Steering Social Media Promotions with Effective Strategies

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Abstract—On social media platforms, companies, organizations and individuals are using the function of sharing or retweeting information to promote their products, policies, and ideas. While a growing body of research has focused on identifying the promoters from millions of users, the promoters themselves are seeking to know what strategies can improve promotional effectiveness, which is rarely studied in literature. In this work, we study a new problem of promotional strategy effect estimation which is challenging in identifying and quantifying promotional strategies, as well as estimating effectiveness of promotional strategies with selection bias in observational data. Here we study a series of strategies on both context and content levels. To alleviate the selection bias issue, we propose a method based on Propensity Score Matching (PSM) to evaluate the effect of each promotional strategy. Our data study provides three interpretable and insightful ideas on steering social media promotions, including (1) three significant and stable strategies, (2) a critical trade-off, and (3) different concerns for promoters of different popularity. These results provided comprehensive suggestions to the practitioners to steer social media promotions with effective strategies.

I. INTRODUCTION

Promotion is expensive. People always wonder how to use a small marketing budget for a smart promotion. The administration of the US President spent nearly $700 million dollars to promote the Obamacare1. The Starbucks spent $485 million dollars for media advertising in 2010-20142. Governments and companies have realized the great value of promotion on social media. However, there is a lack of data-driven approaches to find effective strategies for steering social media promotions. Thanks to the works on identifying promoters [8][11][12] in social media, we are able to observe various strategies operated by the promoters. For example, as “Strategy 1” shown in Figure 1, there are groups of promoters that believe repeat promotion can attract repeat customers. Thus, they promote the same message (e.g., “Up to 30% Off Coupon Code”) more than once. Another strategy, “Strategy 2”, is to decorate the promoters’ messages according to the profiles or interests of recipients (e.g., adding “30% Off for Prada and Gucci” when sending it to young ladies), called personalized decoration. They believe their personalized feature attract the target customers better. The question is, what are the most effective strategies in social media promotions?

To answer this question, we realize there are two major challenges as follows. First, there is a lack of study on social media promotional strategies, while we spot many in real data. Besides the repeat promotion and personalized decoration, the promoters make their strategies of different content, user, network and timing factors. Although the research literature of cascade prediction [6][15] and influence maximization [5] are proposed to analyze the patterns of natural propagation or select the top influential users in network. This problem has never been studied on the promoter side and from the data-driven angle: given the social network and a group of promoters that a company can manipulate, what strategies will achieve good effectiveness?

Second, the issue of selection bias is serious in evaluating the effectiveness of a strategy. In observational studies, the selection bias is a principal problem in the estimation of treatment effect which here refers to the effect of a treatment variable (whether and to what extent it adopts the strategy) on an outcome variable (the number of users infected by this promotion). The selection bias issue in observational studies is induced by that the treatments are not randomly assigned to units, which makes the different distributions of other features among the units with different treatment value. Since the different distribution of other features which may be associated with outcome variable, we can not distinguish the

1http://freebeacon.com/issues/govt-spent-700-million-promoting-obamacare/
effect from treatment variable and other features, leading to
imprecise estimation of the treatment effect. Hence, we have to
reduce the selection bias when estimating the treatment effect
in observational studies.

In order to address these two challenges, in this paper,
we provide in-depth study of the social media promotional
mechanism with Weibo (a Twitter like social platform in
China) data: we not only extract a large set of static features of
promotion from the perspectives of root user (who generates
the message first), root message content and promoter, but also
present as many as 17 promotional strategies that we observe
in context level (e.g., personalized decoration) and context
level (e.g., repeat promotion). To the best of our knowledge,
this is the first time that investigates social media promotional
strategies with rich complex behavioral data.

We propose a method based on the propensity score match-
ing method to reduce the selection bias and address the novel
problem of promotional strategy effect estimation. In particu-
lar, conditioned on the propensity score [13], the distribution of
observed features will be similar between treated and untreated
promotions. (A treated promotion is a promotion that adopts
given strategy.) Thus, our PSM method can successfully
reduce the selection bias for treatment (promotional strategy)
effect estimation from observational data.

