Personalized Execution Time Optimization for the Scheduled Jobs

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ABSTRACT
Scheduled batch jobs have been widely used on the asynchronous computing platforms to execute various enterprise applications, including the scheduled notifications and the candidate pre-computation for the modern recommender systems. It is important to deliver or update the information to the users at the right time to maintain the user experience and the execution impact. However, it is challenging to provide a versatile execution time optimization solution for the user-basis scheduled jobs to satisfy various product scenarios while maintaining reasonable infrastructure resource consumption. In this paper, we describe how we apply a learning-to-rank approach plus a “best time policy” in the best time selection. In addition, we propose an ensemble learner to minimize the ranking loss by efficiently leveraging multiple streams of user activity signals in our scheduling decisions of the execution time. Especially, we observe the cannibalization cross use cases to compete the user’s peak time slot and introduce a coordination system to mitigate the problem. Our optimization approach has been successfully tested with production traffic that serves billions of users per day, with statistically significant improvements in various product metrics, including the notifications and content candidate generation. To the best of our knowledge, our study represents the first ML-based multi-tenant solution of the execution time optimization problem for the scheduled jobs at a large industrial scale cross different product domains.

CCS CONCEPTS
• Computing methodologies → Supervised learning. • Information systems → Social networks.

KEYWORDS
execution time optimization, best time policy, notifications, pre-computation, scheduled job, learning-to-rank

1 INTRODUCTION
A job scheduler or task queue system has largely been deployed in the modern distributed computing architectures to ensure the execution and delivery of tasks for billion-scaled volume process requests, including Airbnb Dynein [7], Meta FOQS [19], Google Cloud Task Queue [16], AWS Job Queue EC2 [25]. The advantages of the scheduled tasks on the asynchronous computing architecture include the decoupling from user request, the reduced request latency, the better scalability and management with the rate-limiting, retry, and priority control [16]. The scheduled jobs are particularly suitable for various high-complex applications with affordable toleration delays, such as graph processing, notifications, video encoding service, and language translation. Those scheduled applications can be personalized and executed at per user basis by providing the user information with its execution timestamps in the task queue via the job scheduler. In social network, it is important to deliver or update information to users at the right time to maintain the user experience and the execution impact. However, no mature personalized execution time optimization solutions for the scheduled jobs have been reported in the industrial applications.

Notifications are important recommendation channels in social network products to deliver information to users and the delivery time has been demonstrated to be an important factor in the delivery process [21] [12]. In the real-world, a user receives over 65 notifications on average per day and almost 50% of notifications have been reported to interrupt the users’ daily work tasks [22]. A wide range of factors has been reported to contribute to the user engagement with notifications, including the device context and status [20], real-time environment, and the content relevance of the notifications [22]. Different from the notifications directly triggered by user activities (e.g., direct messages), the notifications for promotional purposes (e.g., suggesting new friends to connect) are generally scheduled in advance [18]. Due to the nature of the scheduled job, the device-level or environment signals cannot be directly used to improve the delivery time of promotional notifications.

A successful execution time optimization service not only protects the user experience from interruption by notifications but also improves the execution efficiency by avoiding overwhelming infrastructure resource consumption. The modern recommender system faces a dilemma in how to maintain the timely update and quick response to user actions while consume reasonable infrastructure resource, especially under the exponential growth of massive candidate pools [15]. The periodic candidate generation approach has been widely used in various billion-scale web applications, including LinkedIn [1], YouTube [5], and Amazon [17]. Due to the infrastructure resource constraint, it is challenge to update the candidate generation to users at the right time to reflect the up-to-date information, especially for the large group of non-daily active users. A reinforcement learning approach has been introduced to optimize the personalized number of execution time in the scheduled job to balance daily metrics and resource consumption [18], and the following question is how to define the personalized execution timestamp(s) after the number of execution time is determined in the job scheduler.
In this paper, we frame the execution time optimization as a learning-to-rank problem to select the best execution time slots for the scheduled jobs. We encounter four major challenges in the execution time optimization service development process. First, as opposed to the traditional learning-to-rank problems, the best time selection problem demonstrates strong dependency and interactions among each ranking object, i.e. the selection of one time slot will largely affect the utility function performance on the other time slots, similar to the problems in slate ranking [2]. Second, the single-channel utility function may not fit each use case, especially on the channel-inactive users. We then propose a signal assembly approach to ensemble the user temporal activity signals cross different channels in the best time decision making. Third, the number of execution time varies a lot in different product use cases (from once per week to 24 daily), which makes it infeasible to implement a generic conditional probability-based approach. We propose a simple yet robust technique termed “best time policy” to solve the best time ranking problem. Last, we observed cannibalization cross use cases to compete the user’s peak time slot and impair the global user experience. We propose a tiered coordination system to mitigate the best time cannibalization issue. We make the following novel contributions in this study:

