ABSTRACT
Randomized experimentation (also known as A/B testing or bucket testing) is very commonly used in the internet industry to measure the effect of a new treatment. Often, the decision on the basis of such A/B testing is to ramp the treatment variant that did best for the entire population. However, the effect of any given treatment varies across experimental units, and choosing a single variant to ramp to the whole population can be quite suboptimal. In this work, we propose a method which automatically identifies the collection of cohorts exhibiting heterogeneous treatment effect (using causal trees). We then use stochastic optimization to identify the optimal treatment variant in each cohort.

We use two real-life examples — one related to serving notifications and the other related to modulating ads density on feed. In both examples, using offline simulation and online experimentation, we demonstrate the benefits of our approach. At the time of writing this paper, the method described has been deployed on the LinkedIn Ads and Notifications system.

KEYWORDS
Heterogeneous causal effects, Stochastic optimization, Personalization, Online decision parameter

1 INTRODUCTION
In large-scale social media platforms, the member experience is often controlled by certain parameters in conjunction with machine-learned models. Such parameters could be independent of the machine-learned models, for instance, the background color and font of the platform. Alternately, they could be key decision parameters that operate on the output of machine-learned models to determine the overall member experience.

An example is the decision to send or drop a notification depending on a threshold parameter, which is used directly on the output of a machine learning model. If the score of the notification obtained from a machine-learned model is greater than the threshold, we decide to send the notification otherwise we drop it [10]. The machine learning model controls the relevance of the item, while the threshold controls certain business metrics. An argument for not having a global threshold is to prevent a member who has many high-scoring notifications from getting too many and to have another member who has no high-scoring ones to still get some in special scenarios (e.g., a new member).

A second example of such an influential parameter is the gap between successive ads on a newsfeed product. The parameter in question, which operates independently of the related machine learning models, specifies the number of organic updates that are shown between two successive ads. The machine learning models control the ranking of both the ads and organic updates.

In an ideal situation, we would often want such parameters to be fully personalized. However, in order to do so, we would need randomized data across the different choices of parameters for each individual. But that is an extremely challenging problem since many members may not visit frequently enough for us to collect such data, and even for the members who do, such expansive data collection could severely compromise the member experience for too many members. A potential solution is to fix a global parameter (e.g., ads gap or notification threshold) for all members and then iterate on the choice of this parameter through A/B testing. However, that may very well be a suboptimal solution. There can be a potential group of users, for whom if we had chosen a different parameter, we could have had an improved overall objective. More formally, estimating the heterogeneous causal effects from a randomized experiment [14, 26] is critical in providing a more personalized experience to the member and maximizing business objectives.

In this paper, we describe a formal mechanism which allows us to use randomized experiment data, identify a set of heterogeneous cohorts of members and apply an optimized parameter for
each such cohort to maximize one business metric while satisfying constraints on others. Throughout this paper, we assume that we have the ability to run randomized experiments on members with different values of the parameter in question, and capture the member related actions (i.e., business metrics) such as clicks, comments, views, scrolls, etc. This assumption is very reasonable since such randomized experiments would be conducted regardless to identify the globally optimal value. Once we have the data, we use the recursive partitioning technique [5] to generate the heterogeneous cohorts along with an estimate of the causal effect for each cohort. Then we solve the optimization problem based on the cohort definition using a modified version of the algorithm from [15] to generate the optimal parameter value for each cohort group.

We show the benefit of our proposed approach on two different applications at LinkedIn. The first problem is estimating the threshold for notifications sent from LinkedIn, and the second one is determining the minimum gap for ads in the LinkedIn feed. For an overview of these problems, please see [4, 10, 16]. Note that our procedure is general and can be applied to any similar problem. Through relevant offline simulations and online A/B testing experiments, we show that our solution performs significantly better than estimating one global parameter for both of these examples.

The rest of the paper is organized as follows. In Section 2, we describe the generic problem formulation while focusing on LinkedIn Notifications and Ads system. We then describe our overall methodology in Section 3. After describing the data generation mechanism in Section 4, we briefly describe the engineering architecture required to solve the problem in production in Section 5. Offline and online experimental results are discussed in Section 6, followed by some of the related works in Section 7. We finally conclude with a discussion in Section 8.

2 PROBLEM SETUP

It is well known that individual member behavior can be distinctly different even when the same treatment or intervention is applied [5]. Hence, member-level personalization is a crucial problem in any web-facing company. It has become a standard practice for web-facing companies to estimate causal effects in order to evaluate new features and guide product development [14, 25, 28].

There are two major challenges in using randomized experiments to fully personalize product development. First, it may not be possible to obtain large amounts of data on every single individual, without compromising the member experience of the entire population by a huge amount. Such a compromise is generally deemed unacceptable and for good reason. Secondly, the lack of sufficient data leads to a large variance in any member-level personalization model. Thus, instead of going towards member-level personalization, we frame the problem of personalizing (or customizing) at a member cohort level. This hits the sweet spot by achieving a more optimal solution that the single global parameter while containing the risk of data collection. Choosing a global parameter usually gives a lower Pareto optimal curve, while choosing ad-hoc cohorts can improve it a bit. What we are truly interested in, is to identify the optimal cohorts and an optimal parameter for each such cohort so that we keep improving on the Pareto optimal front. See Figure 1 for details.

| Symbol | Meaning |
|--------|---------|
| $J$    | Total number of parameter values or choices. |
| $K$    | Total number of guardrail metrics |
| $C_i$  | $i$-th cohort for $i = 1, \ldots, n$. |
| $U_{ij}$ | Vectorized version of $U_{ij}^k$, which is the causal effect in metric $k$ by parameter $j$ in cohort $C_i$. |
| $\mu_k$ | Mean of $U_k$ |
| $\sigma_k^2$ | Variance of $U_k$ |
| $x$    | The assignment vector. |

To describe the generic problem formulation, let us begin with some notation. Let $J$ denote the total number of different choices or values of the parameter that we wish to optimize. We assume that there are $K + 1$ different metrics that we wish to track, where we have one primary metric and $K$ guardrail metrics. Let $C_1, \ldots, C_n$ denote the set of distinct, non-intersecting cohorts which exhibit heterogeneous behavior with respect to $K + 1$ metrics when treated by the parameter value in question.

