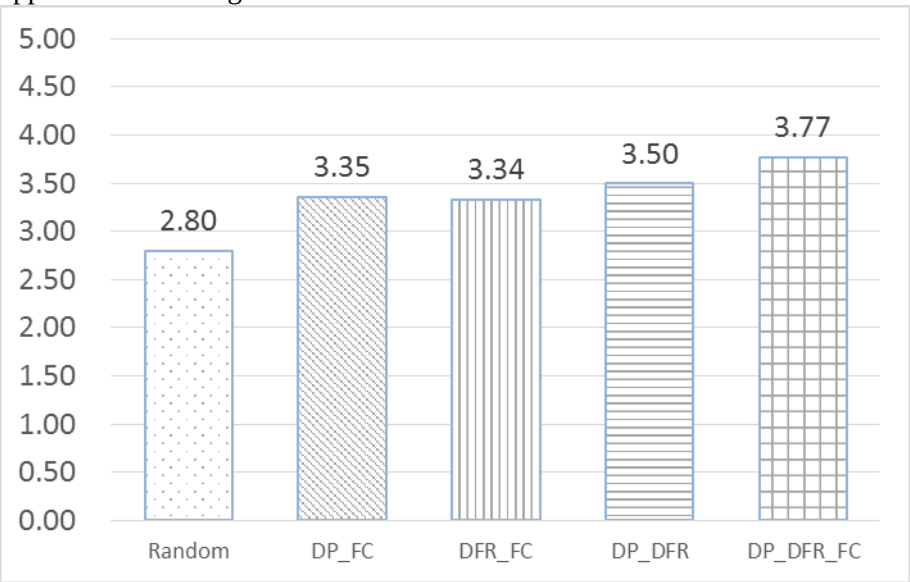

Figure 3. Willingness of campaign soliciting.

Next, we utilize paired-samples t-test to verify the difference of other approaches and we set the confidence interval at 95% and the result shown in below. We are able to prove that the proposed mechanism has higher satisfaction than other approaches.

Paired Group		Mean	Std. Deviation	Std. Error Mean	t	Sig. (2-tailed)
DP_DFR_FC	Random	.973	1.143	.071	13.786	.000
	DP_FC	.416	1.259	.078	5.349	.000
	DFR_FC	.435	1.076	.066	6.543	.000
	DP_DFR	.275	.684	.042	6.500	.000

Table 4. Verification results for willingness.

5 CONCLUSIONS

In this research, we will propose a non-profit fundraising recommendation mechanism, with which the donor will be more willing to provide giving. In our proposed mechanism, we consider the factors of fundraising campaign, donor preference, and relationship between donor and fundraiser. We list the potential contribution of the research from three aspects as follows: For fundraisers, they can use our mechanism to reduce entry barrier of donor and enhance a donor's willingness of giving. For donors, they can receive fundraising campaign which is most appropriate and meet new charity things because they would not or rarely touch the non-profit field before. For the public, the world needs the crowd to help other people or to solve the social problem. It would require enormous money and effort, and we try to reduce the entry barrier of a donor, and make the giving more easily.

There are some related issues desirable for further research. First of all, Facebook recently release the extension of liked function called "Reactions". We think other type of reactions can represent different emotion levels of liked and even negative emotion, such angry reaction. Second, our recommendation system focuses on monetary issue. For some social issues, charity requests materials or even volunteers. Those are involved geography problem. Hence, further research can be studying how to enhance recommendation mechanism by combining with physical materials or volunteers via Location Based Service (LBS) or other solutions. Lastly, the report shown that nearly 14% of online

transactions use mobile device to giving (Blackbaud, 2016). Thus, in the future, mobile will become next novel channel for giving. However, mobile devices generally limited by its performance or screen size, it cannot use too many procedure to donate. In the future, mobile device will be a good channel for donor with simple and rapid payment (such as mobile payment or even Bitcoin). Thus, our proposed mechanism would be able to integrate into mobile device via web interface or even native app and try to provide donor a rapid and high willingness service.

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