It is worthwhile to highlight our contributions as follows.

• Novel problem: We propose the problem of promotional
strategy effect estimation for social media promotions.

With Weibo’s real data, we identify and quantify a large
set of promotional strategies from context and content
levels.

• Selection bias reducing: To overcome the serious issue of
selection bias that correlation based methods suffer from,
we propose PSM based method to estimate the effect of
promotional strategies from observational data.

• interpretable insights: We finally summarize three in-
sightful and practical points for steering social media
promotions: (1) three significant, stable strategies, (2) a
critical trade-off, and (3) different strategies for promoters
with different popularity.

II. RELATED WORK

Evaluating treatment effect in observational studies often re-
quires adjustment for selection bias in pre-treatment variables.
In literature, Rosenbaum and Rubin [13] proposed a statis-
tical framework based on propensity score adjustment. Such
framework has been widely used in observational causal study,
including matching, stratification, weighting and regression on
propensity score [2][1][3][14][4]. Austin et al. [2] described
these four propensity score methods. Sinan et al. [1] used
propensity score matching to distinguish peer-to-peer influence
from homophily in dynamic network. [3][14] evaluated the
effect of online advertisement based on propensity score. [4]
made propensity score matching on network structure. In this
work, we introduce the propensity score matching method for
promotional strategy effect estimation in social media, which
is a brand new problem to our research community.

III. PROBLEM STATEMENT

Before we define the promotional strategy effect estimation
problem, we give the definitions of “promoter”, “promotion”,
and “promotional effectiveness” ordinarily.

Definition 1 (Promoter): A promoter \( u_{pro} \in U_{pro} \) in
social media (e.g., Twitter) is one of a group of users that
are manipulated by companies, organizations or individuals
and operated to retweet target message (denoted by “\$”) for
monetary incentives or other purposes.

In this paper, we use a state-of-the-art effective and scalable
algorithm called CrossSpot [11] to label every user as
whether a promoter or not.

Definition 2 (Promotion): Given a target message “\$” in so-
cial media (e.g., Twitter), a promotion \( p \) is a retweet “\$+c(p)’’
generated by a promoter \( u_{pro} \), where \( c(p) \) is the comment
added by \( u_{pro} \) when promoting “\$”.

The promoter expects high effectiveness of their promotion,
i.e., the promotion will be adopted as many times as possible.

Definition 3 (Promotional effectiveness): The effectiveness
of a promotion \( p \) is the number of the ordinary users who adopt
the promotion (e.g., retweeting/resharing the promotion) in the
future. Formally, the promotional effectiveness of promotion
\( p \), denoted by \( PE(p) \), is the size of the ordinary users set
\( U_{adp}(p) \) who adopt the promotion \( p \): \( PE(p) = |U_{adp}(p)| \).

In order to improve the effectiveness, the promoters are
seeking effective strategies that have significant effect on
promotional effectiveness. Here we focus on the fundamental
problem: how to define and select the effective strategies.

Problem 1 (Promotional Strategy Effect Estimation): Given
a promotion \( p \) and multi-faceted information including the
social network, the target message “\$” and comment \( c(p) \), and
given a set of static features \( S_{static} \) and a set of promotional
strategies \( S_{pro} \), our task is to evaluate the effect of each
promotional strategy on promotional effectiveness \( PE(p) \).

With the effect of strategies, we can select the top-\( k \) effective
strategies by their absolute effect on promotional effectiveness
for steering social media promotions.

IV. FEATURES AND PROMOTIONAL STRATEGIES

In this section, we briefly list static features, and investigate
promotional strategies from context and content dimensions.

A. Static features

Before we estimate the effect of strategies on the promo-
tional effectiveness, we have to eliminate the selection bias
induced by static features, which cannot be changed by anyone
in the social networks. Table I lists the static features from
three domains: the promoter’s popularity, the content of the
target message, and the characteristics of the root user.

