Graph Representation Learning for Merchant Incentive Optimization in Mobile Payment Marketing

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ABSTRACT

Mobile payment such as Alipay has been widely used in our daily lives. To further promote the mobile payment activities, it is important to run marketing campaigns under a limited budget by providing incentives such as coupons, commissions to merchants. As a result, incentive optimization is the key to maximizing the commercial objective of the marketing campaign. With the analysis of online experiments, we found that the transaction network can subtly describe the similarity of merchants’ responses to different incentives, which is of great use in the incentive optimization problem. In this paper, we present a graph representation learning method atop of transaction networks for merchant incentive optimization in mobile payment marketing. With limited samples collected from online experiments, our end-to-end method first learns merchant representations based on an attributed transaction networks, then effectively models the correlations between the commercial objectives each merchant may achieve and the incentives under varying treatments. Thus we are able to model the sensitivity to incentive for each merchant, and spend the most budgets on those merchants that show strong sensitivities in the marketing campaign. Extensive offline and online experimental results at Alipay demonstrate the effectiveness of our proposed approach.

CCS CONCEPTS

• Computing methodologies → Neural networks; • Applied computing → Marketing;

KEYWORDS
incentive optimization; mobile payment marketing; graph representation learning

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1 INTRODUCTION

In recent years, mobile payment services (e.g., Alipay Pay1 operated by Ant Financial, or Apple Pay2 operated by Apple, etc.) have been playing much more important roles in users’ daily lives. One major commercial goal of these mobile payment operators is to attract more merchants and customers to engage in their mobile payment services, instead of using traditional payment services.

To encourage certain mobile payment activities, the operators of the payment services would need to launch effective marketing campaigns. One way of promoting the payment activities is to offer the merchants with some kinds of incentives, e.g., commissions, coupons, value-added services and so on, when the merchants can attract customers to pay through the specific payment services.

Taking the above mobile payment marketing as a concrete example at Alipay, each merchant of Alipay is assigned with a unique

1 https://en.wikipedia.org/wiki/Alipay
2 https://en.wikipedia.org/wiki/Apple_Pay

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incentive QR Code\textsuperscript{3} and is encouraged to ask their customers to scan, so as to share the incentives to the customers. The customers can redeem the shared incentives, similar to any other credit card points, only by making a proper payment through Alipay. At the same time, each successful redemption made by the customer can award an equivalent amount of incentives as commissions to the merchant who shares the incentive. With the incentives propagated and redeemed under such a mechanism (i.e. incentives first be shared from merchants to customers, then be redeemed through a proper payment), the more proper payments customers can accomplish, the more commissions merchants can gain. We illustrate the marketing campaign in Figure 1.

The amount of commissions assigned to merchants are simply rule-based in traditional marketing strategies \textsuperscript{4}. However, in practice different merchants could respond differently in a marketing campaign. For instance, for merchants with limited enthusiasms or abilities, the number of payments they can attract may remain unchanged no matter what amount of commissions they get, while others may show strong positive correlations between the commissions they acquired and the number of payments they can attract. That is, the merchants’ sensitivities to the incentives could vary a lot. On the other hand, the budget of a marketing campaign is always limited. Therefore, in order to maximize the commercial objective of a payment marketing campaign under a limited budget, incentive optimization is the key to success. To summarize, the operators should be able to target the merchants who show strong positive correlations between incentives (e.g. commissions) and objectives (e.g. the number of payments), and spend more budgets on those sensitive merchants.

However, modeling the correlations between incentives and objectives for each merchant is non-trivial. The effect of the treatment\textsuperscript{5} on each merchant should be observed in a long term because in practice each merchant could only be aware of the treatment based on an accumulation of incentives in a long enough period. Due to the limited budgets, what we can do is to conduct “treatment-limited” online experiments by assigning a fixed treatment (say 1 Chinese Yuan randomly sampled from a set of limited treatments \{1, 2, 5, 10, 20\}) to each merchant, and to observe the objectives (say the number of payments) the merchant can attract after then. That is, it is infeasible to collect the whole objective-incentive curve empirically for any specific merchant (i.e. all the objectives one merchant can achieve under all the treatments \{1, 2, 5, 10, 20\}). As such, we summarize the following two challenges. First, we require a representation learning method that can help embed merchants with similar “sensitivities to the incentives” to the similar representations in the vector space, thus can help collect statistical significant data for estimating the objective-incentive curve for a group of similar merchants. Second, the objective-incentive curve of each merchant we need to estimate could be arbitrarily complex in well-defined function spaces \[9, 15\]. The variance of the estimation could be large if we do not place any reasonable priors on our model.