- Formulate the execution time optimization problem as a learning-to-rank problem and propose to solve the best time selection for the scheduled jobs with a “best time policy”.
- Propose an ensemble learning approach to minimize the ranking loss by leveraging different user temporal activity signals in the best time decision making process.
- Observe the cannibalization effect cross different use cases in the best time selection.
- Evaluate our method with production traffic that serves billions of users per day, and demonstrate positive gains in daily metrics in several applications.

To our best knowledge, our work has been the first ML-based algorithm to support the multi-tenant application to solve the execution time optimization problem for the scheduled jobs at a large industrial scale cross different product domains.

2 RELATED WORK

The works relevant to this study come from large-scale server-site social media or delivery platform. Multiple email marketing services have been developed for clients to schedule email campaign and distribute emails at the optimal time per day [14], including MailChimp and Selligent. Pinterest reported a budget pacer to allocate weekly notification budge cross days of the week to each user and then scheduled the notification to be delivered at the user’s peak time of the day [29]. However, those optimization solutions can only provide limited peak time slots (e.g. once) per day and thus cannot satisfy the business needs to daily schedule a diverse range of the number of execution time. In addition, the delivery/update of various types of notifications or candidate generation at the same peak time slot raises the cannibalization risk cross different use cases to impair the user experience. Several studies have been published on the volume or channel selection optimization of LinkedIn notifications [9] and a logistic regression model was proposed to make a send/drop decision for each generated email [10]. However, those studies focus on the delivery phase filtering instead of the execution time optimization in the scheduling-phase. In the candidate computation applications, YouTube reported a batch-oriented precomputation approach to calculate the video recommendations to minimize the serving latency and it updates data sets several times per day to mitigate the delay between the recommendation generation and the recommendation serving [6]. LinkedIn reported a fast OLAP serving system Avatar to provide rich structured data insights to users, which is updated multiple times per day [27]. Unfortunately, no execution timing strategy have been reported in these enterprise applications.

The learning-to-rank has been widely applied in the information retrieval and other recommender systems [3]. Most of those applications implicitly assume independence in the ranking object relevance and return the top sorted candidates to the users. The diversity issue or the popularity bias has been proposed in the long-tail recommendation to impact the recommendation quality [28]. In addition, a conditional probability distribution approach has been proposed to represent the relation information among ranking objects in the global ranking [23]. One of the similarities of these learning-to-rank applications is that the ranking decisions result in “one-off” impact on the users and the viewer generally view the ranked results (e.g. search ranking) as a whole. In contrast, the best time ranking problem releases its effect on users in a time-series fashion with strong interaction among ranking objects.

There is relevant branch of research on the notification timing optimization using various heuristic rules [8], supervised learning [21] or reinforcement learning approach [12]. However, these studies focus on the real-time mobile device-site optimization with various device and context signals, and thus they are largely different from our server-site applications which are scheduled in advance (e.g. one day ahead of delivery).

3 METHODOLOGY

To start, we formalize the execution time optimization problem for the scheduled jobs. Given our formulation, we present a high-performing centralized approach that can scale to hundreds of billions of decisions made by hundreds of product use cases per day.

3.1 Problem overview

Given a job that has needs to be executed within a time range, the task of timing optimization for the scheduled jobs is to identify the best \( N \) time slots. The best time slots are those that i) optimize product-specific downstream metrics, and ii) minimize infrastructure load to avoid overwhelming the services in the execution phase. For example, when we schedule the promotional notifications, we need to determine the execution timestamps for each user in the task queue so that the notifications are delivered to the users at the right time. The time slots are defined based on the server-site timezone to be consistent with the server-site logging. In practice, the execution time range and the number of time slots defined in the scheduling request vary significantly (e.g. from once per week to up to 24 times daily) among different product use cases. In addition, the number of time slots in the scheduling request can be fixed or
personalized value in the same use case [18]. To provide a centralized multi-tenant scheduled jobs optimizer, our solution needs to be highly transparent, stable, and customizable to accommodate significant variation in the execution time optimization problem.

