Assessing the Effects of Applying Ranking-Boosting Strategy on Friends Recommendation System on User Activeness on Kuaishou Short-Video Social Network Platform

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Abstract

User relationship recommendation, or friend recommendation, is a common design on social media platforms, where users are receiving recommendations of people they may know or like and being recommended to others via different interfaces on the platforms. It is worthwhile analyzing the effect of these recommendations on user activeness and engagement. Our work assessed the effect of a ranking-boosting strategy deployed on the friend recommendation system of a short-video-based social network, Kuaishou[1], on the online activeness of the users whose rankings on the recommendation list are boosted and therefore being followed by other users. Assessing the effects could be challenging. The average rate of following a recommended user is quite low (10%), which created a gap in assigning and receiving treatment. Non-compliance exists in strategy assignment. A proper measurement of the outcome is required. We chose to measure the number of days a user logs in to the app (Lifetime-7, LT7) in the next 7 days. Our analysis demonstrated statistically significant causal effects of deploying ranking-boosting strategy, which is 0.29 days (SE 0.06). We also showed that users who launched app relatively less frequently during last few days are more sensitive to the treatment. Our results would serve as a reference to design more efficient friend recommendation algorithms and strategies which promote user activeness.

1 Introduction

Imagine you are a user of a video-based social media platform. What are the key factors that would make you stay on this platform, or even, get addicted to it? Studies have shown that the contents [DSA+11] on the platform and recommending new friends you may know [WWX+20] play a crucial part of user retention.

User relationship recommendation, or friend recommendation, is common on social media platforms. In our study, we use Kuaishou, a short-video-based social network with over 2000 million users and 400 million daily active users, as research object. The social network of Kuaishou can be accessed via two apps, Kuaishou Flagship and Kuaishou Express, where they share same video contents and user base, while Kuaishou Express takes less storage space and has more simplified functions. In the apps, users are provided a list of recommended users in several scenarios. The major interfaces of friends recommendations, as shown in Figure 1, named "Red Hat" and accessed from the "ADD NEW FRIENDS" icon on the user's own profile page in both apps, provides a list of recommended users to follow (or follow back). The following action is directional. Two users who follow each other are regarded as friends and can further interact mutually on the network. Other recommendation interfaces and ways to befriend users exist on the apps, but we only consider this "Red Hat" scenario.

The impact of this friend recommendation mechanism of Kuaishou has been tested by large-scale randomized field experiments [WWX+20]. It reveals that the existence of the user recommendation function promotes online community participation of users in terms of numbers of posts, views, likes, comments, and viewing time. It also shows that the impacts vary from users depending on their age, gender, location, numbers of friends and followers.

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[1] https://www.kuaishou.com/en/products