B. Context-level Strategies

We investigate the context level strategies mainly for an-
swering when to promote will be better, that is the timing.
We study it from many perspectives, for example, how long it
has been since the root message was generated, which hour the
promotion will be posted, and the time interval between former
TABLE I: Static features of a promotion: it has a few facets that cannot be changed by strategy, including the promoter’s popularity, the content of the target message, and the characteristics of the root user.

<table>
<thead>
<tr>
<th>Promoter (u_pro)</th>
<th>Target message (“$”</th>
<th>Root user (u_root)</th>
</tr>
</thead>
<tbody>
<tr>
<td>num-of-followers-of-u_pro</td>
<td>length-of-message-“$”</td>
<td>if-u_root-is-promoter</td>
</tr>
<tr>
<td>num-of-followees-of-u_pro</td>
<td>num-hashtags-of-message-“$” (“#XXX”)</td>
<td>num-of-followers-of-u_root</td>
</tr>
<tr>
<td>PageRank-value-of-u_pro</td>
<td>num-emotions-of-message-“$” (“D”)</td>
<td>average-PE-of-u_root</td>
</tr>
<tr>
<td>average-PE-of-u_pro</td>
<td>num-question-marks-of-message-“$” (“?”)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>num-exclamation-marks-of-message-“$” (“!”)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>num-URLs-of-message-“$” (“http...”)</td>
<td></td>
</tr>
</tbody>
</table>

TABLE II: Promotional strategies of a promotion: we present both context-level and content-level strategies. Practitioners can easily compute the values after reading the descriptions.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>depth-in-path</td>
<td>Depth of the promotion $p$ in the propagation path (i.e., parent-retweets)</td>
</tr>
<tr>
<td>num-of-repeat</td>
<td>Number of repeat: the promoter $u_{pro}$ may repeat retweeting the content “$”</td>
</tr>
<tr>
<td>user-active-time</td>
<td>Users’ activity in the hour of the promotion $p$ (i.e., periodic pattern)</td>
</tr>
<tr>
<td>time-after-the-root</td>
<td>Time interval between the root (target) message “$” and the promotion $p$</td>
</tr>
<tr>
<td>interval-before-the-root</td>
<td>Time interval between the former promotion and the current one</td>
</tr>
<tr>
<td>length-of-comment</td>
<td>Length of promotional comment $c(p)$</td>
</tr>
<tr>
<td>num-of-hashtags</td>
<td>Number of hashtags (“#XXX”) in promotional comment $c(p)$</td>
</tr>
<tr>
<td>num-of-mentions</td>
<td>Number of mentioned users (“@XXX”) in promotional comment $c(p)$</td>
</tr>
<tr>
<td>num-of-emotions</td>
<td>Number of emotions (“D”) in promotional comment $c(p)$</td>
</tr>
<tr>
<td>num-of-question-marks</td>
<td>Number of question marks (“...?”) in promotional comment $c(p)$</td>
</tr>
<tr>
<td>num-of-exclamation-marks</td>
<td>Number of exclamation marks (“...!”) in promotional comment $c(p)$</td>
</tr>
<tr>
<td>num-of-URLs</td>
<td>Number of URLs (“http...”) in promotional comment $c(p)$</td>
</tr>
<tr>
<td>topic-popularity</td>
<td>Popularity of the topics in the comment $c(p)$ (see Eq. 1)</td>
</tr>
<tr>
<td>topic-diversity</td>
<td>Diversity of all the topics of the comment $c(p)$ (see Eq. 3)</td>
</tr>
<tr>
<td>topic-novelty</td>
<td>Difference between topics of the comment $c(p)$ and target message “$” (see Eq. 4)</td>
</tr>
<tr>
<td>topic-interest</td>
<td>Similarity between the comment $c(p)$ and recipient’s interest (see Eq. 5)</td>
</tr>
</tbody>
</table>

and current promotion or current and the next promotion. We also study the depth of the promotion on the promoted message’s information propagation path, i.e., how many parent retweet nodes does this promotion node has in the path.