### 3.2 Time Slots Ranking

The optimizer takes as input a scheduling request \( r \), which contains the product use case \( p \) and the user \( u \). To enable our optimizer to handle multiple different problem settings simultaneously, each request also includes the execution time range \([t_{start}, t_{end}]\), the number \( N_{u,p} \) of time slots to return, and the length \( l \) of each time slot (e.g., one hour). Given \( l \), we assume the execution time range is partitioned into a set of contiguous candidate time slots \( T = \{t_1, t_2, \ldots, t_k\} \) (\( k \geq N \)), though the proposed methodologies can be applied to a more general space (e.g. infrastructure off-peak hours) with minor modifications.

The request also specifies the prediction metric \( m \) to optimize for, and a best time policy \( \pi \), which is a pre-defined policy that acts on a time slot ranking to generate a list of execution time as output. This output, \( T_c \), is returned to the job scheduler and stored in the task queue. To prevent a spike in the infra load during the execution, we generally apply a random delay \( e \in [0, 1] \) to the execution time in the job scheduler, which results in a uniform distribution of the actual execution timestamps within each time slot.

To generate the time slot ranking, we create a user temporal activity map \( V_{u,m} \), that maps the time slot to its personalized predicted value \( m_{u,t} \). This value is generated by a learned utility function \( f_{m}(u,t) \) to represent the user’s activity on \( t \). These predicted values can be used to directly rank time slots, or multiple relevant values can be combined via a signal assembler to generate a time slot ranking.

### 3.3 Features

The features we use to represent the user’s activity on each time slot is important to the performance of the utility predictor \( f_{m}(u,t) \). We define the feature vector \( F(u,t) \) for each user - execution time slot pair as follows:

- **User features**: This feature class includes the user’s profile features (country, age, etc), and the user’s activity level (daily active user or not, etc)
- **Local time features**: This feature class transforms the server-site time slot to the user’s local time (day of the week, hour of the day, sunrise and sunset time, holiday or not, etc)
- **User activity features**: This hourly resolution feature class represents the major ranking signals in the best time ranking problem. The user’s historical activity data are processed to generate the user’s activity features for the user \( u \) at the time slot \( t \) of the day \( d \) within a series of tracking window \( k \) (e.g. the range of \([t-4\, hours, t]\) and \([t, t+4\, hours]\)). In addition, the 7-day signals are then aggregated to generate the weekly user hourly activity signals.

### 3.4 Utility Functions

We provide a series of utility functions \( f_{m} \) to represent the user’s activity \( m_{u,t} \) in each time slot on various offsite (e.g. push, email) and in-app channels. These utility functions fall into the following three categories:

- **pClick models**: Classification models that predict the likelihood of a user \( u \) clicking the notifications if delivered on the time slot \( t \).
- **Activity models**: Regression models that predict the user \( u \)’s activity metric \( m \) on the time slot \( t \).
- **Activity counters**: Real-time stream processing service to store the user \( u \)’s activity counter on the time slot \( t \).

These scores are normalized to \([0.0, 1.0]\) by taking

\[
m_{u,t} = \frac{m_{u,t} - \min(m)}{\max(m) - \min(m)}
\]

where \( \max(m) \) and \( \min(m) \) are the maximal and minimal prediction value of metric \( m \) across all users and time slots, respectively.

### 3.5 Best Time Signal Assembly

As a multi-tenant optimization service, it is infeasible to provide a perfect utility function for each use case given the limited infrastructure resources. In addition, the model quality of the product-specific utility functions cannot be well maintained due to the sparsity of positive labelling. Accordingly, it is important to leverage the off-the-shelf users activity signals to support different product optimization requests. Moreover, by leveraging the users activity signals across different channels, we can mitigate the impact of user inactivity on certain delivery channel, which is a common issue in the notifications [9].