In this paper, we present a graph representation learning approach to incentive optimization of merchants in the payment marketing scenario. First, based on the intuition that the customers who interacted with are strong signals to indicate whether a merchant has high potentials to promote the desired payments or not, we analyze the sensitivities of merchants located in different regions in section 3.2.1. This motivates us to characterize each merchant by considering the distribution of customers who made payments with the merchant, thus resort to a variant of classic graph representation learning approach. Second, we analyze the objective-incentive curves using random samples from real data, and show that the curve should lie in linear, monotonic function spaces. That is, if we let the number of transactions be the commercial objective, the number of transactions should increase linearly with the incentives. Extensive experiments on real data show that our approach is effective. Finally, we formalize the final decision making process under certain budget (assign the optimal amount of incentive to each merchant) as a linear programming problem, and show our online experimental results at Alipay.

2 BACKGROUND

In this section, we briefly discuss related literatures to our problems. Basically, we would first talk about related problems such as price optimization, and then review the literatures related to graph representation learning approaches that forms the basis of our approach.

2.1 Price Optimization

Basically, price optimization uses data analysis techniques to address two problems. (1) Understanding how customers will react to different pricing strategies for products and services. (2) Finding the best prices for a given company, considering its commercial goals. Price optimization techniques can help retailers evaluate the potential impact of sales promotions or estimate the right price for each product if they want to sell it in a certain period of time.

Basically, the approaches to price optimization consist of two stages. (1) Utilizing machine learning techniques to estimate sales quantity of products \[10\], sale probabilities from partially observable market data \[13\], or historical lost sales and predict future demand of new products \[5\]. (2) With those estimates, one can formalize optimization problems for the commercial goals to get the optimal strategies.

Similar to price optimization, mobile payment services play the similar roles as retailers, and aim to promote their products, i.e. specific payments in our cases. Most of existing works exploit linear models to estimate the sales \[6, 10\]. In our setting we are required to estimate the sensitivities to different treatments for a huge number of merchants with limited samples, which have few related works to our best of knowledge. We contribute a brand new model for estimating the sensitivities of each merchant (product).

\textsuperscript{3}Check https://intl.alipay.com/doc/redpacket/ctmz6b for more details. The incentive in this campaign is in the form of operation commissions. The merchant can earn an operation commission from each customer’s redemption of the Alipay Red Packet QR Code (a specific form of incentive QR Code).

\textsuperscript{4}We define one treatment in our case as a choice of a certain amount of incentive selected from a set of candidates. For example, award “1 Chinese Yuan for every proper payment the merchant has attracted” is a treatment in case we have a set of candidates, say \{1, 2, 5, 10, 20\} in Chinese Yuan.
2.2 Graph Representation Learning

In this section, we review the literatures related to graph representation learning [8], especially graph neural networks approaches that aim to encode the patterns of nodes’ subgraphs as latent features.

Assuming an undirected graph \( G = (V, E) \) with \( N \) nodes \( i \in V \), \(|E| \) edges \((i, j) \in E\), the sparse adjacency matrix \( A \in \mathbb{R}^{N \times N} \), a matrix of node features \( X \in \mathbb{R}^{N \times P} \), and graph Laplacian operator \( L = I - D^{-1/2} A D^{-1/2} \) [3]. The approaches aim to learn to aggregate a subgraph of neighbors associated with each target node. For instance, Hamilton et al. [7] proposed GraphSAGE, that defines a set of aggregator functions in the following framework:

\[
H_{t+1}^i = \sigma \left( \text{CONCAT} \left( \phi(A, H^t), H^t \right) W^t \right),
\]

where \( H_0^i = X \), \( W^t \) is the layer-specific parameters, \( \sigma \) denotes the activation function, and \( \phi(\cdot) \) is a pre-defined aggregator function over the graph, that could be mean, max pooling operators. By stacking the graph aggregation layers \( T \) times, each node can aggregate signals from its neighbors to \( T \) hops.

To alleviate the limited representation capacity by doing aggregation only on “pre-defined” subgraphs [12], Veličković et al. [16] proposed attention based mechanisms to parameterize the aggregator functions. Liu et al. [12] propose an adaptive path layer to further adaptively filter the receptive field of each node while doing aggregation on the subgraphs. Such methods have proven to achieve state-of-the-art results on several public datasets. For users who are interested in the detailed literatures please follow the comprehensive surveys [17].