C. Content-level Strategies

For answering how to promote will be better, we investigate the content level, that is, the comment $c(p)$ that the promoter promotes on the target message. We group the content-level strategies into two classes: (1) word-count based strategies and (2) topic-distribution based strategies. The first class of strategies is easy to compute, such as the length of comment, the number of hashtags, mentions, emoticons, question marks, exclamation marks and URLs. The second class relies on LDA topic models, that have been incorporated into many tasks [7][9][10]. We denote by $Pr(z|c(p))$ the probability distribution over topic $z \in Z$ assigned to the comment $c(p)$, where $Z$ is the set of all the 100 topics. We define the following topic-distribution based strategies, including topic-popularity, topic-diversity, topic-novelty, and topic-interest.

The topic-level popularity describes how popular the topics in a given promotional comment of promotion are:

$$\text{topic-popularity}(p) = \sum_{z \in Z} Pr(z|c(p)) \cdot \text{popularity}(z),$$ (1)

where $\text{popularity}(z)$ is the popularity of topic $z$ in social media, which is defined as follow:

$$\text{popularity}(z) = \sum_{p \in P} Pr(z|c(p)) \cdot PE(p),$$ (2)

where $P$ is the set of the all promotions set in our training dataset.

The topic-level diversity describes how much the topics in the comment of the promotion differ. We define it as the Shannon entropy of its topic distribution:

$$\text{topic-diversity}(p) = -\sum_{z \in Z} Pr(z|c(p)) \cdot \log(Pr(z|c(p))).$$ (3)

The topic-level novelty has been adopted to evaluate paper quality [7]. It was measured by the difference between a particular paper and other related papers. Here we define it as the difference between the topic distributions of the comment $c(p)$ and the target message $S$:

$$\text{topic-novelty}(p) = \sum_{z \in Z} Pr(z|c(p)) \ln \frac{Pr(z|c(p))}{Pr(z|S)}.$$ (4)

The topic-level interest describes the similarity between the comment $c(p)$ and the recipient’s interesting of promoter $u_{pro}$:

$$\text{topic-interest}(p) = \sum_{z \in Z} Pr(z|c(p)) \cdot \text{recipient-interest}(u_{pro}, z),$$ (5)

where $\text{recipient-interest}(u_{pro}, z)$ is the recipient’s interest of promoter $u_{pro}$ on topic $z$, which is defined as follow:

$$\text{recipient-interest}(u_{pro}, z) = \sum_{p \in P_{u_{pro}}} Pr(z|c(p)) \cdot PE(p).$$ (6)

where $P_{u_{pro}}$ is a set of previous promotions by promoter $u_{pro}$.

V. PROMOTIONAL STRATEGY EFFECT ESTIMATION WITH PROPENSITY SCORE MATCHING

In this section, we present our Propensity Score Matching (PSM) algorithm to estimate the effect of promotional strategies with reducing the selection bias in observational studies.

In practical, we evaluate the effect of each promotional strategy $s_i$ by setting it as treatment $T$, other strategies $S_{pro} - \{s_i\}$ and static features $S_{static}$ as confounders $X$ and
the promotional effectiveness $PE(.)$ as outcome $Y$. Then, for each promotion $p$, we observe a vector of other strategies and static features $X_p$, and a potential outcome $Y_p(t) = PE(p)$ which corresponds to its treatment $T = t$, where $t \in T$ and $T$ is a set of potential value of treatment $T$.

To evaluate the effect of a given treatment $T = t$ on the outcome $Y$, we have to remove the selection bias induced by confounders $X$. And there are two standard assumptions [13] usually made for unbiased evaluating the treatment effect.

**Assumption 1: Stable Unit Treatment Value.** The distribution of potential outcome for one unit is unaffected by the particular treatment assignment of another unit given the confounders.

**Assumption 2: Unconfoundedness.** The distribution of treatment is independent of the potential outcome given the confounders. Formally, $Y(t) \perp T|X$ for all $t \in T$.

