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.**

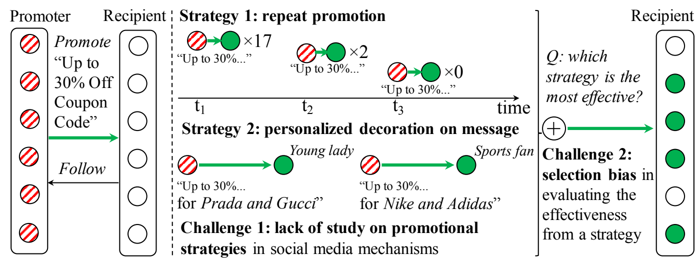


Fig. 1: *What are the promotional strategies, and which is the most effective?* There is a lack of study on social media promotional strategies, while we spot many in real data, for instance, repeat promotion and personalized decoration on message. However, it is difficult to answer the above questions due to the selection bias in evaluating their effectiveness.

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 Obamacare[1]. The Starbucks spent $485 million dollars for media advertising in 2010-2014[2]. 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

[1]http://freebeacon.com/issues/govt-spent-700-million-promoting-obamacare/
[2]http://www.statista.com/statistics/275195/starbucks-advertising-spending-in-the-us/

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 content 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 matching method to reduce the selection bias and address the novel problem of promotional strategy effect estimation. In particular, 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 a 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 insightful 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 requires adjustment for selection bias in pre-treatment variables. In literature, Rosenbaum and Rubin [13] proposed a statistical 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" ordinally.

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 social 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 promotional 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 answering 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.

Promoter (u_{pro})	Target message ("\$")	Root user (u_{root})
num-of-followers-of-u_{pro} num-of-followees-of-u_{pro} ratio-of-female-followers-of-u_{pro} PageRank-value-of-u_{pro} average-PE-of-u_{pro}	length-of-message-"\$" num-hashtags-of-message-"\$" ("#XXX") num-mentions-of-message-"\$" ("@XXX") num-emoticons-of-message-"\$" (":D") num-question-marks-of-message-"\$" ("...?") num-exclamation-marks-of-message-"\$" ("...!") num-URLs-of-message-"\$" ("http:...")	if-u_{root}-is-promoter num-of-followers-of-u_{root} num-of-followees-of-u_{root} PageRank-value-of-u_{root} average-PE-of-u_{root}

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.

	Strategy	Description
Context	$depth\text{-}in\text{-}path$	Depth of the promotion p in the propagation path (*i.e.*, #parent-retweets)
	$num\text{-}of\text{-}repeat$	Number of repeat: the promoter u_{pro} may repeat retweeting the content "\$"
	$user\text{-}active\text{-}time$	Users' activeness in the *hour* of the promotion p (*i.e.*, periodic pattern)
	$time\text{-}after\text{-}the\text{-}root$	Time interval between the root (target) message "\$" and the promotion p
	$interval\text{-}after\text{-}the\text{-}former$	Time interval between the former promotion and the current one
	$interval\text{-}before\text{-}the\text{-}next$	Time interval between the current promotion and the next one
Content	$length\text{-}of\text{-}comment$	Length of promotional comment $c(p)$
	$num\text{-}of\text{-}hashtags$	Number of hashtags ("#XXX") in promotional comment $c(p)$
	$num\text{-}of\text{-}mentions$	Number of mentioned users ("@XXX") in promotional comment $c(p)$
	$num\text{-}of\text{-}emoticons$	Number of emoticons (":D") in promotional comment $c(p)$
	$num\text{-}of\text{-}question\text{-}marks$	Number of question marks ("...?...?") in promotional comment $c(p)$
	$num\text{-}of\text{-}exclamation\text{-}marks$	Number of exclamation marks ("...!...!") in promotional comment $c(p)$
	$num\text{-}of\text{-}URLs$	Number of URLs ("http:...") in promotional comment $c(p)$
	$topic\text{-}popularity$	Popularity of the topics in the comment $c(p)$ (see Eq. 1)
	$topic\text{-}diversity$	Diversity of all the topics of the comment $c(p)$ (see Eq. 3)
	$topic\text{-}novelty$	Difference between topics of the comment $c(p)$ and target message "\$" (see Eq. 4)
	$topic\text{-}interest$	Similarity between the comment $c(p)$ and recipient's interest (see Eq. 5)

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 strategies, that is, the comment $c(p)$ that the promoter decorates 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 are 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 $topic\text{-}popularity$, $topic\text{-}diversity$, $topic\text{-}novelty$, and $topic\text{-}interest$.

