Accelerating E-Commerce Search Engine Ranking by Contextual Factor Selection

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ABSTRACT

In industrial large-scale search systems, such as Taobao.com search for commodities, the quality of the ranking result is getting continually improved by introducing more factors from complex procedures, e.g., deep neural networks for extracting image factors. Meanwhile, the increasing of the factors demands more computation resource and raises the system response latency. It has been observed that a search instance usually requires only a small set of effective factors, instead of all factors. Therefore, removing ineffective factors significantly improves the system efficiency. This paper studies the Contextual Factor Selection (CFS), which selects only a subset of effective factors for every search instance, for a well balance between the search quality and the response latency. We inject CFS into the search engine ranking score to accelerate the engine, considering both ranking effectiveness and efficiency. The learning of the CFS model involves a combinatorial optimization, which is transformed as a sequential decision-making problem. Solving the problem by reinforcement learning, we propose the RankCFS, which has been assessed in an off-line environment as well as a real-world on-line environment (Taobao.com). The empirical results show that, the proposed CFS approach outperforms several existing supervised/unsupervised methods for feature selection in the off-line environment, and also achieves significant real-world performance improvement, in term of service latency, in daily test as well as Singles’ Day Shopping Festival in 2017.

KEYWORDS

e-commerce search engine; effectiveness and efficiency; reinforcement learning;

1 INTRODUCTION

Information retrieval and machine learning applications play an important role in industrial and commercial scenarios, ranging from web searching engine (Google.com, Baidu.com, etc.) to e-commerce websites (Taobao.com, Amazon.com). The major applications, i.e., search and recommendation, usually require to rank a large set of data items in terms of response to users’ requests under an on-line circumstance. To support these applications, there are generally two issues: a) Effectiveness such as how accurate and reliable the search results in the final ranking list are and b) Efficiency as how fast the search engine’s response to the user’s queries in a timely manner and whether the computational burden of ranking is as low as possible from a system’s perspective. It is a challenge to address both issues in large-scale applications for providing excellent user experience and an efficient performance solution.

Generally speaking, to address the high computational cost of more deep models as well as large-scale traffic requests, the search engine system has to degrade the service level in the aspect of effectiveness, i.e., reducing the number of recalled items, off-lining some unnecessary service and so on, in order to avoid access delay or even unavailability, which severely affects the users’ experience. Though successful, these methods only adopts a compromise between the search engine processing performance and the service availability in a hard way, which means there must be unnecessary sacrifice of revenue in real world business practice. Consequently, this raises a question whether we are able to design a “soft” or “intelligent” solution, which allows to achieve both of effectiveness and efficiency.

The answer seems to be promising. Liu et al. proposed a cascading ranking model to address the trade-off between effectiveness and efficiency in the large-scale e-commerce search applications [20]. Their method mainly focuses on reducing the number of items in the ranking process, however, their model sheds a light on us to optimize the e-commerce search engine in another possible way. In a search engine, a set of factors is applied to the ranking process and we conjecture that not all of those factors are necessary in the real-world applications. After thorough investigation in the real world operational environment, we discover that there are still relatively high correlations between those ranking factors in our system. See Figure 1 for details. Therefore, on the one hand, there exists redundancy of factors in our on-line operational environment. On the other hand, we also realize that the conversion rates vary on items under different contexts. For instance, the users with higher purchase power always have a higher conversion rate under some long-tail (low-frequency) queries. Based on aforementioned analysis, we consider that some computational efficient factors may be sufficient for achieving effectiveness under such

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1Here, the \((u, q)\) user-query pair denotes the context.
contexts. The above observations show the possibility of keeping the effectiveness by carefully selecting a subset of all factors under certain circumstances, which indeed is a standard combinatorial optimization problem, but with auxiliary context description.