The primary interest in estimating the treatment effect is the distribution of $Pr(Y(t))$ for each $t \in T$. Due to the fact that we observed only one potential outcome $Y(t)$ for each unit, therefore, in order to obtain $Pr(Y(t))$, we have to condition on the observed treatment assignment and confounders. With assumption 2, we have

$$Pr(Y(t)|T = t, X) = \frac{Pr(T = t|Y(t), X)Pr(Y(t)|X)}{Pr(T = t|X)} = Pr(Y(t)|X),$$

hence,

$$Pr(Y(t)) = \int_X Pr(Y(t)|T = t, X)Pr(X)dX.$$  

In principle, we can model $Pr(Y(t)|T = t, X)$ directly, but the result will be strongly biased if the relation between $T$ and $X$ is omitted or misspecified [3]. Matching and subclassification according to $X$ can avoid the bias. But as increasing of the dimension of $X$, these methods become infeasible.

To address the high dimensional issue of confounders $X$, we employ the balancing score, denoted by $b(X)$, to summarize the information required to balance the distribution of $X$. The balancing score was proposed in [13] and it had been proved that the treatment assignment is unconfoundedness when giving the balancing score. Formally, $Y(t) \perp T|b(X)$ for all $t \in T$. The propensity score, denoted by $e(X)$, which is the most commonly used balancing score, is defined as the conditional probability of treatment when giving the confounders.

$$e(X) = Pr(T = 1|X).$$

With the unconfoundedness of propensity score, we have

$$Pr(T = t|Y(t), e(X)) = Pr(T = t|e(X)).$$

Hence we obtain $p(Y(t))$ as

$$p(Y(t)) = \int_X Pr(Y(t)|T = t, e(X))Pr(e(X))de(X).$$  

In practical, we approximate the integral in Eq. (11) by PSM algorithm, which matches the units into $K$ ($K$ is the number of treatment in $T$) groups with different value of treatment $t \in T$ but similar value of propensity score $e(X)$. Then we estimates the average treatment effect $Y(t) - Y(t_0)$ within each group, where $t_0$ is the baseline treatment. Our PSM algorithm is summarized in Algorithm 1.

For simplifying the problem, we make the treatment $T$ as binary, that is $T = \{0, 1\}$. Then at the $1^{st}$ step of algorithm 1, we estimate the propensity score $e(X)$ with linear logistic regression model. That is,

$$e(X) = p(T = 1|X) = \frac{1}{1 + e^{-\alpha - \beta X}},$$

where $\alpha$ and $\beta$ are the parameters to learn.

At the $2^{nd}$ step of Algorithm 1, we match the units (i.e., promotions in our paper) into 2 groups (treated group where $T = 1$ and untreated group where $T = 0$) by employing the nearest neighbor matching method.

Specifically, for each treated unit $i$ with $T = 1$, find its closest match among the units with treatment status $T = 0$:

$$match(i) = \arg \min_{T = 0} |e(X_i) - e(X_j)|.$$  

We drop unit $i$ if $match(i) > \epsilon$. In this step, we reduce the selection bias in data by units matching with propensity score and obtain the matched promotions set $P_{matched}$, including the matched treated and untreated promotions.

At the $3^{rd}$ step, we calculate the average outcome of treated group and untreated group, respectively. And at the $4^{th}$ step, we estimate the Average Treatment Effect ($ATE$) as:

$$ATE = \frac{\sum_{p \in P_{matched}, T(p) = 1} PE(p)}{\sum_{p \in P_{matched}, T(p) = 0} PE(q)} - 1.$$  

The propensity score matching algorithm helps us to reduce the selection bias and evaluate the treatment (promotional strategy) effect more accurately. Then we rank the promotional strategies by their estimated effect and select the top-k effective strategies to steer social media promotions.