On each cohort $C_i$ for $i = 1, \ldots, n$, let $U_{ij}^k$ denote the causal effect in metric $k$ by applying treatment value $j$ vs control. We further assume that each such random variable $U_{ij}^k$ is distributed as a Gaussian random variable having mean $\mu_{ij}$ and standard deviation $\sigma_{ij}^k$. For notational simplicity, for each metric $k = 0, \ldots, K$, let us denote $U_k$ as the vectorized version of $U_{ij}^k$ for $i = 1, \ldots, n$, $j = 1, \ldots, J$. Using a similar notation we get,

$$U_k \sim N_{nJ} \left( \mu_k, \text{Diag}(\sigma_k^2) \right)$$

Finally, let us denote $x_{ij}$ as the probability of assigning the $j$-th treatment value to the $i$-th cohort and $x$ be its vectorized version. For ease of readability, we tabulate these in Table 1.

Figure 1: Pareto Optimal Curves for Objective vs Guardrail metrics

Table 1: The meaning of each symbol in problem formulation
Based on these notations, we can formulate our optimization problem. Let \( k = 0 \) denote the main metric. We wish to optimize the main metric keeping the guardrail metrics at a threshold. Formally, we wish to get the optimal \( x^* \) by solving the following:

Maximize \( x^T U_0 \)

subject to \( x^T U_k \leq c_k \) for \( k = 1, \ldots, K \).

where \( c_k \) are known thresholds. Based on these, the overall problem can be formalized into two steps.

1. Identifying member cohorts \( C_1, \ldots, C_N \) using data from randomized experiments
2. Identifying the optimal parameter \( x^* \) by solving the optimization problem (1).

Before discussing the methodology of the solution in more detail (in Section 3), let us provide more context on the two motivating applications — Adjusting Notifications threshold and personalizing density of advertisements at LinkedIn.

2.1 Notifications delivery at LinkedIn
LinkedIn notifications have become an increasingly critical channel for social networks to keep users informed and engaged, as a result of continuously growing mobile phone usage. LinkedIn, as a professional social network site, implemented a near real-time optimization system for activity-based notifications [10]. The system is composed of response prediction models to predict users’ interests (click through rate on positive and negative signals).

As we serve those time-sensitive activity-based notifications (example in Figure 2a) in a streaming fashion, we introduced a model threshold parameter to make send or drop decision on each candidate notification. To avoid overwhelming users, the system introduced a per-user constraint that enforces each user to receive at most a few notifications per day. As a result, the choices of the model threshold parameter would have an impact on both the quantity and the quality of notifications.

The system initially had a global model threshold which was sending sub-optimal quality notifications to active users while failing to send notifications to some less active users. To improve the system, we introduced a personalized threshold strategy to reshape user coverage in finer granularity. In prior work, we grouped users into four segments according to their activeness: daily, weekly, monthly, and dormant users. Then, we fine-tune the parameters to personalize at the pre-defined group level. However, the choice of the cohorts was ad-hoc and not necessarily the optimal for having the strongest heterogeneous effects across the metrics at hand.

Thus, the main problems that we solve in this paper are:

- Automatically identifying cohorts which show the strongest heterogeneous effects across the treatments (e.g., send threshold)
- Solving an optimization problem to assign optimal treatment to each of these cohorts.

Once we know the exact cohorts, the optimization problem in this example can be written out exactly as (1) where the primary metric is sessions, while the guardrail metrics are contributions, send volume, click through rate, notification disabled users and total notification disables.

2.2 Ranking Ads in LinkedIn Feed
LinkedIn Feed contains various types of updates. At a high level, they can be split into two categories: sponsored (ads) and organic updates. Organic updates are the main driver for engagement, while
sponsored updates are the source of revenue. Both engagement and revenue are important yet conflicting because slots on the newsfeed are shared. How to rank both organic and sponsored updates to balance engagement and revenue is a critical problem \[1 - 3\].

One solution is slotting sponsored updates at fixed positions for all members. A simplistic solution is to control the ads density using a parameter minGap, that controls the number of organic updates between two consecutive ads. Figure 2b shows an example of how minGap controls the position of ads. This solution is suboptimal because it cannot capture the variability in members’ preference of ads density using a single global parameter.

Instead, we formulate it as an optimization problem to select the best gap for each cohort of members. The objective is to maximize revenue with constraints on organic and ads engagement utility. Mathematically, the problem can be formulated as:

\[
\begin{align*}
\text{Maximize} & \sum_{i=1}^{n} \sum_{j=1}^{\text{minGap}} x_{ij} r_{ij} \\
\text{such that} & \sum_{i=1}^{n} \sum_{j=1}^{\text{minGap}} x_{ij} c_{ij} \geq w_{c} c_{\text{control}} \\
& \sum_{i=1}^{n} \sum_{j=1}^{\text{minGap}} x_{ij} o_{ij} \geq w_{o} o_{\text{control}} \\
& \sum_{j} x_{ij} = 1, \forall i, \quad 0 \leq x_{ij} \leq 1.
\end{align*}
\]

where \(r_{ij}\) is the estimated causal effect on revenue (the primary metric), and \(c_{ij}\) and \(o_{ij}\) are the estimated causal effect on ads engagement and organic engagement respectively (the guardrail metrics) for cohort \(C_i\) and treatment \(j\). \(w_c\) and \(w_o\) denote the weights for the tradeoff when comparing with the control for both the utilities. Note that this optimization problem is also an explicit example of the generic problem stated in (1).