In our scenario, we exploit graph neural networks to embed each merchant by their customers who made payments in the transaction networks. Such encoding can help describe the characteristics of customers each merchant makes transactions with, so as to evaluate the ability a merchant may possess, and to describe the similarity of merchants’ responses to different incentives. Intuitively, merchants that have diverse customers could possibly have much stronger abilities to attract more customers compared with merchants that have limited customers. Two merchants physically located in the same region should share similar customers, thus they may have similar enthusiasms to share the incentives. Such patterns can be well modeled based on the graph learning approaches atop of the transaction network discussed later.

3 OUR METHODOLOGY

In this section, we first introduce our online experiments to collect samples. After then, we present a variant of graph neural networks for incentive optimization. Finally, we formalize the optimal strategy of treatments as a linear programming problem, based on the estimates of merchants’ personalized objective-incentive curve (or say sensitivities to the marketing campaign), in a limited budget online setting.

3.1 Online Experiments and Analyses

We aim to target those merchants who are able to boost the future commercial objectives (e.g. the number of transactions using Alipay in our case) as the operators stimulate greater incentives. That is, we need to discern merchants with different sensitivities to the incentives. To obtain the sensitivities of each merchant to the marketing campaign, we need to estimate the so-called objective-incentive curve of each merchant. The curve describes the mapping between incentives under different treatments and the commercial objectives that a merchant can achieve after receiving the treatment. Accurate estimations of the curves can help operators to make decisions by choosing the best strategies.

We choose to launch online experiments by randomly choosing a certain treatment for each merchant in the online environment at Alipay, and observe the commercial objectives each merchant can achieve. The online experiment involves millions of merchants and lasts for several days. The possible treatment is sampled from a set of incentives in Chinese Yuan. Hence, we can assume that the merchants who show similar sensitivities should be uniformly sampled over all the treatments.

However, we can only observe one merchant’s future objective under one treatment, while we are aiming to estimate the whole objective-incentive curve of each merchant. That means we need to represent merchants with similar capacities and enthusiasms similarly, and have to place appropriate priors to constrain the functions estimating the curve.

First, the abilities of propagating incentives and attracting proper payments can be naturally described through the distribution of customers with which the merchants are interacting. For example, merchants that have transactions with diverse customers are more competitive compared with merchants who have limited customers. Merchants make transactions with the same group of customers could possibly be located together, hence their enthusiasms of marketing the payment services may be similar. To illustrate the relations between locations and sensitivities of merchants, we group the merchants according to regions, and calculate the “sensitivities of regions” denoted by \( \text{AP}(3.0, c)/\text{AP}(0.6, c) \), where \( \text{AP}(t, c) \) means the number of payments averaged over all merchants from region \( c \) with commission \( t \). We plot the “sensitivities of regions” in figure 2.
In this section, we present our models for incentive optimization based on the samples observed from our online experiments. Estimating the objective-incentive curve for each merchant is non-trivial because this requires a huge number of samples. We propose two methods to alleviate the potential high variance in estimation. First, we resort to graph neural network based methods, and hopefully can embed merchants with similar characteristics to similar embeddings in the vector spaces, thus results into statistical significant amount of observations with various treatment for a group of similar merchants. Second, we propose a monotonic linear transformation to map the graph embeddings learned for each merchant to the final objective-incentive curve. Our end-to-end model jointly optimizes the graph neural networks and the monotonic linear transformation.

### 3.2 Models

#### 3.2.1 Merchant Embedding based on Graph Neural Networks

In this part, we introduce how to embed merchants based on transaction graphs. As we discussed above in section 3.1, the merchants’ distribution of customers could be represented from different dimensions, e.g., the location, the diversity of customers, and so on. Therefore, we build a graph based on payments to connect merchants and customers.