Combinatorial optimization is a fundamental problem in computer science. Recently, Bello et al. show that reinforcement learning is capable of solving combinatorial optimization problem like TSP via pointer network [2, 28]. In this paper, we try to address above challenges by designing an innovative model via reinforcement learning algorithms. We formally define our optimization problem with a general framework and a loss function which is able to reflect both of ranking effectiveness and efficiency. Then, we transform the contextual combinatorial optimization problem to a sequential decision-making one by incorporating the contextual setting and factor selection into the state and action of an MDP, respectively. The reward is designed to encourage to save the computational cost of factors as well as ensure that the ranking results are still effective. The final solution can be obtained via the state-of-the-art reinforcement learning algorithms such as Asynchronous Advantage Actor-Critic (A3C) in this paper. Based on the correlation among factors as well as the context dependency in our system, our method is capable of handling contextual factor selection in terms of user and query, while ensuring to minimized the influence on business indicators, i.e., gross merchandise value (GMV), click-through rate (CTR) and so on.

We show our algorithm outperforms comparative algorithms in both of off-line and on-line evaluation. In Singles’ Day Shopping Festival, 2017, we also demonstrate the capabilities of this new method in real-world large-scale system.

The contributions of this paper can be summarized as: i) injecting contextual factor selection into search engine ranking score for engine acceleration, ii) formulating the contextual factor selection for ranking as a contextual combinatorial optimization problem, iii) deriving a reinforcement learning based solution to the proposed optimization problem, iv) demonstrating the effectiveness of our technique in both of off-line and on-line environments.

The rest of the paper is organized as follows: Section 2 introduces the background; Section 3 provides some related work; In section 4, we define our problem in a view of optimization; Section 5 proposes actor-critic method to resolve the problem in section 4; We show the experimental results in section 7. Finally, section 8 summarizes the whole paper.

\section{RANKING IN E-COMMERCE SEARCH}

Suppose that $O$ is the set of all available items in the database, $Q$ is the set of all possible queries and $U$ denotes the set of all users’ information. Let $\{(u,q)_1, (u,q)_2, \ldots, (u,q)_m\}$ be a set of user-query pairs, where $(u,q)_i \in U \times Q$ denotes the $i$-th user-query pair from the search requests. $O_i = \{o_{i1}, o_{i2}, \ldots, o_{in_i}\}$ is the set of items associated with the $i$-th user-query request, where, $n_i$ is the number of the related items. The ranking problem in e-commerce scenario can be then formally defined as a task to generate a permutation function $\pi_i \in \Sigma_i$, where $\pi_i$ is an one-to-one correspondence from $\{1,2,\ldots,n_i\}$ to itself and $\Sigma_i$ denotes the set of all the possible permutations on $O_i$. The goal is to maximize the probability of purchase under the permutation. The permutation is usually generated by a ranking function $F((u,q)_i, o_{i,j}) \rightarrow \mathbb{R}$ which scores each item $o_{i,j} \in O_i$ for the request $(u,q)_i$. Let $x^{i,j} \in \mathbb{R}^n$ be the corresponding factor vector of item $o_{i,j} \in O_i$ under query $(u,q)_i$, where $i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n_i$. Some factors in the factor vector depends on the user-query pair $(u,q)_i$ and the item $o_{i,j}$. Without loss of generality, the ranking model is defined by

$$F((u,q)_i, o_{i,j}) = f \left( x^{i,j} \right), \quad (1)$$

where $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is the ranking function. It could be any function such as a linear model, a deep neural network or a tree model.

The ranking function is usually trained from a dataset $\mathcal{D} = \{(x^i, y^i)_1, \ldots, (x^i, y^i)_N\}$ logged from the real system, where $N$ is the number of training examples and $y^i = \{y_{i1}, y_{i2}, \ldots, y_{in_i}\}$ denotes the labels associates with items. Specifically, $y_{ij} \in \mathcal{Y} = \{\text{view}, \text{click}, \text{buy}\}$ represents the feedback of the user on the $j$-th item. The training can be conducted in point-wise way [9, 18], pairwise way [6, 11, 34], or list-wise way [7, 8, 33]. It is worth noting that, in this paper we assume that a trained ranking function is given and consider the general case that the ranking function is provided as a black box, i.e., with no access to the gradient or even the Hessian matrix.