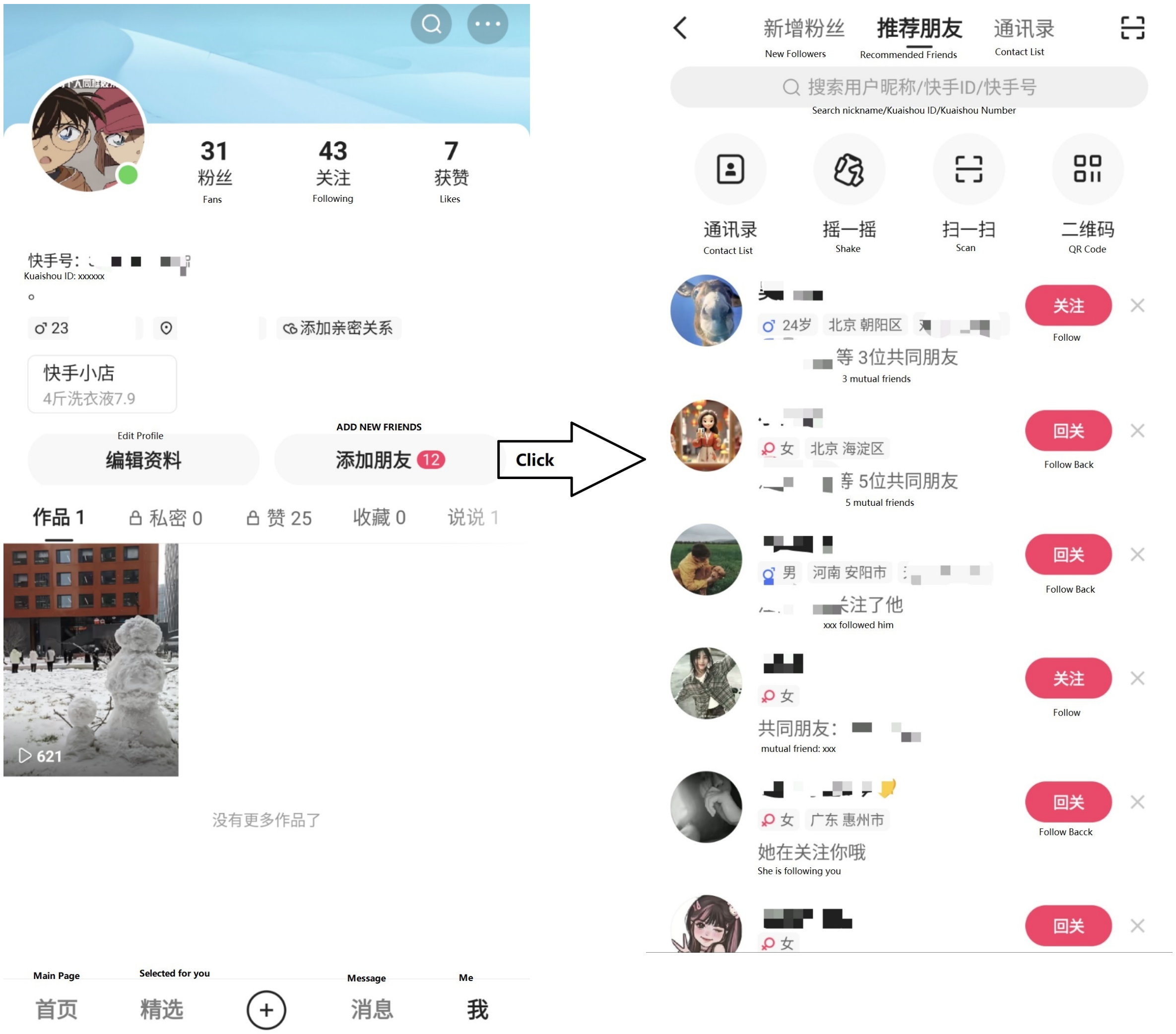

Figure 1: On the left: Author's own Kuaishou profile page. Clicking the "Add New Friend" icon would lead to the figure on the right: Friends Recommendation Interface on Kuaishou apps. A list of users were provided to me with their basic information and brief recommendation reasons such as "having mutla friends". Sensitive private information masked. Language originally in Chinese, with essential English translations added near the text.

Apart from friend recommendation, other mechanisms or incentives[ALG+22] could be assessed for treatment effects on user behaviours, as treatments could be dictated and directly assigned by the researchers and then received by the users. However, we intended to assess the effect of friend recommendation on users in a different way by raising the question: "How much would you be motivated to be active on the platform if you are more likely to be followed by other users?

To generate the list of recommended users in Figure 1, Kuaishou has in-house algorithms and models based on users' profile information and history behaviours to recall potential users, assign scores to them, and sort into a list. Specifically, in the last step to generate the list, we may rearrange the ranking of certain users to make them appear in a higher position, potentially increasing the probability of them being followed by the target of this friend recommendation interface.

A pilot experiment was conducted. A sample of users were selected by systematic sampling using their Kuaishou IDs. For users in the experiment group, we manually added an empirically-estimated bonus to their ranking scores, so that their rankings on the friend recommendation interfaces (Red Hat) of other users were boosted to higher positions. During a calendar day, once the user is followed via friend recommendation interface, its ranking will no longer be boosted until next day. In control group, no modification is made on the base recommendation mechanism. The average active days in a 30-day period were recorded, in which the experiment group is 0.03% (p-value: 0.045) higher than the control group.