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

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

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

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

where P is 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:

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

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 \$:

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

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

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

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

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

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 $\mathbf{X}$ 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 a its treatment $T = t$, where $t \in \mathcal{T}$ and $\mathcal{T}$ 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 $\mathbf{X}$. 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: Uncofoundedness. The distribution of treatment is independent of the potential outcome given the confounders. Formally, $Y(t) \perp T|\mathbf{X}$ for all $t \in \mathcal{T}$.

The primary interest in estimating the treatment effect is the distribution of $Pr(Y(t))$ for each $t \in \mathcal{T}$. Due to the fact that we observed only one potential outcome $Y(T = t)$ 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

$$Pr(Y(t)|T = t, \mathbf{X}) = \frac{Pr(T=t|Y(t), \mathbf{X}) Pr(Y(t)|\mathbf{X})}{Pr(T=t|\mathbf{X})} = Pr(Y(t)|\mathbf{X}), \quad (7)$$

$$\text{hence}, Pr(Y(t)) = \int_{\mathbf{X}} Pr(Y(t)|T = t, \mathbf{X}) Pr(\mathbf{X}) d\mathbf{X}, \quad (8)$$

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

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

$$e(\mathbf{X}) = Pr(T = 1|\mathbf{X}). \quad (9)$$

With the unconfoundedness of propensity score, we have

$$Pr(T = t|Y(t), e(\mathbf{X})) = Pr(T = t|e(\mathbf{X})). \quad (10)$$

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

$$Pr(Y(t)) = \int_{e(X)} Pr(Y(t)|T = t, e(\mathbf{X})) Pr(e(\mathbf{X})) de(\mathbf{X}). \quad (11)$$

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 $\mathcal{T}$) groups with different value of treatment $t \in \mathcal{T}$ but similar value of propensity score $e(\mathbf{X})$. 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 $\mathcal{T} = \{0, 1\}$. Then at the 1^{st} step of algorithm 1, we estimate the propensity score $e(\mathbf{X})$ with linear logistic regression model. That is,

Algorithm 1 (Propensity Score Matching Algorithm)

Input: the outcome Y_i, the treatment T_i, and the confounders X_i of units indexed by $i = 1, 2, \cdots, N$.

Output: the estimated average treatment effect $Y(t) - Y(t_0)$.

1: estimating propensity score $e(\mathbf{X})$ for each unit such that the treatment $T \perp \mathbf{X}|e(\mathbf{X})$;

2: matching the units into K groups with different treatment value T but similar propensity score $e(\mathbf{X})$;

3: calculating average outcome $Y(t)$ of units in each group;

4: **return** the average treatment effect $Y(t) - Y(t_0)$, comparing with baseline treatment t_0.

TABLE III: *Data statistics:* we identified 21K promoters from 194M users, and collected over 4M messages that were generated after the promoters posted 814K retweets.

Description	Value
Number of users	193,998,829
Number of promoters	21,378
Number of target messages	13,314
Number of promotions	814,824
Number of adopted promotions	4,213,545

$$e(\mathbf{X}) = p(T = 1|\mathbf{X}) = \frac{1}{1 + e^{-(\alpha + X\beta)}}, \quad (12)$$

where α and β 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 $T = 0$:

$$match(i) = \arg\min_{j:T_j=0} |e(X_i) - e(X_j)|. \quad (13)$$

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:

$$ATE = \frac{\sum_{p \in P_{matched}, T(p)=1} PE(p)}{\sum_{q \in P_{matched}, T(q)=0} PE(q)} - 1. \quad (14)$$

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. 9^{th}, 2011 to Dec. 22^{th}, 2011, from Tencent Weibo, a Twitter-style social platform in China. For

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: ***: $p < 0.001$, **: $0.001 \leq p < 0.01$, *: $0.01 \leq p < 0.05$, NO star: $p \geq 0.05$. Non-significant strategies are omitted for space.