\section{RELATED WORK}

There are a lot of work that attempts to resolve the effectiveness and efficiency challenge and we review will some of them.

Cascade learning is originally proposed to address the effectiveness and efficiency issue in traditional classification and detection problems such as fast visual object detection [5, 26, 29]. Liu et al. develop a cascade ranking model for a large-scale e-commerce search system and deploy it in Taobao.com [20]. However, they only exploit optimization in terms of the number of ranking items, we mainly focuses on the factor usage during the ranking process.

Feature selection tries to remove irrelevant and/or redundant features to improve learning performance [13]. Traditional feature selection techniques roughly fall into two categories, i.e., filter methods and wrapper methods. Filter methods use learner-irrelevant measurements to evaluate and select features, such as information gain and Relief [14]. Wrapper methods involve the final learner
in the feature selection process, such as using the accuracy as the evaluation criterion for the goodness of features. Liu et al. proposed the TEFE (Time-Efficient Feature Extraction) approach, which balances the test accuracy and test time cost by extracting a proper subset of features for each test object [19]. In learning to rank literature, Feature selection is a common strategy to improve the efficiency. In general, a set of crucial factors are selected from a complete set of all possible factors according to some criteria such as importance to the ranking [12, 30, 31]. Geng et al. propose a selection method based on factor importance in a query-free manner, but they do not consider the real computational cost and query-dependent factor [12]. There are also some methods that are query-dependent, in which the cost (delay) of the query is considered [30, 31]. In contrast, we consider the computational cost (delay) of individual factor.

Ensemble pruning is a class of approaches that tries to select a subset of learners (factors) to comprise the ensemble learner [35]. Recently, Benbouzid et al. apply Q-learning algorithm to ensemble pruning, in which a reinforcement learning agent tries to decide whether or not to skip the base learner. However, their method is context-free and lacks of evaluation in a real-world large-scale application.

4 CONTEXTUAL FACTOR SELECTION FOR RANKING

4.1 The CFS framework

In this subsection, we describe a general framework of Contextual Factor Selection (CFS), for constructing a search engine optimizer which achieves both of effectiveness and efficiency in terms of e-commerce search engine. As mentioned above, a factor vector $x_{i,j} \in \mathbb{R}^p$ is assigned to the corresponding item $o_{i,j} \in O_i$, in which each dimension of the factor vector is calculated on-line and varies on the computational cost. Let $x_{i,j} = \{x_{1,i,j}, x_{2,i,j}, \ldots, x_{p,i,j}\}$ be the factor vector associated with a cost vector $c = \{c_1, c_2, \ldots, c_p\}$, where $c_k$ denotes the computational cost of the $k$-th factor. Let $\Omega$ be the set of all factors and $S$ be a subset of $\Omega$. The indicator function of a subset $S$ of the set $\Omega$ is defined as

$$I_S(k) = \begin{cases} 1 & x_k \in S, \\ 0 & x_k \notin S. \end{cases}$$ (2)

From a practical point of view, some of the factors are not necessary in terms of ranking. For example, given a set of factors $\Omega = \{x_{k,i,j} \mid k = 1, 2, \ldots, p\}$, a subset $S$ of $\Omega$ with highly confident factors might be sufficient under some contexts. Therefore, given an item $o_{i,j}$ and indicator function $I_S$, the computational cost function can be written as $\sum_{k=1}^{p} I_S(k)c_k$, where the indicator function determines whether or not we use the factor to participate the sorting process. Thus, given a set of items $O_i$, the total computational cost is

$$\sum_{j=1}^{n_i} \sum_{k=1}^{p} I_S(k)c_k.$$ (3)

As defined in Equation 1, the ranking model with all factors can be written as $F_\Omega(o_{i,j}) = f(x_{1,i,j}, x_{2,i,j}, \ldots, x_{p,i,j})$ and the one with a subset $S$ is written as

$$F_S(o_{i,j}) = f(I(s(1)x_{1,i,j}, I(s(2)x_{2,i,j}, \ldots, I(s(p)x_{p,i,j}))$$ (4)