To further analyze the effect of ranking-boosting in friends recommendation on users, there are challenges we have to address:

First, although the boosting strategy could be assigned manually and randomly by researches, both the treatment (action of following) and outcome (user activeness) are realized completely on users. We name the users appearing on the friend recommendation list (potentially being ranking-boosted) as reco_users, and those who receive recommendations as target_users. A user can be both reco_user and target_user on the platform. We explored instrumental variable framework [AIR96] and the propensity [CK08] of reco_users being followed if they are rank-boosted to reduce the bias created by target_users' behaviors.

Second, empirically, on Kuaishou, target_users only follow 10% of the reco_users on average, which means that the strategy assignment would transfer into user activeness outcome on a low rate. Reco_users who have been boosted may not receive followers, while other reco_users may receive new followers as usual. In our study, we only consider following actions taken place in the Red Hat interfaces on reco_users whose rankings were boosted.

Third, in pilot experiment, the bonus used to boost ranking was set based on experience. The ranking of a reco_user may have been elevated by several positions ranging from 0 to the length of the list. To reduce the variance caused by the magnitudes of the boosting effects, we modified the strategy to raise the designated reco_user to the second place in the ranking.

Fourth, as the pilot study showed, the overall effect could be small, partially due to the low following rate. A common measurement for user activeness on social network is the Daily Active Users (DAU) [NRC08] which counts how many unique users (by ID) use the app at least once in a calendar day. However, DAU could introduce large variance as it depends on the date and miss to capture the trend in user behaviors and the long-term effect of the boosting strategy. We chose to use LT7 (Lifetime-7) [LSY+22], the number of days a user is active during a 7-day period. We estimated the mean of LT7 for different groups of users, and it could serve to reflect the economic gain for the app by assessing the Lifetime Value (LTV).

Addressing those challenges presented on studying ranking-boosting strategy on Kuaishou's friends recommendation, our analysis demonstrated positive treatment effects in LT7 from elevating reco_users' probability of being followed (CACE=0.29 days, SE=0.06), which could serves as a reference to design friends recommendation algorithms to encourage user engagement and economic gains. We also revealed that certain groups of users (medium history activeness) are more sensitive to the treatment.

2 Study and Experiment Details

2.1 Settings

Our study was conducted on Kuaishou Flagship and Kuaishou Express mobile apps. Both apps share the same social network of Kuaishou. Target_users receive lists of reco_users as friends recommendations in the Red Hat interface. Target_users may choose to follow or not follow the reco_users presented. Once a reco_user is followed by a target_user, they will be notified by their app (a highlighted text "+1" would appear on the "Fans" count on their own profile page (on the left of Figure 1)). A subset of users will have their ranking boosted to the second place on the Red Hat interface when they are considered as reco_users. Once a such user is followed via Red Hat interface, its ranking would not be boosted until next day.

2.2 Experiment Design

The experiment was conducted from 24$^{\text{th}}$ October 2023 to 31$^{\text{st}}$ October 2023 and the study gathered data from 15$^{\text{th}}$ October 2023 to 31$^{\text{st}}$ October 2023. A subset from all non-silent 2.2 users on the Kuaishou social network was selected by systematic sampling design [LL13] using the digits of their Kuaishou ID (a 11-digit integer). The subset consists of over a million unique users. A random sub-sample of 96893 users are available to our study. We denote those users as $\{U_1, U_2, ...U_n\}$. For each user U_i, a set of profile and behavioral information was recorded in the beginning of 24$^{\text{th}}$ October 2023 as a vector X_i, including:

- Number of fans the user has;
- Number of users the user is following;
- Number of friends (bidirectionally followed) the user has;
- Number of posts and videos the user posted during last 7 days;
- A series of binary values denoting whether the user had logged in to the app at least one time on the days from 15^{th} October 2023 to 24^{th} October 2023;
- A series of numbers denoting how many time the users logged in (launched) to the app on the days from 15^{th} October 2023 to 24^{th} October 2023;
- The degree of activeness of the user: "Full", be active 30 days in last 30 days; "High", be active 20 29 days; "Middle", be active 10 19 days; "Low", be active 1 9 days; "Silent", never active during last 30 days.