3 METHODOLOGY

So far, we have described a generic problem (1) and two explicit examples in the LinkedIn ecosystem. In this section, we detail out our proposal to solve the problem. We first begin with how we can automatically identify the cohorts of members who show the most heterogeneous effect instead of picking them in an ad-hoc manner. We then describe how we solve the optimization problem to assign parameter values to each cohort.

3.1 Heterogenous Cohorts

Estimation of heterogeneous treatment effects is a well-studied topic in social and medical sciences \[5, 26\]. In this paper, we follow the potential outcomes framework from Rubin (1974) \[21\] and consider the following assumptions:

- **Stongly Ignorable Treatment Assignment** \[20\], which combines the assumption of unconfoundedness and overlap. We refer to \[20\] for the details.

Throughout this section, we assume that we have access to data from randomized experiments. That is, we have observed the values for each metric \(k = 0, \ldots, K\), by giving treatment value \(j\) to a randomized group of experimental units, for \(j = 1, \ldots, J\). For each treatment \(j\) and each metric \(k\), we use the recursive partitioning technique from \[5\] to identify the heterogeneous causal effects. The Causal Tree Algorithm from \[5\] generates a tree and hence a partition of the entire set of members into disjoint cohorts \(\{C_1, \ldots, C_n\}_j\). The subscript \(jk\) signifies the cohort definition from treatment \(j\) and metric \(k\). For sake of completeness, we briefly describe the causal tree algorithm and how we combine the \(j(K + 1)\) different trees to finally get one cohort definition.

3.1.1 Causal Tree Algorithm. The causal tree algorithm \[5\] is based on the conventional CART algorithm \[7\], which recursively partitions the observations of the training sample to build the initial tree and uses cross-validation to select a complexity parameter to prune the tree. There are major differences in estimating heterogeneous causal effects versus the standard response prediction problem which CART tries to solve. Specifically,

- The goal is to estimate the delta effects between the treatment and control groups \(\tau_i = Y_{1i} - Y_{0i}\), instead of the outcome variable \(y_i\).
- As member-level treatment effects is not observable (a member cannot be in both treatment and control groups at the same time), we would need to estimate \(\tau_i\) based on the conditional average treatment effects of units in the same leaf \(\ell\) as \(\tilde{\tau}_\ell = \tilde{E}(Y_{1\ell}) - \tilde{E}(Y_{0\ell})\) where \(i \in \ell\).

Due to these differences, the causal tree algorithm modifies the CART criteria, to generate the heterogenous cohorts. In order to ensure high confidence on the leaf-level estimations, the algorithm introduces a new regularization term in the splitting objective to minimize leaf level variance. \[5\] introduces a procedure called homogeneity splitting criterion of the objective; \(p\) represents the fraction of records in treatment out of total for each leaf \(\ell\). After the training phase, we conduct cross-validation similar the standard prediction problem to maximize the cross validation objective.

3.1.2 Combining Multiple Trees. Note that for each treatment level \(j\) and each metric \(k\) we can identify heterogenous cohorts using the Causal Tree Algorithm. One of the major challenges is to
Algorithm 1 Merging Trees

1: Input : A set of L collection of cohorts: \( \{C_1^\ell \}_{\ell = 1, \ldots, L} \).
2: \( c_{in}^\ell = \{c_{ij}^\ell \}_{i = 1} \)
3: for \( \ell = 2, \ldots, L \) do
4: \( c_{base} = c_{out} \)
5: for \( S_1 \in c_{base} \) do
6: for \( S_2 \in \{C_1^\ell \}_{\ell = 1} \) do
7: \( S_{int} = S_1 \cap S_2 \)
8: if isStatSig\((S_{int}, (S_1 \setminus S_{int}))\) then
9: Update \( c_{out} \) by splitting \( S_1 \) into \( S_{int} \) and \( S_1 \setminus S_{int} \)
10: Set \( S_1 = S_1 \setminus S_{int} \)
11: end if
12: end for
13: end for
14: end for
15: return \( c_{out} \)

combine these \( J(K + 1) \) different trees into a single tree so that we can have a single collection of cohorts.

One option is to estimate member-level metric impacts by using all the trees and then assign the decision parameter at the member level. However, that would have scalability concerns in the optimization problem. A better alternative is to merge the tree models into a single cohort assignment. Various mathematical and data mining approaches can be used in this task [23].

We explored an idea that sequentially merges pairs of trees, which is illustrated as Algorithm 1. We start by picking a base cohort definition and consider every other cohort definition through a looping mechanism. We pick any cohort \( S_1 \) in our base partition and depending on the sub-partition due to the other cohort definition, we consider splitting \( S_1 \) if all splits are statistically significant for some metric \( k \). For further details please see Section 9. We leave it as future work to identify more formal ways of defining a single collection of cohorts across multiple treatments and multiple metrics.

3.2 Stochastic Optimization

Note that, the problem (1) is stochastic since both the objective function and the constraints used in the optimization formulation are not deterministic but are coming from a particular distribution (Gaussian in the above case). More formally, we can rewrite the optimization problem in (1) as:

Maximize \( f(x) = \mathbb{E}(x^T U_0) \)

subject to

\[
g_k(x) := \mathbb{E}(x^T U_k - c_k) \leq 0, \quad k = 1, \ldots, K.
\]

(4)

\[
\sum_j x_{ij} = 1 \quad \forall i, \quad 0 \leq x \leq 1
\]

Note that in the above optimization formulation, the objective function \( f \) and the constraints \( g_j \) are not directly observed but observed via the realizations of the random variables \( U_0, \ldots, U_K \).