We adopted a strategy to provide a variety of generic utility functions to cover the user’s activity on different delivery channels. These signals are combined using a product-specific signal assembler to generate a personalized utility metric \( M_{u,t} \) for each product use case \( p \). To make it well explainable and debuggable, we define the signal assembler as the weighted sum of various user activity signals \( m_{u,t} \):

\[
M_{u,t,p} = \sum_{m \in M} \omega_{m,p} \times A_{u,m} \times m_{u,t}
\]

where \( \omega_{m,p} \) are the product-specific metric weights and \( A_{u,m} \) is the user’s activity on the offsite or in-app channel associated with \( m \). The optimal weights \( \omega_{m,p} \) can be tuned based on the online experiments or via an offline ensemble learning approach as follows. Given a product use case \( p \) and its ground-truth orders of the user’s sorted active time slots ranking lists \( T_{u,p} \), we define the ensemble ranking loss function as the average of the squared differences between the actual rank index and the weighted sum of the predicted rank index from various user activity signals for each user’s active time slots. We observed that weights learned from this loss function is more aligned with online experiment results than those from NDCG as loss function.

\[
Loss_{p} = \frac{1}{n} \sum_{u} \sum_{t \in T_{u,p}} (\hat{rank}_{u,t,p} - rank_{u,t,p})^2
\]

where \( rank_{u,t,p} \) is the index of \( t \) in \( T_{u,p} \) and \( \hat{rank}_{u,t,p} = \sum_{m \in M} \omega_{m,p} \times A_{u,m} \times m_{u,t} \). We then used the feature-weighted linear stacking [24] to learn the optimal \( \omega_{m,p} = \arg\min(Loss_{p}) \).
3.6 Best Time Policy

We observed that the execution decision on one time slot may strongly affect the outcomes of executing on others, and as a result the top N ranking approach generally does not result in optimal performance (Table 2). We propose an explainable yet robust technique called “Best Time Policy” on top of the utility functions. These policies return the best time slots based on the provided temporal activity map and the number of best time slots. An example of the best time selection using the avoid nearby policy is shown in Figure 1 and its implementation is documented in the Algorithm 1. Our optimizer can be further extended to support more use case-specific best time policy based on the product context.

3.7 Best Time Coordination

Cannibalization is a general platform-level issue and we ask whether different use cases in our optimization service compete for the user’s peak time slot and impair the global delivery impact. We classified the use cases into two tiers based on their business context. In the low priority group, we remove and thus avoid selecting the top peak time slot from the candidate time slots during the best time policy implementation.

4 APPLICATIONS AND EXPERIMENTS

4.1 System Overview

We built the optimization service and tested with production traffic that serves billions of users per day. The user temporal activity metric predictions are stored in seven key-value storage services to support the scheduled jobs on a day of the week basis. The clients are able to test different combinations of the prediction metric and the best time policy to further optimize their use case in the online experiments. An overview of our system is summarized in Figure 2 and the design pattern is abstracted in Figure 3.

Algorithm 1 Avoid w-slot nearby best time policy

1. function π(p, V_{u,m}, n, w)
   2. ▷ Return n best time slots with w avoidance window
   3. best_time_list ← ∅
   4. if use case p is low priority then
      5. remove top peak time slot from V_{u,m}
   6. end if
   7. while n > 0 do
      8. n ← n − 1
      9. identify top time slot best_time from V_{u,m}
     10. best_time_list.append(best_time)
     11. for t : m_{u,t} in V_{u,m} do
        12. ▷ %Remove peak and nearby slots%
        13. if t ≥ best_time − w and t ≤ best_time + w then
           14. remove t : m_{u,t} from V_{u,m}
        15. end if
      16. end for
     17. return best_time_list
  18. end function
4.2 Model Training
The training data were collected from randomly sampled 1% production traffic and daily-shuffled small exploration traffic (≤0.1%) in the best time decision making. The training group was joined with the server-site tracking data to generate the activity labels for the user $u$ on the time slot $t$. We filled the training label with 0 if the user does not have any activity or no delivery event on the time slot $t$ to make sure the whole training data are balanced on each time slot. For regression labels, we used the stratified sampling strategy to balance the long-tailed data distribution and then apply a natural log transformation to normalize the labels. A reverse transformation was applied to the original prediction scores in the model inference pipelines. We then trained the boosted decision trees models with logistic regression [11] using the ML platform [26] and kept the recurring model update.