Intuitively, we can treat the permutation generated by $F_\Omega$ as the optimal one since it includes all the factors we have during the ranking process. Thus, given a $(u, q)_i$ request, the objective is

$$\min_{S \subseteq \Omega} D^O(F_\Omega || F_S) + \lambda n_1 \sum_{k=1}^{p} I_S(k)c_k,$$ (5)

where $D^O(F_\Omega || F_S)$ denotes the distance between function $F_\Omega$ and $F_S$ over the item set $O_i$, which could be any distance between two functions, i.e., Kullback-Leibler divergence [17], the second term is the computational costs of factors in the set $S$, $\lambda > 0$ is the trade-off parameter and $n_1$ is the number of items in query $i$. Intuitively, the objective implies that it reduces the usage of factors as many as possible, while approximating the original ranking function $F_\Omega$ by function $F_S$ as close as possible.

However, Equation 5 is intractable even for a single $(u, q)_i$ request, which is able to reduced to the optimal subset selection problem. Consequently, it is a NP-hard problem in general [10, 22]. Moreover, we need to do the contextual factor selection, i.e., solving a general NP-hard problem for every $(u, q)_i$, which is impractical in a large-scale system even with a small number of contexts. To overcome this challenge, we try to generalize the solution of Equation 5 at the contextual level. That is, we do not directly search the optimal subset $S^*$ and define:

$$S_{(u,q)} = H((u,q) \mid \theta)$$ (6)

where $H$ is a model parameterized by $\theta$ and the user-query pair $(u, q)$ characterizes the context. Such formulation reduces the solution space to a global parameter from the original multiple optimal subset selection problems, based on the assumption that similar $(u, q)$ representations should have similar optimal subset structure. Thus, our goal is to search for the global parameter vector $\theta$ to minimize the loss defined in Equation 5 over all the $(u, q)$ requests.

To illustrate our method, we adopt the linear ranking functions as a demonstration, and other representations, i.e., deep neural network and tree based ranking function, can be derived by similar way. In the linear setting, the score of item $o_{i,j}$ under user-query $(u, q)_i$ is

$$f(x_{1,i,j}, x_{2,i,j}, \ldots, x_{p,i,j}) = \sum_{k=1}^{p} w_{k,i,j} x_{k,i,j},$$ (7)

where $w_{k,i,j}$ is the corresponding weight of factor $x_{k,i,j}$.

In another point of view, the permutation $\sigma_i \in \Sigma_i$ significantly depends on the factors used to calculate the scores. Formally, given an user-query pair $(u, q)_i$ and a corresponding weight vector $w^{(u,q)}_i$, the linear ranking function

$$f\left(I_{S_{(u,q)_i}}(1)x_{1,i,j}, I_{S_{(u,q)_i}}(2)x_{2,i,j}, \ldots, I_{S_{(u,q)_i}}(p)x_{p,i,j}\right) = \sum_{k=1}^{p} I_{S_{(u,q)_i}}(k)w_{k,i,j} x_{k,i,j}$$ (8)

where $I_{S_{(u,q)_i}}(k)$ is the indicator function, which depends on the user-query pair $(u, q)_i$. For convenience, $I_{S_{(u,q)_i}} \in \{0, 1\}^p$ denotes...
the binary vector with respect to the factor vector $x^{t,i}$. Therefore, the ranking permutation $\sigma_i$ highly depends on the ranking function $f(\cdot)$ and the indicator function $I_{\{u,q_i\}}$, assuming the weight vector is fixed if the ranking model is given. Thus, the crucial part of ranking optimization is to learn an indicator function $I_{\{u,q_i\}}$ to determine the utilization of the factors. See Figure 2 for illustration. To simplify the notation, we write $I_{\{u,q_i\}}$ as $I_q$, where the parameter $\theta$ characterizes the factor subset $S_{\{u,q_i\}}$. Hence, the ranking permutation $\sigma^q_i$ is induced by the ranking function $f(\cdot)$ and the indicator function $I_q$. Thus, we can rewrite the distance function $D^{O_i}(F_{\Omega_i^{1:q}}||F_{\Omega_i^{2:q}})$ as $D^{O_i}(\sigma_1||\sigma_2)$, where $\sigma_1$ and $\sigma_2$ are permutations reduced by ranking function $F_{\Omega_i^{1:q}}$ and $F_{\Omega_i^{2:q}}$, respectively.