One method of solving such a problem in literature is known as sample average approximation (SAA) [13]. In SAA, instead of solving the stochastic problem, it replaces the stochastic objective and the stochastic constraints via its empirical sample expectation. In many cases, such as ours, the SAA solution might lead to an infeasible problem, due to the large variance in the random variable. Capturing the mean may not be enough. Moreover, SAA is computationally challenging for a general function \( \hat{g}_j \). Another method of solving a similar problem is known as stochastic approximation (SA) [19], which has a projection step onto \( \{g_j(x) \leq 0\} \) which may not be possible in this situation.

To have a more formal solution we generalize the Coordinated Stochastic Approximation (CSA) algorithm from [15]. The CSA algorithm in [15] solves the problem with a single constraint which we modify to work with multiple expectation constraints. Specifically, we start by framing the above problem as

Minimize \( f(x) := \mathbb{E}(U_0(F(x, U_0))) \)

subject to

\[
g_k(x) := \mathbb{E}(G(x, U_k)) \leq 0 \quad \text{for } k = 1, \ldots, K.
\]

\( x \in X \)

(5)

here \( X \) denotes the set of non-stochastic constraints.

Our algorithm, which we call Multiple Coordinated Stochastic Approximation (MCRA), is an iterative algorithm which runs for \( N \) steps. At each step \( t \) we start by estimating the constraint function. Specifically, we simulate \( U_{k,t} \) for \( \ell = 1, \ldots, L \) and estimate,

\[
\hat{G}_{k,t} = \frac{1}{L} \sum_{\ell = 1}^L G_k(x, U_{k,t}).
\]

(6)

Then if all the estimated constraints \( \hat{G}_{k,t} \) are less than a threshold \( \eta_{k,t} \), we choose our gradient to be the stochastic gradient of the objective function, \( F'(x_t, U_{0,t}) \). Otherwise, from the set of violated constraints \( k : \hat{G}_{k,t} > \eta_{k,t} \), we choose a constraint \( k^* \) at random and consider the gradient to be the stochastic gradient of that constraint, \( \hat{G}_{k^*,t} \). We then move along the chosen gradient for a particular step-size \( \gamma_t \) and apply the traditional proximal projection operator to get the next point \( x_{t+1} \). Our final optimal point is the weighted average of those \( x_t \) where we have actually travelled along the gradient of the objective. The overall algorithm to solve (5) is now written out as Algorithm 2.
It has been theoretically proven in [15] that if there was a single stochastic constraint, then the number of iterations \( N \) required to come close to the optimal both with respect to the objective and the constraint is of the order \( O(1/\epsilon^2) \). Following a very similar proof strategy it is not hard to see that we can carefully choose the tolerances \( \eta_k, \gamma \), such that if we follow Algorithm 2 for \( N \) steps, then
\[
\mathbb{E}(f(\hat{x}) - f(x^*)) \leq \frac{c_0}{\sqrt{N}} \quad \text{and} \quad \mathbb{E}(g_k(\hat{x})) \leq \frac{c_k}{\sqrt{N}} \quad \forall k \in \{1, \ldots, K\}
\]
We do not go into the details of the proof in this paper for brevity. Please see [15] for further details.

4 DATA COLLECTION

Now we illustrate the process of data collection and processing to personalize and optimize parameters in both the notifications and ads use cases. We collect experimental data to test a collection of parameters where the treatment assignment are random and the regular assumptions of causal inference [20] hold. To measure the effect of the parameters, we carefully select a list of primary and guardrail metrics for each use case. In addition to the metric data, we also keep track of the allocation of treatments and control groups and appropriate features.

4.1 Personalize Notification Thresholds

A set of prior experiments exist which tested a few model threshold for the daily active users (DAUs) while holding the thresholds for the rest of users the same. We leverage those past tests data to generate cohort-parameter mapping for our validation tests. We collected two weeks of the experimental data where the metrics of interest are described in Table 2. We include three major categories of features in the heterogeneous cohorts learning the process as follows:

- User profile features, such as country, preferred language, job title, etc.
- Notification specific features, such as past notifications and emails received.
- Other activity features including past visits, feed consumptions, likes, shares, comments, etc.
- Features from users’ network (such as the number of connections/followers).

Table 2: Metrics of Interests for Notifications Usecase

| Metrics             | Descriptions                                      |
|---------------------|---------------------------------------------------|
| Sessions (Objective)| Total sessions (a measure of visits).              |
| Daily Contributors  | Daily unique number of users who generate or distribute (e.g.: share, like, comment, message) contents |
| Notification Sends  | Total volume of notifications send to users        |
| Notification CTR    | Click through rate on in-app notifications         |
| Notification Disable Users | Number of users who disable the notification       |
| Notification Disables| Total number of disables on notifications          |

4.2 Personalize Ads Density

We conduct experiments to rank ads in the LinkedIn feed based on different \( \text{minGap} \) parameter. We collect three months of experimental data. The metrics of interest, composed of the primary metric: revenue and a set of guardrail metrics, are illustrated in Table 3. In addition to the user profiles, activities, network features that were included in the ads study, we add a set of ads specific features (such as user and ads affinity features like past click-through rates (CTRs) and interactions on ads) in identifying the heterogeneous cohorts.