In the chosen subset, half of the users were randomly chosen to be applied ranking-boosting strategy as reco_users when they appear on friends recommendation interfaces of all users on the network. For each user U_i, we use $Z_i \in \{0,1\}$ to record if it is being ranking-boosted to the second place. Whether U_i was ever followed is completely up to the target_users who received U_i in their Red Hat recommendation list. We recorded it as $D_i \in \{0,1\}$. For outcome measurement, we use $Y_i \in \{0,1,2,3,4,5,6,7\}$ to record how many days that U_i launched the app during 25^{th} October 2023 to 31^{st} October 2023. We chose this time frame because there was no major holiday during that time in China, which is Kuaishou's major user base.

A summary of X_i, Z_i, D_i, Y_i is shown in Table 1

	mean	standard deviation	min	median	max
# of launches on 15th Oct	9.715	15.388	0.0	4.0	346.0
if active on 15th Oct	0.913	0.28184	0.0	1.0	1.0
# of launches on 16th Oct	4.7466	8.9108	0.0	2.0	331.0
if active on 16th Oct	0.8468	0.36018	0.0	1.0	1.0
# of launches on 17th Oct	3.9985	8.1861	0.0	1.0	268.0
if active on 17th Oct	0.65995	0.47373	0.0	1.0	1.0
# of launches on 18th Oct	3.8049	7.867	0.0	1.0	178.0
if active on 18th Oct	0.64131	0.47962	0.0	1.0	1.0
# of launches on 19th Oct	3.6806	7.9095	0.0	1.0	224.0
if active on 19th Oct	0.63028	0.48273	0.0	1.0	1.0
# of launches on 20th Oct	5.7548	11.241	0.0	2.0	260.0
if active on 20th Oct	0.72732	0.44534	0.0	1.0	1.0
# of launches on 21th Oct	9.6561	18.076	0.0	3.0	972.0
if active on 21th Oct	0.77723	0.41611	0.0	1.0	1.0
# of launches on 22th Oct	7.8346	13.024	0.0	3.0	236.0
if active on 22th Oct	0.93766	0.24177	0.0	1.0	1.0
# of launches on 23th Oct	6.0456	9.0141	0.0	3.0	240.0
if active on 23th Oct	0.87551	0.33014	0.0	1.0	1.0
if active on 24th Oct before 12pm	0.49044	0.49991	0.0	0.0	1.0
# of videos posted in last 7 days	0.4815	3.3986	0.0	0.0	681.0
# of fans	1385.4	5.5318e+04	0.0	54.0	9.6287e+06
# of following	611.98	1047.0	0.0	159.0	5004.0
# of friends	278.4	644.79	0.0	22.0	4994.0
Y_i	4.309	2.1382	0.0	5.0	7.0
D_i	0.10223	0.30295	0.0	0.0	1.0
Z_i	0.50351	0.49999	0.0	1.0	1.0

Table 1: Summary of features of selected users in the experiment sub-sample.

2.3 Data Approval

The experiment was conducted by the author during his internship at Kuaishou. The data is desensitized and consented by Kuaishou to use for academic purposes.

3 Assessing Causal Effects

We focused on evaluating the treatment effect of making certain users more likely to be followed in a recommendation system on users' future engagement on the platform. Half of the users in the experiment were assigned to be boosted into second place as reco_users, the treatment of following actions were realized by target_users on the platform, and we observed the LT7 of users in the experiment.

We will discuss the methods to address the challenges we raised to estimate treatment effects, and the models to identify group of users who are more sensitive to the treatment.

3.1 Random Assignment

In the experiment, half of the users (group_exp) were randomly chosen to be boosted to second place on the list when they appear on friends recommendation interfaces of all users on the network as reco_users. The other half (group_base) did not receive any boost but appear on recommendation recommendation interface as usual. The assignment of the two groups was random, which means $Z_i \perp\!\!\!\perp X_i$.