**VI. EXPERIMENTS**

**A. Datasets and Experimental Setup**

We crawled a large dataset of both user and tweet information during Nov. 9th, 2011 to Dec. 22nd, 2011, from Tencent Weibo, a Twitter-style social platform in China. For

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of users</td>
<td>193,998,829</td>
</tr>
<tr>
<td>Number of promoters</td>
<td>21,378</td>
</tr>
<tr>
<td>Number of target messages</td>
<td>13,314</td>
</tr>
<tr>
<td>Number of promotions</td>
<td>814,824</td>
</tr>
<tr>
<td>Number of adopted promotions</td>
<td>4,213,545</td>
</tr>
</tbody>
</table>
the user information, we have a social graph of nearly 200 million users; for the tweet information, we have retweeting paths (i.e., parent-to-child retweeting relationships) consisted of 13,314 target messages and over 4 million retweets as well as their content including comments and timestamps. The data statistics can be found in Table III.

In matching step of PSM algorithm, we set $\epsilon = 0.05$ as default threshold parameter for the nearest neighboring matching.

### B. Experimental Results

In this section, we evaluate the effect of each strategy on promotional effectiveness with our PSM algorithm.

#### 1) Strategies effect discovery

Before we present our strategies effect analysis, we show strong evidences that we reduce the selection bias by our PSM algorithm.

**Selection bias reduction.** Given a specific strategy as treatment, we examine the data distribution between the treated and the untreated units (i.e., promotions) that have been matched based on the propensity score. Quantile-quantile plot (Q-Q plot) provides a standard visualization to examine the distributions. We expect that the treated and untreated units can have a perfect matching (dots are closely aligned with $y = x$ in Q-Q plot) for every confounder. For example, when we choose user-active-time as the treatment, Figure 2 shows Q-Q plots of three confounders: followers-of-pro, num-of-repeat, and length-of-comment. A dot represents a matching of a treated unit and an untreated one with the same quantile. We observe that the green circle-dots (original dataset without PSM) deviate the red dashed line $y = x$, but the blue triangle-dots (with PSM) are closely aligned with $y = x$, which indicates that the distributions of confounders are very similar between the matched treated and untreated objects after selection bias reducing with our PSM algorithm.

Therefore, we can better estimate the effect of promotional strategies by our PSM method with selection bias reduction.

**Strategies effect analysis.** For different levels of the number of the promoters’ followers and different promotional strategies, we discuss the polarity (positive or negative), degree of strategies effect and its significance level, as shown in Table IV. And we have the following observations.

**Observation 1. Three significant, stable strategies.** We find that three strategies topic-interest (1.316 in average, positive), user-active-time (0.313 in average, positive), and depth-in-path (-0.209 in average, negative) have strong and robust effects on promotional effectiveness. First, promotions that are generated when the users are active in the social media can be very effective. Therefore, strategy user-active-time has strong positive effect on the promotional effectiveness. Second, given an target message, if the promoter decorates it with well-designed comments that match the recipient’s personal interest, it is more probable to be adopted by him/her. So topic-interest or personalized decoration can work as such an effective strategy in social promotion. Third, in a propagation path, the grandchild promotion retweet (i.e., the retweet of the target message’s retweet) often has fewer adoptions than the child promotion retweet (i.e., the retweet of the target message). Thus, we find that more depth-in-path indicates weaker promotional effectiveness. The potential reason is the recipients of the grandchild may have received the same message from the child and its siblings.

**Observation 2. A critical trade-off in the context-level strategies.** The trade-off between the value of num-of-repeat and the negative influence of its growth on a specific promotional effectiveness. As we have introduced in Figure 1, the more a promoter repeats the same promoted content, the fewer adoptions he/she will harvest. However, the total number

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**TABLE IV: The effect of strategies on promotional effectiveness:** A positive (negative) value of the effect means that a higher (smaller) value of the strategy will achieve better effectiveness with standard error of the mean (SEM) in parentheses. In a paired t-test, a smaller $p$-value indicates high significance of the strategy: 

* $p < 0.001$, ** $0.001 \leq p < 0.01$, * $0.01 \leq p < 0.05$.

Non-significant strategies are omitted for space.