Table 3: Metrics of Interests for Ads Usecase

| Metrics          | Descriptions                                      |
|------------------|---------------------------------------------------|
| Revenue (Objective) | Total Estimated Revenue.                           |
| Ads CTR          | Click Through Rate on all advertisements.         |
| Ads Views        | Views on all advertisements.                      |
| Feed Viral Actors | Unique number of users who make viral actions (like, share, comment) at Feed. |
| Feed Interactions | Total interactions at Feed.                       |

5 SYSTEM ARCHITECTURE

We outline the design of the engineering architecture for the parameter personalization and optimization system in Figure 3. It consists of two major components: one for heterogeneous cohorts learning and the other for stochastic optimization of the parameters. Both systems would leverage tracking data (metrics and features) and randomized experiment data (the allocation of users in treatments or control groups).
and generate the cohorts for each treatment level $j$ and each metric of interest $k$.

- A flow to combine multiple trees to come up with a final cohort definition via Algorithm 1.

The output of the first system (a finalized cohort definition) together with the tracking and experiment allocation data serve as the inputs for the stochastic optimization system. In this stage, we estimate the cohort level effects for each treatment level $j$ and metric of interest $k$ and fit the estimations in the stochastic optimization pipeline to generate final cohort-parameter maps.

We developed the whole system offline using Apache Spark for data processing and leveraged packages in R for causal tree model training and stochastic optimization. The system produces the cohort definition and the mapping between cohorts and parameters which can be encoded as a model file. Applying the personalized parameters in an online system only requires a light-weight tree model scoring and post-processing flows to assign the parameters. The solution would apply to a wide range of online systems without introducing a significant level of additional latency.

6 EXPERIMENTS

6.1 Offline Analysis

In this section, we present the offline analysis results for both Notification and Ads use cases and share our learnings and some practical tips. All results shown in section are statistically significant with a $p$-value < 0.05, obtained from repeated experiments.

6.1.1 Personalize Notification Threshold. As we briefly mentioned in Section 2, the baseline model for notification is personalized to the pre-defined cohort’s level. For the initial validation tests, we directly leveraged the past experiment data that tune the threshold for daily active users (DAU). Therefore, our experiment would first focus on personalizing and optimizing thresholds for DAUs.

Figure 4a-1 visualizes the cohorts generated using an optimized value of $\alpha$. We have seen from our experiments that a lower value of $\alpha$ would lead to smaller number of cohorts and lower variance (hence higher confidence) on the cohort-level effect estimations; and a high value of $\alpha$ would result in a larger set of cohorts and lower confidence in estimation. With a finalized cohorts set and the cohort-level effect estimations, we ran stochastic optimization analyses using both SGD and Adagrad options.

We observe the SGD method converges faster than Adagrad in the Notification use case as seen from Figure 4a-2. Offline analysis suggested very promising results as seen in Table 4. We can potentially lift the sessions metric without any tradeoff on the other guardrail metrics (e.g. daily contributors, notification CTR, notification disable users).

6.1.2 Personalize Ads Density. Figure 4b-1 shows the visualization of the heterogeneous cohorts selected in terms of two metrics: the objective: revenue and one of the major constraints: Ads CTR. The x-axis shows the average treatment effect per cohort on the revenue metric, and the y-axis represents the impacts on Ads CTR. The horizontal and vertical error bars accordingly represent the standard deviation of the effects on revenue and Ads CTR. It is clear from the figure that the cohorts are nicely separated especially in terms of heterogeneity in revenue effects.

Figure 4b-2 shows the expected effect on the revenue metric along with the increase of iterations for both SGD and Adagrad. We attempt to increase revenue without lifting the total Ads views while Ads revenue directly depends on the views. Due to the conflicting nature between the objective and constraint, it is difficult to achieve constraints while improving the objective. Unlike the case in Notifications, we observe that the Adagrad method tends to converge much faster than SGD in this scenario.

We also conducted a few more tests using simulated data and observed that usually, SGD performs better than Adagrad in terms of convergence if the constraints are easy to satisfy. On the other hand, for hard to satisfy constraints, Adagrad generally tends to outperform SGD.

Table 5 demonstrates our offline estimation of the total effects on Ads use case. We present a comparison of applying pre-defined cohorts (based on member activeness level) vs the causal tree based cohorts, where both cases utilized the stochastic optimization to select parameters. Offline estimations show that the causal tree based solution would outperform the pre-defined cohorts solution. We estimate a much higher revenue lift (+2.66% compared with +0.45%) with a similar trade-off on the guardrail metrics (e.g.: ‘Feed Viral Actors’ and ‘Feed Interactions’).

### Table 4: Offline Estimation on LinkedIn Notification

| Metrics (Good Direction)                  | SGD   | Adagrad |
|-------------------------------------------|-------|---------|
| Sessions (Up)                             | +0.49%| +0.49%  |
| Daily Contributors (Up)                   | +0.12%| +0.12%  |
| Notification Send Volume (Up)              | +0.59%| +0.63%  |
| Notification CTR (Up)                     | +0.02%| +0.01%  |
| Notification Disable Users (Down)         | −0.02%| −0.02%  |
| Notification Total Disables (Down)         | −0.1% | −0.1%   |

### Table 5: Offline Estimations for LinkedIn Ads with Ads View Constraint

| Metrics (Direction)       | Cohorts         | Adagrad | SGD   |
|---------------------------|-----------------|---------|-------|
| Revenue (Up)              | Pre-defined     | +0.48%  | +0.42%|
|                           | Causal Tree     | +2.66%  | +1.32%|
| Ads CTR (Up)              | Pre-defined     | +0.44%  | +0.45%|
|                           | Causal Tree     | +0.38%  | +0.33%|
| Ads Views (Down)          | Pre-defined     | −0.08%  | −0.01%|
|                           | Causal Tree     | −0.01%  | 0%    |
| Feed Viral Actors (Up)    | Pre-defined     | +0.02%  | +0.02%|
|                           | Causal Tree     | +0.05%  | 0%    |
| Feed Interactions (Up)    | Pre-defined     | +0.01%  | −0.01%|
|                           | Causal Tree     | −0.02%  | −0.02%|

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5SGD and Adagrad are different choices of the proximal projection operator in Algorithm 2. For further details please see Section 9

6See Section 9 for further details
6.2 Online Experiments
Online A/B testing has become the golden standard in evaluating product developments for web-facing companies. We launched online tests to further validate our method. Due to the high cost of implementing the pipeline and launching online A/B tests, we designed our initial online validation tests differently for the Notification and Ads use cases to ensure covering a few different aspects. All reported metric lifts in this section have a \( p \)-value of less than 0.05. Otherwise we report the lift as neutral.