3.2 Treatment and Compliance

After being assigned to the second place on reco_users list, the realization of treatment by touching the "follow" icon is purely up to the target_users. As the summary in Table 1 shows, approximately 20% of the assigned users got followed at least once in the group_exp, which means the existence of non-compliance. In group_base, as we only count follows that occurred on ranking-boosted reco_users, no one would be marked as "followed" ($D_i = 0, \forall i \in \{1, 2, ...N\} s.t. Z_i = 0$).

The treatments could vary among reco_users. First, two or more users in group_exp could appear on the same list in a friends recommendation interface. This rarely happen, as the users selected in our experiment only make up less than 0.5% of the whole user base of Kuaishou, but when this conflict happened, we randomly assigned those n users into the 2^{nd} to $(2 + n - 1)^{\text{th}}$ place on the list. Second, treatment could occur multiple times. Third, the target_users that perform the treatment (action to follow) could lead to different effects. Empirically, some users may react well when followed by someone they know, others may like to befriend strangers on social network. We decided to assume the occurrence of conflict placement and the difference in identities of target_users could be ignored, and we only recorded the difference in being treated (followed) or not.

3.3 Average Causal Effect (ACE)

Here we discuss our base estimand in an optimal condition where there is no non-compliance and confunding. Given X_i, Z_i, D_i, Y_i for each user U_i, we want to estimate the causal effects by considering their potential outcomes. Let Y_{i1} denotes U_i's potential outcome when $D_i = 1$ (be boosted), and Y_{i0} denotes U_i's potential outcome when $D_i = 0$ (not boosted), the causal effect of our ranking-boosting strategy on U_i is $Y_{i1} - Y_{i0}$.

In a randomized experiment with perfect compliance (all boosted reco_users are followed), we may estimate the average causal effect by using the difference of sample means [SVS+21] $A\hat{C}E = \mathbb{E}(Y_i|D_i = 1) - \mathbb{E}(Y_i|D_i = 0)$ as our base estimator. However, the existence of non-compliance in group_exp, propensity to follow and be followed, and confunding variables between Z_i and Y_i lead us to explore further assumptions and methods.

3.4 Instrumental Variable Framework

We use the instrumental variable framework [AIR96] to resolve the non-compliance. We use the random assignment Z_i as an instrument for the treatment D_i. We use D_{i1} to denote U_i's potential receipt of treatment if it's boosted, and D_{i0} to denote U_i's potential receipt of treatment if it's not boosted. As the experiment designed, $D_{i0} = 0, \forall U_i$ such that $Z_i = 0$, but when $Z_i = 1$, we have two types of users in group_exp: "Need-attention" ($Z_i = D_i = 1$), "Never-followed" ($Z_i = 1, D_i = 0$). Need-attention receive new followers when their rankings are boosted, Never-followed do not receive new followers even if they are given more exposure in friend recommendation interfaces.

Compliers (C) are all users in group_base and Need-attentions. We may estimate the Complier Average Causal Effect (CACE) as $\hat{CACE} = \mathbb{E}(Y_{i1} - Y_{i0}|i \in C)$. To apply the instrumental variable framework, several assumptions need to be stipulated.

- Monotonicity, that there is no "defiers" ($D_i = 1, Z_i = 0$). Our experiment measurement prevented the existence of this situation
- Instrumental conditions [HR06]:
  - Relevance, that there is a non-zero association between Z_i and D_i. We have $D_i = 0$ when $Z_i = 0$, and $D_i = f(Z_i, X_i, X_i')$, where X_I' are some features of U_i that we did not take into our experiment
  - Exclusive Restriction, that Z_i must only affect the outcome Y_i through the mediation of D_i. We argue that the assignment (boost to second place) would only increase the probability of being followed and thus affect LT7
  - The assignment Z_i does not share causes with outcome Y_i. As the assignment is random, we have $Z_i \perp\!\!\!\perp Y_i$
- Stable Unit Treatment Value Assumption (SUTVA) [Rub80]. This assumption is commonly required and made in experiment designs. In our study, it means that the assignment and treatment to U_i have no effect on the D_j, Z_j, Y_j of user U_j. In the experiment, conflict on reco_users list may mutually affect the probabilities of being followed; Boosting the users in group_exp may reduce the probabilities of other users being followed. As the scale of our experiment is small compared to the size of Kuaishou network, we argue that those potential violations could be negligible. If the ranking-boosting strategy were to be applied in a larger scale or integrated into recommendation algorithms, the effects of the conflicts in the list should be addressed.