<table>
<thead>
<tr>
<th>Context</th>
<th>Num. followers of promoter</th>
<th>Pct. such promotions in data</th>
</tr>
</thead>
<tbody>
<tr>
<td>depth-in-path</td>
<td>(-0.163 ***) (0.018)</td>
<td>[0, 100] 36%</td>
</tr>
<tr>
<td>num-of-repeat</td>
<td>0.066 (0.047)</td>
<td>[100, 1,000] 14%</td>
</tr>
<tr>
<td>user-active-time</td>
<td>0.158 *** (0.010)</td>
<td>(1,000, 10,000) 8%</td>
</tr>
<tr>
<td>time-after-the-root</td>
<td>0.043 (0.017)</td>
<td>(10,000, 100,000) 11%</td>
</tr>
<tr>
<td>interval-after-the-former</td>
<td>-0.006 (0.010)</td>
<td>(100,000, +\infty) 31%</td>
</tr>
</tbody>
</table>

**Content**

| (+) length-of-comment |
| 0.188 *** (0.035) |
| 0.274 *** (0.063) |
| 6.749 *** (0.668) |
| -0.040 (0.023) |
| -0.122 (0.092) |

| (+) num-of-hashtags “#XXX” |
| 0.766 * (0.360) |
| -0.124 (0.131) |
| -0.085 (0.579) |
| -0.096 (0.082) |
| -0.216 (0.237) |

| (+) num-of-mentions “@XXX” |
| 0.171 * (0.083) |
| -0.184 (0.146) |
| -0.439 (0.385) |
| -0.094 (0.385) |
| -0.208 (0.322) |

| (+) num-of-emoticons “D” |
| 0.101 ** (0.037) |
| 0.016 (0.071) |
| -0.198 (0.223) |
| -0.008 (0.027) |
| 0.478 *** (0.141) |

| (+) num-of-questions “...?” |
| 0.567 * (0.279) |
| 0.539 (0.453) |
| 0.874 (0.954) |
| -0.089 (0.026) |
| -0.246 (0.097) |

| (+) topic-interest |
| 1.062 *** (0.118) |
| 1.154 *** (0.235) |
| 3.251 *** (0.506) |
| 0.199 *** (0.052) |
| 0.914 *** (0.161) |
of adopted promotions is monotonic nondecreasing with the number of promotions increasing. The promoter may hope to get as many as adoptions as possible but should stop promoting when its benefit becomes zero.

Observation 3. Different promoters should focus on different promotional strategies. Specifically, the context-level strategies are significant for popular promoters, while ordinary promoters should focus on the content-level strategies. Table IV shows that for the promoters who have more than 100,000 followers, the context-level strategies including num-of-repeat (0.525), user-active-time (0.418), interval-after-the-former (-0.336), and time-after-the-root (-0.263) have significant effect on promotional effectiveness. However, if a promoter is not that popular, for example, if he/she has not more than 100 followers, the promoter must focus on content-level instead of context-level strategies. More appropriate decorations will be more appreciated by the recipients. such as using hashtags (0.766) to explicitly represent its topic, using question marks (0.567) to inspire users to respond, using longer comments (0.188) to decorate with interesting content, using mentions (0.171) to notify some users, and using emoticons (0.101) to make the message look sentimental.

With the estimated strategies effect as shown in Table IV, we can select the top-k effective strategies by their absolute impact on promotional effectiveness. With different popularity. Our in-depth study may inspire the future of more productive promotions for products and public policies.

VII. CONCLUSIONS

In this paper, we proposed a novel real-world problem that how to make strategy for high promotional effectiveness in social media. We introduced a series of promotional strategies in both context and content levels, and presented their effect analysis after selection bias reduction by propensity score matching (PSM) method in observational data. The results provided comprehensive suggestions to the practitioners (promoters) to operate (i.e., when and how to promote the messages) for steering social media promotions. We conducted extensive experiments on a large social platform of over 300 million users, and demonstrated the effect of each promotional strategy for promoters with different level of number of followers. Moreover, we provided three insights of making promotional strategy: (1) three significant, stable strategies, (2) a critical trade-off, and (3) different strategies for promoters with different popularity. Our in-depth study may inspire the future of more productive promotions for products and public policies.

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