6.2.1 Notification Tests. As the notification use case already had a fine tuned cohort level threshold as the baseline, we directly launched our full solution trained by past notification experiment data. We observed a significant positive impact on the session metric especially for DAUs, while the impacts on the constraint metrics mostly remain neutral (also observe a lift in daily contributors metric for DAUs) as shown in Table 6. The results are very close to our offline estimations. The validation test demonstrates the huge potential of our mechanism in online setting. We are confident the impacts of the method will be much larger when we expand the work to personalize model thresholds for all LinkedIn users (current work focused on DAUs).

Table 6: Notification Experiment Results

| Metrics                   | Delta % Effects |        |        |        |
|---------------------------|----------------|--------|--------|--------|
|                           | All Users      | DAUs   |        |        |
| Sessions                  | +0.37%         | +0.56% |        |        |
| Daily Contributors        | Neutral        | Neutral| +0.42% |        |
| Notification Send Volume  | Neutral        | Neutral| Neutral|        |
| Notification CTR          | Neutral        | Neutral| Neutral|        |
| Notification Disable Users| Neutral        | Neutral| Neutral|        |
| Notification Total Disables| Neutral       | Neutral| Neutral|        |

6.2.2 Ads Tests. We conducted online experiment for the solution with activity based cohorts. Table 7 shows the result of a one week experiment for the solution compared to slotting mechanism. All numbers in the table has \( p \)-value less than 0.01. In the problem formulation, we added a constraint on ads impressions to compare the efficiency of two mechanisms: whether we can deliver better revenue and engagement given the same amount of ads impressions. In the offline simulation, the solution on activity based cohort has slightly negative (-0.01\%) ads impressions. However, in online experiment result, we observed a significant drop (-1.09\%) of ads impressions. It’s caused by strong seasonality in the ads ecosystem. The solution learned from past data may not be able to capture new trend in the revenue utility. An improvement is to solve the problem with new data more frequently to accommodate such dynamics. Unfortunately during our experimentation our ads system released a new feature that changed our problem formulation, which is out of the scope of this paper. We keep it as a future work to use the optimal cohorts instead of the ad-hoc activity based cohorts.

Table 7: Ads Experiment Results

| Metrics                  | Delta % Effects |        |        |        |
|--------------------------|----------------|--------|--------|--------|
|                           | All Users      | DAUs   | WAUs   | MAUs   |
| Revenue                  | Neutral        | -1.52\% | +3.47\% | +3.31\% |
| Ads-CTR                  | +0.92\%        | +1.76\% | Neutral| Neutral|
| Ads-impressions           | -1.09\%        | -3.44\% | +3.32\% | +5.84\% |
| Feed Viral Actions       | Neutral        | Neutral| Neutral| Neutral|
| Feed Interactions        | Neutral        | Neutral| Neutral| Neutral|

Note that, by modulating the ads impressions differently in different activity based segments, we were able to reduce the number of overall ads impressions, but we did not see any negative impact in revenue. Engagement metrics were also not hampered in this experiment, which gave us a win-win situation.

7 RELATED WORK
Estimating heterogeneity in causal effect has always been an important research area and well studied by many researchers across domains. In recent years, a growing literature seeks to apply supervised machine learning methods to the problem [9, 12, 24]. Many researchers apply tree models and corresponding ensemble methods since they can automatically identify of nonlinear relationships and interactions [5, 11, 26]. Among the works, the causal tree and forest
algorithms from [5] and [26] stands out as a popular choice which introduces novel honest estimation concept and shows substantial improvements in coverage of confidence intervals.

In this paper, we have also described an algorithm for stochastic optimization with multiple expectation constraints based on the CSA algorithm developed in [15]. Traditionally, stochastic optimization routines were solved either via sample average approximation (SAA) [13, 27] or via stochastic approximation [19]. For details see [6] and [22]. There have been several papers showing improvement over the original SA method especially for strongly convex problems [18], and for a general class of non-smooth convex stochastic programming problems [17]. However, note that these methods may not be directly applicable to the case where each $g_k$ is an expectation constraint. Very recently [29] developed a method of stochastic online optimization with general stochastic constraints by generalizing Zinkevich’s online convex optimization. Their approach is much more general and as a result may be not the optimal approach to solving this specific problem. For more related works in stochastic optimization literature, we refer to [15] and [29] and the references therein.

8 DISCUSSION

In this paper, we introduce a novel mechanism to personalize and optimize parameters using randomized experiment data. The method consists of two major stages: identifying heterogeneous cohorts; and solving a stochastic optimization problem at the cohort level to identify the optimal parameter for each cohort. We applied the method in two LinkedIn use cases: Personalizing Notification model threshold; and Ranking Ads on Feed. Both offline analysis and online experiments show results which validate our approach. As the method leverages randomized experiment data, the estimated effect is causal, leading to the minor offline and online discrepancy. The solutions produced by the approach can be applied in any online system to personalize various decision parameters (including UI parameters) with trivial cost in terms of memory and latency.