	Num. followers of promoter Pct. such promotions in data	[0, 100] 36%	(100, 1,000] 14%	(1,000, 10,000] 8%	(10,000, 100,000] 11%	(100,000, $+\infty$) 31%
Context	$^{(-)}$*depth-in-path*	-0.163 *** (0.018)	-0.131 *** (0.035)	-0.662 *** (0.122)	-0.175 *** (0.034)	0.086 (0.192)
	$^{(-)}$*num-of-repeat*	0.068 (0.047)	0.613 (0.335)	n/a	0.728 (0.839)	-0.525 *** (0.034)
	$^{(+)}$*user-active-time*	0.158 *** (0.010)	0.171 *** (0.031)	0.695 *** (0.138)	0.123 *** (0.012)	0.418 *** (0.052)
	$^{(-)}$*time-after-the-root*	0.043 (0.017)	n/a	n/a	0.010 (0.023)	-0.263 *** (0.075)
	$^{(-)}$*interval-after-the-former*	-0.066 (0.101)	0.068 (0.105)	n/a	-0.029 (0.141)	-0.336 *** (0.075)
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)	-0.121 (0.131)	-0.685 (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)	-0.494 (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)

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 neighbor matching.

B. Experimental Results

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

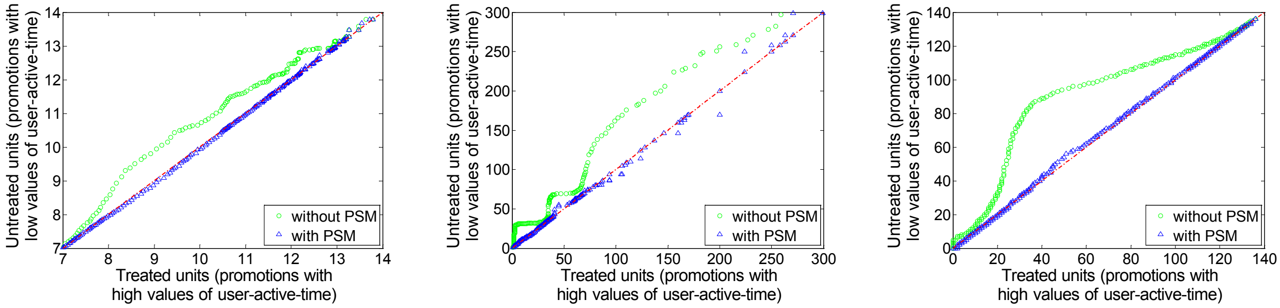
1) Strategies effect discovery: Before we present our strategies effect analysis, we show strong evidences that we reduce the selection bias by our PSM algorithm.

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 $user\text{-}active\text{-}time$ as the treatment, Figure 2 shows Q-Q plots of three confounders: #followers-of-u_{pro}, $num\text{-}of\text{-}repeat$, and $length\text{-}of\text{-}comment$. 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 $topic\text{-}interest$ (1.316 in average, positive), $user\text{-}active\text{-}time$ (0.313 in average, positive), and $depth\text{-}in\text{-}path$ (-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 $user\text{-}active\text{-}time$ 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 $topic\text{-}interest$ 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 $depth\text{-}in\text{-}path$ 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 $num\text{-}of\text{-}repeat$ 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



(a) ln(#followers-of-u_{pro}) (b) $num\text{-}of\text{-}repeat$ (c) $length\text{-}of\text{-}comment$

Fig. 2: *Demonstration of selection bias reducing of three confounders with setting* $user\text{-}active\text{-}time$ *as the treatment.*

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 $num\text{-}of\text{-}repeat$ (-0.525), $user\text{-}active\text{-}time$ (0.418), $interval\text{-}after\text{-}the\text{-}former$ (-0.336), and $time\text{-}after\text{-}the\text{-}root$ (-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 effect for steering social media promotions.

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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