Under those assumptions, we may estimate the CACE by the Instrumental Variable (IV) estimator:

$$\hat{CACE} = \frac{\mathbb{E}(Y_i|Z_i = 1) - \mathbb{E}(Y_i|Z_i = 0)}{\mathbb{E}(D_i|Z_i = 1) - \mathbb{E}(D_i|Z_i = 0)}$$

The numerator estimates the intent-to-treat (ITT) effect, and the denominator estimates the proportion of compliers. We X_i, the profile and behavioral information of U_i, provided, this IV estimator could be improved by adding X_i as covariates into the estimator (shown in Figure 2), written as $\hat{CACE} = \frac{\mathbb{E}(Y_i|Z_i=1,X_i)-\mathbb{E}(Y_i|Z_i=0,X_i)}{\mathbb{E}(D_i|Z_i=1,X_i)-\mathbb{E}(D_i|Z_i=0,X_i)}$. We used Ordinary Least Square (OLS) and 2-Stage Least Square (IV2SLS) to calculate the $\hat{CACE}$

4 Simulation Study

Apart from the experiment data, we synthesized a set of social network users as simulations to validate the IV framework estimates of causal effects. The simulated users follow the following assumptions and models:

- A set of m imaginary users are created, denoted as $\{V_1, V_2, ...V_m\}$
- For each user V_j, $L_{d,j}$ denotes the number of launches V_j made on day d. $L_{d,j}$ follows a Poisson distribution with parameter $\lambda_{d,j}$ times a multiplier $m_{d,j}$
- For each user V_j, $A_{d,j}$ denotes if V_j was active on day d. Notice that $A_{d,j} = 1$ if $L_{d,j} > 0$, $A_{d,j} = 0$ if $L_{d,j} = 0$
- Half of the users would be assumed to be assigned for boosting strategy, denoted as $Z_j = 1$ while the other half are not