Assuming an undirected graph $G = (V, E)$ with $N$ nodes $i \in V$, $|E|$ edges $(i, j) \in E$. Each node could be a merchant, a customer, or plays both roles. Node $i$ has a neighbor $j$ (i.e. there exists an edge $(i, j)$) if there exists a proper payment where $j$ acts as customer and $i$ as merchant in the past several days. We assume the equivalent adjacent matrix $A \in \{0, 1\}^{N \times N}$ of graph $G$, where $A_{i,j} = 1$ means there is an edge $(i, j)$ existed in graph $G$. Assuming $X \in \mathbb{R}^{N \times P}$ as the nodes’ features in $P$ dimensions. Assuming $Z \in \mathbb{R}^{|E| \times D}$ denotes the $D$-dimensional features, describing the payment related informations through the edges. We have the following graph neural network layers to iterate $T$ times (thus propagate neighbors’ signals in $T$ hops), and have the output encoding for node $i$ as $h_i^T \in \mathbb{R}^K$:

$$h_i^{(t+1)} = \sigma \left( W^{(t)}^T \phi \left( \{ h_j^{(t)} \mid j \in N(i) \cup \partial i \} ; \theta \right) \right),$$

where $h_i^{(t)} \in \mathbb{R}^K$ denotes node $i$’s intermediate embedding at the $t$-th hidden layer, $\sigma$ denotes the activation functions, and $\phi(\cdot)$ is the aggregator function parameterized by $\theta$ as defined in [12];

![Figure 3: The architecture of our graph neural networks with monotonic linear mapping (MLM) in the output layer.](image)

![Figure 4: Commercial objectives vary with treatments (each point denotes the average of # payments (y-axis) over merchants under a given treatment (x-axis)).](image)
\[ h_1^{(0)} = W_x^T X_i + \sum_{j \in N(i)} W_e^T Z_{(i,j)}, W^{(i)} \in \mathbb{R}^{K \times K}, W_x^{(i)} \in \mathbb{R}^{P \times K}, \]

and \( W_x^{(i)} \in \mathbb{R}^{D \times K} \) are the parameters. Note that for each merchant our graph neural networks not only capture the distribution over neighbors (i.e., distribution of merchants’ customers), but also the distribution over edges (i.e., the distribution of payments between the merchant and its customers).

### 3.2.2 Monotonic Linear Mapping

Given the embedding of each merchant based on graph neural networks convolved on the transaction networks, we are able to model the objective-incentive curves. Based on the analyses in section 3.1, we have the following mapping:

\[
 f(i, c) = c \cdot \text{SOFTPLUS}(W_g^T h_i^{(T)}) + \text{RELU}(W_p^T h_i^{(T)}) \tag{3}
\]

where \( f(i, c) \) is the estimation of the future objective of merchant \( i \) under treatment \( c \), and \( W_g \in \mathbb{R}^K \) and \( W_p \in \mathbb{R}^K \) are parameters to transform the merchant embeddings to gradient (slope) and intercept. The activation function \( \text{SOFTPLUS}(\cdot) \) is used to guarantee the monotonic linear mapping between treatment \( c \) and objective \( f(i, c) \).

Note that the inferred gradient \( g_i \) of each merchant \( i \) in our model can be used to measure the sensitivity to incentive of merchant \( i \). A small value of \( g_i \) indicates that \( i \) is less sensitive to the marketing, while a greater value of \( g_i \) indicates the opposite.

To summarize, we have the following objective to optimize:

\[
 \arg \min_\beta \sum_{i,c} \ell(f(i, c; \beta), y_{i,c}) \tag{4}
\]

where \( \ell(\cdot) \) denotes the mean absolute error, and \( y_{i,c} \) denotes the observed commercial objective of merchant \( i \) under treatment \( c \). We aim to optimize parameters \( \beta = \{W, W_x, W_e, W, \theta, W_g, W_p\} \) in an end-to-end model. We illustrate the architecture of our model in Figure 3. In practice we use the ADAM [11] to optimize the above objective in a stochastic mini-batch manner, and the model is implemented with tensorflow [1].

### 3.3 Optimal Incentive as Linear Programming

As other price optimization problems, in this section, we show how we formalize incentive optimization as a linear programming problem given the estimates of \( f(i, c) \).

In the online environment, we need to choose the best treatment for every merchant. Since the estimates of each merchant’s “gradient” is positive due to the SOFTPLUS(·) activation function, the best strategy is always choosing the maximum treatment for all the merchants, so that we can maximize the commercial objective. However, under a limited budget, the strategy should consider the value of inferred gradient. Let us denote the best strategy \( a^*(\cdot) \) for merchant \( i \) is treatment \( k \), then we have \( a^*(i, c = k) = 1 \) and \( a^*(i, c = k^-) = 0 \) for the rest strategies. We formalize the following optimization problem:

\[
 \max \sum_{i,c} f(i, c)a^*(i, c), \tag{5}
\]

such that \( \sum_{i,c} a^*(i, c) \cdot c \leq B, \tag{6} \)

then we have the optimal solution \( k = \arg \max_c f(i, c) - c \cdot \lambda \) for each \( i \), where \( \lambda \) denotes the dual optimal.