4.2 CFS with Pairwise Ranking Loss

With the optimal ranking permutation $\sigma_2$ above, then we define the distance over a item set $O_i$ between a permutation $\sigma^q_i$ and the optimal ranking permutation $\sigma_2$ as

$$D^{O_i}(\sigma_1||\sigma^q_i) = \frac{2}{n_i(n_i - 1)} \sum_{j,k=1,j\neq k}^{n_i} 1(\sigma_2(j) < \sigma_2(k)),$$

where $1(\sigma_2(j) < \sigma_2(k)) = 1$ if $\sigma_2(j) < \sigma_2(k)$ and 0 otherwise. The distance of the distance $D$ is the analogue of the averaged pairwise loss in learning to rank literature. The distance measures that how far away is the induced permutation to the optimal one in terms of ranking pairs.

With the distance and total cost function defined above, our goal is, given a user-query pair $(u, q_i)$, the corresponding item set $O_i$ and the ranking function $f$, to learn an indicator function $I_q$ such that minimizes the the distance $D$ function and the total computational costs. Formally, the objective in Equation 5 can be further rewritten as

$$L((u, q_i), O_i, f | \theta) = D^{O_i}(\sigma_1||\sigma^q_i) + \lambda \sum_{j=1}^{n_i} \sum_{k=1}^{p} I_q(k)c_k$$

5 RANKCFS: A REINFORCEMENT LEARNING APPROACH

As mentioned in section 4.1, the optimization problem defined in Equation 10 is NP-hard in general case and finding the exact solution is computationally intractable. Inspired by recent work [2, 3], we propose to optimize the factor usage using reinforcement learning framework in order to learn an indicator function $\theta$, by transforming the assignment of each element in the indicator vector as a sequential decision-making problem. We call it RankCFS.

5.1 Reinforcement Learning and Actor-Critic Methods

In this subsection, we will review some basic concepts in reinforcement learning. This subsection could be skipped If the readers are similar with reinforcement learning.

In reinforcement learning, an agent must sequentially select actions to maximize its total expected pay-off. These problems are typically formalized as Markov decision processes (MDPs) with a tuple of $(S, A, \mathcal{P}, R, \gamma)$, where $S \subseteq \mathbb{R}^d$ and $A \subseteq \mathbb{R}^m$ denote the state and action spaces. $\mathcal{P} : S \times A \times S \rightarrow [0, 1]$ represents the transition probability governing the dynamics of the system, $R : S \times A \rightarrow \mathbb{R}$ is the reward function quantifying the performance of the agent and $\gamma \in (0, 1)$ is a discount factor specifying the degree to which rewards are discounted over time. At each step $t$, the agent is in state $s_t \in S$ and must choose an action $a_t \in A$, transitioning it to a successor state $s_{t+1} \sim \mathcal{P}(s_{t+1} | s_t, a_t)$ as given by $\mathcal{P}$ and yielding a reward $r_t$. A policy $\pi : S \times A \rightarrow [0, 1]$ is defined as a probability distribution over state-action pairs, where $\pi(a_t | s_t)$ denotes the probability of choosing action $a_t$ at state $s_t$.