A few non-trivial, but likely impactful extensions are: (1) The cost of collecting online A/B test data could be large in terms of time and potential negative member experiences for some use cases. Designing a more cost-efficient data collection framework or leveraging observational data to achieve the same performance would be beneficial. (2) Users can potentially move in and out of cohorts. Extending this framework to incorporate the dynamic nature of cohorts could be an interesting research topic. (3) As mentioned in Section 3.1.2, future work on generating one single cohort definition based on effects from multiple treatments with various metrics of interests could further improve the method.

REFERENCES

[1] Deepak Agarwal, Kinjal Basu, Souvik Ghosh, Ying Xuan, Yang Yang, and Liang Zhang. 2018. Online Parameter Selection for Web-based Ranking Problems. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD ’18). ACM, New York, NY, USA, 23–32.

[2] Deepak Agarwal, Bee-Chung Chen, Rupesh Gupta, Joshua Hartman, Qi He, Anand Iyer, Sumanth Kolar, Yiming Ma, Pannagadatta Shivashawamy, Ajith Singh, and Liang Zhang. 2014. Activity Ranking in LinkedIn Feed. In KDD: ACM, New York, NY, USA, 1603–1612.

[3] Deepak Agarwal, Bee-Chung Chen, Qi He, Zhenhao Hua, Guy Lebanon, Yiming Ma, Pannagadatta Shivashawamy, Haoo-Ping Teng, Jiasen Yang, and Liang Zhang. 2015. Personalizing LinkedIn Feed. In Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’15).

[4] Deepak Agarwal, Souvik Ghosh, Kai Wei, and Siyu You. 2014. Budget Pacing for Targeted Online Advertisements at LinkedIn. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’14). ACM, New York, NY, USA, 1613–1619.

[5] Susan Athey and Guido Imbens. 2016. Recursive partitioning for heterogeneous causal effects. Proceedings of the National Academy of Sciences 113, 27 (2016), 7353–7360.

[6] Albert Benveniste, Michel Métivier, and Pierre Priouret. 2012. Adaptive algorithms and stochastic approximations. Vol. 22. Springer Science & Business Media.

[7] Loi Breiman. 2017. Classification and Regression Trees. Routledge.

[8] John Duchi, Elad Hazan, and Yoram Singer. 2011. Adaptive subgradient methods for online learning and stochastic optimization. Journal of Machine Learning Research 12, Jul (2011), 2121–2159.

[9] Jared C. Foster, Jeremy M.G. Taylor, and Stephen J. Ruberg. 2011. Subgroup identification from randomized clinical trial data. Statistics in Medicine 30, 24 (2011), 2867–2880.

[10] Yan Gao, Viral Gupta, Jinyun Yan, Changji Shi, Zhonggen Tao, PJ Xiao, Curtis Wang, Shengyu Pu, Romer Rosales, Ajith Muralsilaharan, and Shaunak Chatterjee. 2018. Near Real-time Optimization of Activity-based Notifications. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD ’18). ACM, New York, NY, USA, 263–292.

[11] Donald P. Green and Holger L. Kern. 2012. Modeling Heterogeneous Treatment Effects in Survey Experiments with Bayesian Additive Regression Trees. Public Opinion Quarterly 76, 3 (09 2012), 491–511.

[12] Kosuke Imai and Marc Ratkovic. 2013. Estimating treatment effect heterogeneity in randomized program evaluations. Ann. Appl. Stat. 7, 1 (03 2013), 443–470.

[13] Anton J Kleywegt, Alexander Shapiro, and Tito Hommen-de Mello. 2002. The sample average approximation method for stochastic discrete optimization. SIAM Journal on Optimization 12, 2 (2002), 479–502.

[14] Ron Kohavi, Alex Deng, Brian Frasca, Toby Walker, Ya Xu, and Nils Pohlmann. 2013. Online Controlled Experiments at Large Scale. In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’13). ACM, New York, NY, USA, 1168–1176.

[15] Guanghui Lan and Zhiquang Zhou. 2016. Algorithms for stochastic optimization with expectation constraints. arXiv preprint arXiv:1604.03887 (2016).

[16] Haishan Liu, David Pardoe, Kun Liu, Manoj Thakur, Frank Cao, and Chonghe Li. 2016. Audience Expansion for Online Social Network Advertising. In Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’16). ACM, New York, NY, USA, 165–174.

[17] Arkadi Nemirovski, Anatoli Juditsky, Guanghui Lan, and Alexander Shapiro. 2009. Robust stochastic approximation approach to stochastic programming. SIAM Journal on Optimization 19, 4 (2009), 1574–1609.

[18] Boris T Polyak and Anatoli B Juditsky. 1992. Acceleration of stochastic approximation by averaging. SIAM Journal on Control and Optimization 30, 4 (1992), 838–855.

[19] Herbert Robbins and Sutton Monro. 1951. A Stochastic Approximation Method. The Annals of Mathematical Statistics 22, 3 (1951), 400–407.

[20] Paul R Rosenbaum and Donald B Rubin. 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 1 (1983), 41–55.

[21] Donald B Rubin. 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. Journal of Educational Psychology 66, 5 (1974), 688.

[22] James C Spall. 2005. Introduction to stochastic search and optimization: estimation, simulation, and control. Vol. 65. John Wiley & Sons.

[23] Pedro Streitel. 2015. A Survey of Merging Decision Trees Data Mining Approaches. In Proc. 10th Doctoral Symposium in Informatics Engineering. 36–47.

[24] Matt Taddy, Matt Gardner, Liyun Chen, and David Draper. 2016. A nonparametric bayesian analysis of heterogeneous treatment effects in digital experimentation. Journal of Business & Economic Statistics 34, 4 (2016), 661–672.

[25] Diane Tang, Ashish Agarwal, Deirdre O’Brien, and Mike Meyer. 2010. Overlapping Experiment Infrastructure: More, Better, Faster Experimentation. In Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’10). ACM, New York, NY, USA, 17–26.