We test our strategies in the online environment at Alipay, and show the online results in section 4.4.

### 4 EXPERIMENTAL RESULTS

In this section, we conduct extensive empirical experiments to study the performance of our models. We first analyze the offline results based on the dataset collected in our online experiments. Next, we show the online results after deploying our approach at Alipay compared with a multi-layer perceptron neural network model, using the same optimal strategy as described in section 3.3.

Note that due to the policy of information sensitivity at Alipay, we will not reveal the detailed numbers that could be sensitive.

#### 4.1 Experimental Settings

In this section, we will introduce our dataset for learning the model, and related experimental settings.

##### 4.1.1 Dataset

Our two experimental datasets are collected from our online experiments (mentioned in section 3.1) launched at Alipay in two separated time periods (15 consecutive days of each), respectively. To collect each of the experimental datasets, 0.2% of random selected merchants were assigned to an experimental bucket that places a fixed treatment. We set up a total of 13 experimental buckets for observing merchants with different treatments. That is, each bucket corresponds to a distinct treatment in the online experiments, and is responsible for providing the merchants under control a fixed amount of commissions. Thus, we can assume that the merchants with different sensitivities to the marketing campaign are randomly sampled in different buckets with different treatments.

There are more than 2 millions of labeled merchants with observed commercial objects (labels or measures include: the number of payments the merchant can accomplish in the next 3 days, the number of days the merchant have payments in next 3 days) under given treatments. We aim to regress over the commercial objectives of each merchant. We build our model on top of the transaction network. The edges of the transaction network consist of the transactions associated with those labeled merchants in 2-hops. That is, the transactions made between the labeled merchants and customers directly, and all the transactions made by those customers.

### Table 1: Experimental Dataset summary.

| Dataset     | \( ||V|| \)     | \( ||E|| \)     | # Node feature dim | # Edge feature dim | # Labeled merchants |
|-------------|-----------------|-----------------|--------------------|--------------------|---------------------|
| Dataset 1   | 90.08 \times 10^6 | 161.7 \times 10^5 | 4998               | 86                 | 2.18 \times 10^6    |
| Dataset 2   | 97.18 \times 10^6 | 172.1 \times 10^5 | 4998               | 86                 | 2.31 \times 10^6    |
We conduct experiments on the real-world dataset collected from online experiments run by Alipay as described above. To evaluate the performance of the models, we choose MAE (Mean Absolute Error) and MSE (Mean Square Error) as our metrics, which are commonly used for evaluating regression methods. Even though such metrics cannot directly measure how well our approach can fit the sensitivities of each merchant, they still reflect how well the models fit our observed measures of each merchant under specific treatments.

As shown in Table 2, DNN model outperforms Linear Regression in terms of MAE, however is doing worse on MSE. This shows that DNN model is more robust due to the final monotonic linear mapping layer (i.e. successfully reduce the risk of high variance), but may mislead the characteristics of different merchants due to the limited representation learning capacity (i.e. cannot well captured merchants with subtle differences). Our GE model produces much better estimates compared with all the other comparison approaches in terms of both MAE and MSE, which implies that graph representation indeed help the representations of merchants and simultaneously depict the merchant’s reactions to treatments.

### 4.3 Objective-Incentive Curves Analyses

In this section, we analyze the estimates of so called “gradient” defined in Eq. (3). ”Gradient” can be used to depict how the merchant is sensitive to the marketing campaign, and describe the objective-incentive curve. An accurate estimation of “gradient” of each merchant is exactly our goal.

Different from the quantitative results reported in section 4.2, the estimated “gradient” of each merchant is hard to evaluate directly. However, a reasonable assumption is that if a model is well estimated, the group of merchants with larger estimated “gradient” should be able to achieve much better results on expectation in terms of commercial objectives, compared with those merchants with smaller estimated “gradient”, while all the merchants are under the same treatment of strong incentives.

We denote $y_h$ as merchants’ commercial objective under a treatment with a larger amount of incentives, and $y_I$ as that under a treatment with a lower amount of incentives. We denote the uplift gain as $u = y_h - y_I$. The uplift gain for the merchants who are sensitive to incentives (i.e. with greater “gradient”) should be comparatively greater than that for less sensitive merchants (i.e. with smaller “gradient”).