Policy gradients [15, 27] are a class of reinforcement learning algorithms that have shown successes in solving complex robotic problems [15]. Such methods represent the policy $\pi_{\theta}(a_t | s_t)$ by an unknown vector of parameters $\theta \in \mathbb{R}^d$. The goal is to determine the optimal parameter vector $\theta^*$ that maximize the expected discounted cumulative reward:

$$J(\theta) = \sum_{t} \mathbb{E}[P(\tau|\theta)\mathbb{R}(\tau)],$$

where $\tau \in [s_0:T], a_0:T$ denotes a trajectory over a possibly finite horizon $T$. The probability of acquiring a trajectory, $P(\tau|\theta)$, under the policy parameterization $\pi_{\theta}(\cdot)$ and discounted cumulative reward $\mathbb{R}(\tau)$ is given by:

$$P(\tau|\theta) = p_0(s_0) \prod_{t=0}^{T-1} p(s_{t+1} | s_t, a_t) \pi_{\theta}(a_t | s_t).$$

$$= \frac{2}{n_i(n_i - 1)} \sum_{j,k=1,j\neq k}^{n_i} 1(\sigma_2(j) < \sigma_2(k))$$

$$+ \lambda \sum_{k=1}^{p} I_q(k)c_k$$

$$\sum_{j=1}^{n_i} \sum_{k=1}^{p} I_q(k)c_k$$

$$\sum_{t=0}^{T-1} p(s_{t+1} | s_t, a_t) \pi_{\theta}(a_t | s_t).$$
with an initial state distribution \( p_0 : X \rightarrow [0, 1] \). Policy gradient methods, such as episodic REINFORCE [32] and Natural Actor Critic [4, 25], typically employ a lower-bound on the expected return \( J(\theta) \) for fitting the unknown policy parameters \( \theta \). To achieve this, such algorithms generate trajectories using the current policy \( \pi_\theta \), and then compare performance with a new parameterization \( \bar{\theta} \).

As detailed in [15], the policy gradient of \( J(\theta) \) can be estimated using the likelihood ratio trick as

\[
\nabla_\theta J(\theta) = \sum_r P(\tau|\theta) \log P(\tau|\theta) \delta(\tau)
\]

which is usually approximated with empirical estimate for \( m \) sample trajectories under the policy \( \pi_\theta \), i.e., \( \frac{1}{m} \sum_{\tau=1}^{m} \nabla_\theta \log P(\tau|\theta) \delta(\tau) \).

The gradient can be applied in every step \( t \) and further improved by introducing a learned bias \( V^\pi \theta(s_t|\mu) \) to reduce the variance of this estimate as in [21]

\[
d\theta \leftarrow \nabla_\theta \log \pi_\theta(a_t|s_t) (V^\pi\theta(s_t|\mu) - \beta)
\]

where \( \beta \) is the discounted cumulative reward from step \( t \) and \( V^\pi\theta(s_t|\mu) \) is the function approximation of \( \beta \) parameterized by \( \mu \), of which the gradient is

\[
d\mu \leftarrow (\beta - V^\pi\theta(s_t|\mu)) \nabla_\mu V^\pi\theta(s_t|\mu)
\]

5.2 Converting CFS to MDP Setting

It is possible to learn a factor subset, in which a subset of factors are chosen for the ranking process, by a reinforcement learning policy, instead of approximating the indicator vector \( \mathcal{I}_\theta \) directly. However, it results in a combinatorial action space which leads to computational intractability and searching failure with a high probability.

To reduce the action space, we introduce a fixed factor sequence so that a policy can sequentially determine the corresponding utility. Formally, for each user-query \( (u, q) \), request, the vector function \( \mathcal{I}_\theta \) can be determined in \( p \) steps, where in the \( k \)-th step \( (1 \leq k \leq p) \), we need to decide whether the \( k \)-th factor should be applied to the ranking function or not for this certain request, i.e., \( a_k \in \mathcal{A} = \{\text{Skip}, \text{Keep}\} \) is the action taken at step \( k \) and \( \mathcal{A} \) is the action space. \( a_k \) is obtained through a policy

\[
a_k = \pi(s_k|\theta),
\]

where \( s_k \) is the state representation of \( k \)-th step. Then we can get

\[
\mathcal{I}_\theta(k) = \begin{cases} 0 & \text{if } a_k = \text{Skip} \\ 1 & \text{if } a_k = \text{Keep} \end{cases}
\]

After \( p \) steps, \( \mathcal{I}_\theta \) is determined and so is ranking permutation \( \sigma^\theta \).