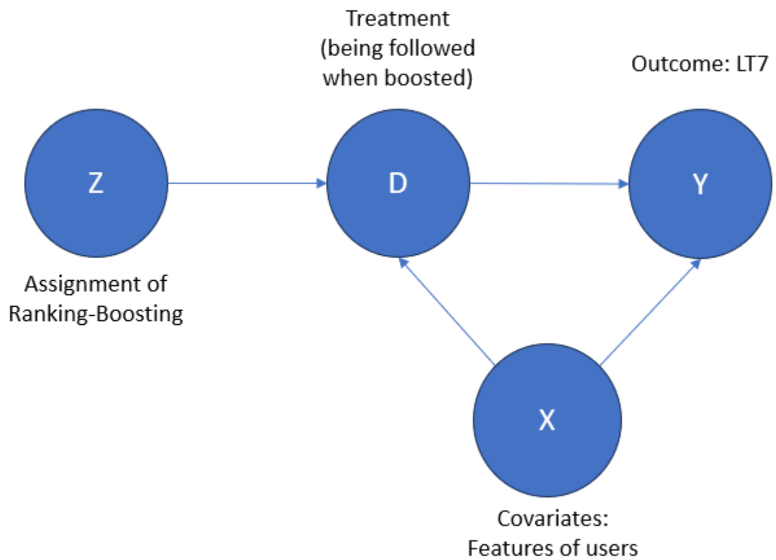

Figure 2: Structure of the Instrumental Variable Framework

- For V_j with $Z_j = 1$, whether it was treated (followed) is denoted as $D_j \in \{0, 1\}$. D_j is constructed as a transformation of linear combination of $L_{d,j}$ with the expected value $\mathbb{E}(D_j|L_{d,j}, Z_j = 1) = \eta_j$
- Y_j denotes the LT7 of V_j. It is constructed by 7 times a Beta distribution with mean equal to average activeness in previous D days ($\sum_D A_{d,j}/D$) plus a Gaussian noise $\epsilon_j \sim \mathcal{N}(0, \sigma_j)$ with mean zero and then round up to an integer.
- For V_j with $D_j = 1$, the elevation of Y_j is estimated by three scenarios:
  - Indifferent: V_j feels indifferent to the treatment. Mean effect on LT7 is $k_{indifferent}$.
  - Moderate: V_j feels moderately encouraged to the treatment. Mean effect on LT7 is $k_{moderate}$.
  - Happy: V_j feels quite happy to the treatment. Mean effect on LT7 is k_{happy}.

  We assigned probabilities ($p_{indifferent}, p_{moderate}, p_{happy}$) of how likely these 3 scenarios would happen. The Compliers Average Causal Effect would be the mean of ($p_{indifferent}k_{indifferent} + p_{moderate}k_{moderate} + p_{happy}k_{happy}$) among users with $D_j = 1$.

We simulated 10000 users with expected CATE=1.2 and standard deviation 0.56 (($p_{indifferent} = 0.2, k_{indifferent} = 0, p_{moderate} = 0.4, k_{moderate} = 1, p_{happy} = 0.4, k_{happy} = 2$)). Applying the IV framework estimator, we got $\hat{CACE} = 0.93$ with standard deviation 0.17. The estimation is quite close and reasonable. Notice that the LT7 (Y_j) can not exceed 7 by design, so that the effect of a moderate or happy scenario would be reduced if the user is already quite active (with $Y_j = 6$ or 7). The results from simulation study validate our application on the Kuaishou experiment data.

5 Results

In our sampled data from the experiment, there are 96893 unique Kuaihsou users, of which 48787 were assigned ranking-boosting strategy ($Z_i = 1$) while 48106 were not. In the assigned users, 9905 users were followed at least once in their respective ranking-boosted friend recommendation interfaces. Average LT7 among those with $Z_i = 1$ is 4.33 days, with $Z_i = 0$ is 4.28 days, with $D_i = 1$ is 4.36 days.

Using Instrumental Variable estimator without covariates, we estimated the Intend-To-Treat effect as 0.05 days (s.e. 0.01), and Compliers Average Causal Effect as 0.25 days (s.e. 0.07).

Adjusting the estimator by X_i with users' profile and behavior information as covariates, our adjusted causal effects of ranking-boosting strategy on users activeness in terms of LT7 are:

$$\hat{ITT} = 0.06(s.e.0.01)days \tag{1}$$

$$\hat{CACE} = 0.29(s.e.0.06)days \tag{2}$$

To perform the analysis, the two-stage least squares implementation (IV2SLS) from the package statsmodels in Python was used. Source code from paper [SVS+21] was adapted to facilitate programming.

6 Causal Forest

To better assess the causal effects in subgroups of users, a causal forest [ATW19] was fitted. A tree visualization of major node splitting is shown in Figure 3. We may interpret that users with less friends and lower degree of activeness in previous days would react stronger given higher probabilities of being followed on friends recommendation interfaces. The gain of applying ranking-boosting to users who are already quite active and have relatively large amount of friends may be negligible or even negative.