[26] Stefan Wager and Susan Athey. 2018. Estimation and Inference of Heterogeneous Treatment Effects using Random Forests. J. Amer. Statist. Assoc. 113, 523 (2018), 1228–1242.

[27] Wei Wang and Shabbir Ahmed. 2008. Sample average approximation of expected value constrained stochastic programs. Operations Research Letters 36, 5 (2008), 515–519.

[28] Hao Yu, Nan Yu, Addrian Fernandez, Omar Simno, and Annam Bhaisn. 2015. From Infrastructure to Culture: A/B Testing Challenges in Large Scale Social Networks. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD ’15). ACM, New York, NY, USA, 2227–2236.

[29] Hao Yu, Michael J Neely, and Xiaoshan Wei. 2017. Online Convex Optimization with Stochastic Constraints. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS ’17). Curran Associates Inc., USA, 1427–1437.
9 REPRODUCIBILITY

In this section, we describe some further details that should help the reader to reproduce the methodology described in this paper. We also provide the R code that has been used to run all experiments. Due to the sensitive nature of the data, we are not able to disclose that actual data used in our experiments but the practitioner can use the details in this section and the code provided to run this system for their dataset.

9.1 Details on Algorithm 1

The choice of the first cohort which is set in line 2 is important since it determines the final set of cohorts. In our experiments, we have set that to be the cohort definition corresponding to the primary metric \( k = 0 \) and the treatment \( j \) which showed the highest lift in treatment effect across the different cohorts.

For completeness, we now describe the details of the \( \text{isStatSig}(\cdot) \) function which has been used in Algorithm 1. The function takes in a collection of sets and identifies if each set is statistically significant or not when compared across all the \( K + 1 \) metrics. If there exists a metric \( k \in \{0, \ldots, K\} \) for which all the sets show statistically significant treatment effect, then we return \text{true}, else we return \text{false}. More formally, the details are given in Algorithm 3.

Algorithm 3 Testing For Statistical Significance: \( \text{isStatSig}(\cdot) \)

1: \textbf{Input}: A collection of Sets \( \{S_1, \ldots, S_n\} \).
2: \textbf{for } \( k = 0, \ldots, K \) \textbf{do}
3: \hspace{1em} Set flag = \text{true}
4: \hspace{1em} \textbf{for } \( S \in \{S_1, \ldots, S_n\} \) \textbf{do}
5: \hspace{2em} \textbf{if } \text{not Statistically Significant} \text{ for metric } k \text{ then}
6: \hspace{3em} Set flag = \text{false}
7: \hspace{2em} Break inner loop
8: \hspace{1em} \textbf{end if}
9: \hspace{1em} \textbf{end for}
10: \hspace{1em} \textbf{if } flag = \text{true} \text{ then}
11: \hspace{2em} return \text{true}
12: \hspace{1em} \textbf{end if}
13: \hspace{1em} \textbf{end for}
14: \textbf{return false}

9.2 Details on Algorithm 2

The proximal projection function \( P_{x_t}(\cdot) \) used in Algorithm 2 is defined as

\[
P_{x_t}(\cdot) := \arg\min_{x \in X} \{ f(x) + B_{\psi_t}(x, x_t) \} \tag{7}
\]

where \( B_{\psi_t}(x, x_t) \) is the Bregman divergence with respect to the 1-strongly convex function \( \psi_t \), defined as

\[
B_{\psi_t}(x, y) = \psi_t(x) - \psi_t(y) - \langle \nabla \psi_t(y), x - y \rangle. \tag{8}
\]

For more details we refer the reader to [8]. In this paper, we have focused on two specific forms of functions \( \psi_t \).

1. \textit{Stochastic Gradient Descent}: In this case, we use

\[
\psi_t(x) = x^T H_t x
\]

2. \textit{Adagrad}: Here we pick \( \psi_t(x) = x^T H_t x \) where

\[
H_t = \delta I + \text{diag} \left( \sum_{j=1}^{t} h_j^T h_j \right)^{1/2}
\]

and \( h_j \) are the chosen gradients in steps 5 and 8 of Algorithm 2.

The comparison of each of the above two choices has already been discussed in Section 6. Since we could not attach the real data due to privacy concerns, we are adding a simulated result, which the reader can reproduce using the code given below.

We consider a problem having a success metric and two guardrail metrics and a treatment having 10 different levels. We generate a random distribution for each metric \( k \) and each treatment level \( j \). We run the algorithm for \( N = 200 \) iterations and choose 50 samples to estimate the constraint at each step. We repeat both SGD and Adagrad 10 times and show the growth of the objective and the restriction on the constraint as the iterations increase in Figure 5.

![Simulated Results](image)

Figure 5: Simulated Results

Note that we are not claiming that one method is better than the other. However in our simulations, we have usually observed that in simpler problems, SGD tends to converge faster, while in tougher problem, Adagrad tends to work better.

9.3 Code Details

We share example scripts for merging trees and running stochastic optimization algorithms with simulation data in the following Github link: https://github.com/tuye0305/kdd2019prophet. The source code contains two main files:

1. \textit{MergeTreesSimulation.R} - This code helps us combine different cohorts corresponding to each metric and each treatment into a single cohort definition.

2. \textit{StochasticOpSimulation.R} - This code runs the stochastic optimization routine to identify the optimal parameter in each cohort. Running the code as is should generate the plot as shown in Figure 5.

We have also used the open source R library called Causal Tree (https://github.com/susanathy/causalTree) to identify the cohorts for each treatment \( j \) and metric \( k \). Using these, the entire methodology discussed in this paper can be easily reproduced for any similar problem of interest.