To conduct the experiments, we first infer the “gradient” for each merchant in the test data. By sorting the merchants by “gradient” in descending order, we can separate the merchants into two groups, the incentive sensitive group and incentive insensitive group, denoted as $\Omega_+$ and $\Omega_-$ respectively. To evaluate an incentive optimization model, we need to inspect if the $\Omega_+$ and $\Omega_-$ are separated properly.

For the incentive sensitive group of merchants $\Omega_+$, we calculate the corresponding uplift gain as $u_+ = y_{h+} - y_{l+}$, where $y_{h+}$ and $y_{l+}$ denote the commercial goals of merchants under treatment of high

### Table 2: MAE of Linear Regression with our proposed method

| Dataset 1 | MAE     | MSE     |
|-----------|---------|---------|
| LR        | 0.1432  | 0.0415  |
| DNN       | 0.1404  | 0.0433  |
| GE        | 0.1357  | 0.0400  |

| Dataset 2 | MAE     | MSE     |
|-----------|---------|---------|
| LR        | 0.1441  | 0.0417  |
| DNN       | 0.1409  | 0.0441  |
| GE        | 0.1361  | 0.0408  |
and low incentives respectively. Similarly we have \( u_- \) as the uplift gain obtained from insensitive group of merchants. The greater the difference of the uplift gains \( u_+ - u_- \) is, the better the model should be. We illustrate the values of \( u_+ \) and \( u_- \) inferred from both DNN and GE models in Fig. 5. We show the value of \( u_+ \) using brown bars, and the value of \( u_- \) with blue bars. The gap between two bars of GE model is significantly greater than that of dnn model, which implies that the GE model has learned better merchants’ sensitivity to incentives.

Note that the linear regression model cannot produce personalized “gradient”, and we will not report the results accordingly.

For DNN and GE model, we sort the merchants in test data by the inferred “gradient” in descending order, and separate the merchants into five groups equally. We show the uplift gain of each group in Table 3. For the most sensitive merchants, GE model produces a better uplift gain compared with the DNN model. For the least sensitive 20% merchants, uplift gain produced by GE model is relatively smaller compared with the DNN model, which implies that GE model inferred a relative flat objective-incentive curve for those insensitive merchants.

### 4.4 Online Results

We deployed our model in the mobile payment marketing scenario at Alipay with a standard A/B testing configuration. We conduct our A/B testing experiments beginning with a relatively small traffic, i.e. influencing 1% of merchants, and observe the measures in consecutive 5 days. After that, we gradually increase the traffic from 1%, to 2.5%, 5%, 15%, and observe the measure in 5 days respectively. Finally, we conduct the A/B experiments with traffic 30% from January 10th to January 14th, and make the final decision on deploying the model at Alipay. The online results lasting nearly one month consistently show that our GE model outperforms the comparison model while we were increasing the traffic.

There exists millions of users who visit our App during the period while we were conducting A/B experiments with 30% traffic. In addition to the cost of the marketing campaign, two commercial objectives (Objective 1: the number of payments averaged over merchants, Objective 2: the number of days having at least one payments averaged over merchants) are shown as metrics in our experiments. Table 4 shows the relative improvements of GE model compared to the DNN model using 30% of traffic. Along with the relative improvements, we also show the confidence intervals with 95% confidence level. Compared with the DNN model, our proposed approach significantly saved 2.71% cost while improving the two commercial objectives statistical significantly (with p-value far less than 0.05).

Figure 6 shows the trends of relative improvements on the two commercial goals by applying the strategies optimized using our approach. The figure tells that our approach has been gradually improving the overall commercial goals given our optimal strategies. This is because each merchant is aware of the treatment after they have observed an accumulation of operation commissions.

### 5 CONCLUSIONS

In this paper, we show our best experiences in the mobile payment marketing problem at Alipay. To our best knowledge, this is
the first graph neural network based marketing experience shared by industry and has been deployed on the real-world large scale marketing system. To promote the mobile payment activities, we propose to identify merchants that are sensitive to the marketing campaigns based on a graph representation learning approach over transaction networks. We further place a monotonic linear mapping function to reduce the potential high variance due to limited samples of treatments. We develop uplift gains as a novel metric to measure the goodness of our model, that saves the cost of deploying and observing non-effective models online. Our online results in a standard A/B testing configuration lasting nearly a month shows that our approach is effective.

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