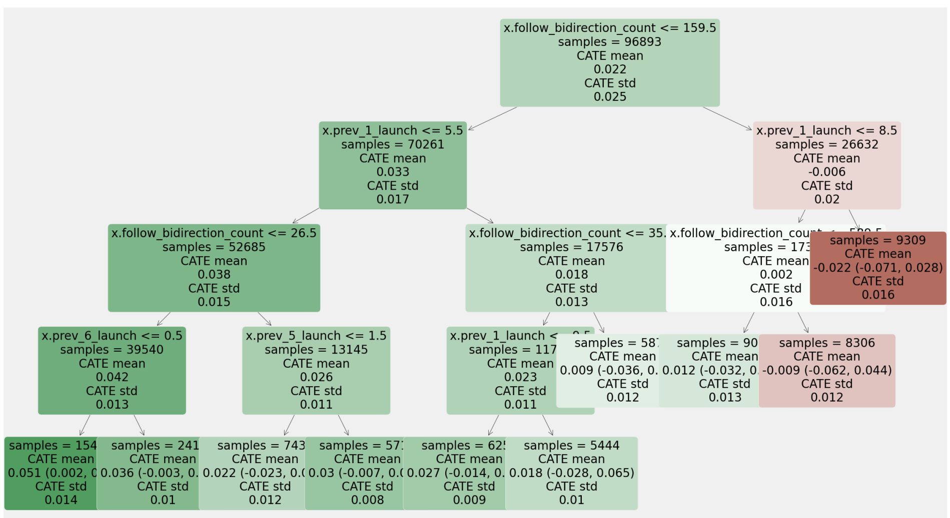

Figure 3: A tree interpreter for the Conditional Average Treatment Effects (CATE) estimated by the causal forest model.

CausalForestDML model from econml package [BDH+19] in Python was used to model causal forest.

7 Conclusion and Discussion

User relationship (friends) recommendation plays an important role in user engagement and retention on online social network. Typically, a user may actively or passively trigger a request for friend recommendation, which will present several users on the platform that they may be interested in following. Efforts have been made to perfect the design and the algorithm to better user experience (more accurate recommendation, more appealing UI, etc.) to make them keep being active on the platform. Our research thinks differently. We used Kuaishou as example to conduct experiment analyzing the causal effect of applying ranking-boosting strategy for reco_users which increases the probabilities of them having new followers on their near future activeness on the platform. We estimated an intent-to-treat effect of 0.06 days and 0.29 days compliers average causal effect on LT7 metrics. We also identified users with relatively less friends and active frequency would response more significant to having new followers.

Our work may serve as a benchmark on refining friends recommendation models. While previous work usually focused on how the recommendation contents affect the target_users, we demonstrated a positive effect of friends recommendation on reco_users. Such positive gain on users activeness may be transferred into longer time spent on the apps, more engagement with friends and videos, and economic values.

We also realized the room for further studies in our work. In the experiment, ranking-boosting could be designed more robustly and assessed by more detailed metric instead of a binary indicator. The ignored conflicts in reco_users placement could be analyzed quantitatively, which should be taken care of if similar strategies are being applied on a larger scale on the network. More features of the users, such a video-viewing patterns, number of messages sent to friends, shared locations or interests between target_users and reco_users in an interface, could be added to better represent the covariates in the models and estimate what users tend to convert assignment into treatment.

A Summary of Simulation Data

	mean	standard deviation	min	median	max
prev_9_launch	5.9187	4.2498	0.0	6.0	27.0
prev_9_act	0.8611	0.34586	0.0	1.0	1.0
prev_8_launch	5.9685	4.2414	0.0	6.0	27.0
prev_8_act	0.865	0.34174	0.0	1.0	1.0
prev_7_launch	5.9979	4.2308	0.0	6.0	30.0
prev_7_act	0.8614	0.34555	0.0	1.0	1.0
prev_6_launch	3.0438	3.056	0.0	3.0	21.0
prev_6_act	0.6337	0.48182	0.0	1.0	1.0
prev_5_launch	3.0243	3.0173	0.0	3.0	21.0
prev_5_act	0.6333	0.48193	0.0	1.0	1.0
prev_4_launch	3.0009	3.0006	0.0	3.0	21.0
prev_4_act	0.6317	0.48237	0.0	1.0	1.0
prev_3_launch	3.0393	3.0084	0.0	3.0	18.0
prev_3_act	0.6357	0.48126	0.0	1.0	1.0
prev_2_launch	6.0843	4.2553	0.0	6.0	27.0
prev_2_act	0.8708	0.33544	0.0	1.0	1.0
prev_1_launch	5.9652	4.271	0.0	6.0	33.0
prev_1_act	0.8606	0.34638	0.0	1.0	1.0
assigned	0.4952	0.5	0.0	0.0	1.0
is_follow	0.127	0.33299	0.0	0.0	1.0
LT7	3.1501	2.1686	0.0	3.0	7.0

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