4.3 Offline Models Evaluation
We use the normalized discounted cumulative gain NDCG [13] as the model ranking quality. The time slots are ranked based on the actual user activity pattern and the prediction rank relevant is assigned to calculate DCG and then normalized by the ideal rank to generate NDCG. The NDCG varies from 0.45 to 0.8 in different prediction metrics. We then performed a user activity cohort analysis on 3 activity models and observed that the model ranking quality is positively correlated with the user daily activity in Figure 4, which suggests that active users have more regular pattern to access the social network products.

4.4 Online Experiments
To avoid the novelty effect, we keep a long-term service-site 1% holdout to measure the performance of the ML-based execution time optimization over a heuristic peak time approach, which selects the top N peak hours based on the user’s in-app historical activity. We observed that the proposed ML-based approach has a significantly better efficiency ratio (i.e. daily metrics / execution volume) than the rule-based approach in various push or in-app channel use cases (Table 1). Nevertheless, we did not observe significant impact on the email notifications, which suggests that the email channel timing optimization space is limited.

4.4.1 Best Time Policy Experiment. We further made a case study and compared various best time policies in the view of execution efficiency improvement and product impact boosting. We observed that the avoid nearby policies have significant better performance than the top N policy (Table 2).

4.4.2 Best Time Signal Assembly Experiment. To evaluate the signal assembly-based execution time optimization, we measured the
After tuning the weight as 0.01 via the ensemble learning, we further confirmed its impact to improve of the best time ranking quality on the user’s activity on channel A. (C) 2-D user activity cohort online experiment analysis of the performance of signal assembly-based ensemble of user activity signals on channel A and B ($m_{u,t,A} + \omega \times A_{u,B} \times m_{u,t,B}$) over the single source signal on channel A ($m_{u,t,A}$).

$$m_{u,t,A} + \omega \times A_{u,B} \times m_{u,t,B}$$  \hspace{1cm} (4)

After tuning the weight as 0.01 via the ensemble learning, we further confirmed its impact to improve of the best time ranking quality NDCG in an offline simulation (Figure 5A). In an online experiment, we observed statistically significant improvement of the execution efficiency (+0.8%) and the execution impact (+0.05%) in the signal assembly group, which leverages both the internal channel signal $m_{u,t,A}$ and the boosted external channel signal $m_{u,t,B}$ from the channel B, especially on the users with high external channel activity (Figure 5B).

### Table 2: Comparison of different best time policies for a scheduled job use case

| top N avoid | 1-hour nearby | 2-hour nearby | 3-hour nearby |
|-------------|-------------|-------------|-------------|
| Execution efficiency | control | +2.1% | +2.2% | +1.65% |
| Execution impact | control | +0.11% | +0.15% | +0.125% |

Figure 5: Best Time Signal Assembly. (A) Ensemble learning. (B) Offline simulation of the effect of $\omega$ on the best time ranking quality on the user’s activity on channel A. (C) 2-D user activity cohort online experiment analysis of the performance of signal assembly-based ensemble of user activity signals on channel A and B ($m_{u,t,A} + \omega \times A_{u,B} \times m_{u,t,B}$) over the single source signal on channel A ($m_{u,t,A}$).

#### 4.4.3 Best Time Coordination Experiment

To test whether cannibalization across use cases exists in the execution time optimization, we selected 10 push notifications use cases (each scheduled once daily), which use the same prediction metric, best time signal assembler, and best time policy in the scheduling requests. In the control condition without coordination, all 10 use cases were scheduled and executed the notifications sending requests on the same time slot to each user. In the test condition, we classified 5 use cases as high priority group, and the others as low priority group where we avoided selecting the top peak time slot in the best time policy implementation. We observed that introducing the coordination system not only significantly improves the notifications delivery efficiency in both groups (high priority +0.13%, low priority +0.7%) but also increase the global product impact (+0.022%).

#### 5 CONCLUSION

In this paper we proposed a methodology for the execution time optimization problem, combining learning-to-rank, ensemble learning, with a best time policy in the best time selection. The experiment results demonstrate that the proposed approach is able to improve daily metrics effectively in the notifications and candidate computation applications at the industrial scale. To our best knowledge, our work represents the first multi-tenant industrial application of the execution time optimization problem in the job scheduler at a large industrial scale cross different product domains.

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