Then we can directly calculate the loss \( \mathcal{L}(\langle u, q \rangle_i, O_i, f \mid \theta) \) to evaluate the result of selected actions, which can be further used to define the total reward of the actions generated in \( p \) steps during the episode. See Figure 3 for illustration. The key idea lies in the state design (base on which the action is generated), the reward design (how to evaluate each action) and the optimization method for this reinforcement learning problem (how to find the optimal policy).

5.3 The State and Reward Design

The optimal policy should generalize over the state space, and the optimal actions for an episode only depend on the \( (u, q) \), request, so ideally, the state can be designed as

\[
s_k = (v_{\langle u, q \rangle}, k) \in R^{l+1}
\]

where \( v_{\langle u, q \rangle} \in R^l \) is the representations for the user-query pair \( (u, q) \). The corresponding reward \( r_k \) is then defined as

\[
r_k = \begin{cases} 0 & 1 \leq k < p \\ -\mathcal{L}(\langle u, q \rangle_i, O_i, f \mid \theta) & k = p \end{cases}
\]

The agent is designed to obtain a reward of 0 when the episode is not terminated, i.e., \( 1 \leq k < p \), and a reward of \(-\mathcal{L}(\langle u, q \rangle_i, O_i, f \mid \theta) \) when the episode ends, like the goal-directed tasks. By above definition and assigning \( y \) to 1, then we can conclude that the objective in this reinforcement learning problem is exactly the negative of the objective in Equation 10:

\[
\varphi(\tau) = \sum_{k=1}^{p} y^{k-1} r_k = -\mathcal{L}(\langle u, q \rangle_i, O_i, f \mid \theta)
\]

This means that maximizing \( \varphi(\tau) \) can directly minimize \( \mathcal{L} \), allowing us to find the optimal solution of \( \mathcal{L} \) with the power of deep reinforcement learning.

However, empirically there are two issues that make learning the optimal policy for above reinforcement learning problem difficult. One is that the reward is sparse over states, known as the sparse feedback problem [16]. The other one is that the reward itself (\( \mathcal{L} \)) distributes widely in the continuous space, making the critic model difficult to converge. Inspired by the reward shaping [23] technique, we consider to slightly change the representations of states and rewards, to alleviate the above issues.

We firstly initialize \( \mathcal{I}_\theta = [1, 1, \ldots, 1] \in R^p \) as an all-one vector, and at the step \( k \) update \( \mathcal{I}_\theta \) as

\[
\mathcal{I}_\theta(t) = \begin{cases} \mathcal{I}_\theta(t) & 1 \leq t < k \\ 1 & k \leq t \leq p \end{cases}
\]

Then we extend our state vector to

\[
s_k = (v_{\langle u, q \rangle}, k, \mathcal{I}_\theta(k)) \in R^{l+p+1}.
\]
Algorithm 1 RankCFS

Input:
\[ D: \text{Training data set } D = \{(u, q, O_i)\}_{i=1}^N \]
\[ f: \text{The ranking function} \]
\[ \gamma, \lambda, \beta, r_c, T_{max}: \text{Parameters of the algorithm} \]

Output:
\[ \theta: \text{Parameters of actor model} \]
1: Initialize the actor network params \( \theta \) and the critic network params \( \mu \)
2: \( T \leftarrow 1 \)
3: repeat
4: for each \( (u, q, O_i) \in D \) (For each page view) do
5: \( T \leftarrow T + 1 \)
6: Initialized the initial state \( s_1 \) as in Eq. 23
7: for \( k = 1, 2, \ldots, p \) do
8: Taking action \( a_k \in \{\text{Skip, Keep}\} \) on the \( k \)-th factor based on \( \pi_\theta(s_k) \), observe \( r_k \) and \( s_{k+1} \).
9: Cache the tuple \((s_k, a_k, r_k, s_{k+1})\)
10: end for
11: \( R \leftarrow 0 \)
12: for \( k = p, p-1, \ldots, 1 \) do
13: \( R \leftarrow r_k + \gamma R \)
14: \( \theta \leftarrow \text{Adam}(\theta, V_\theta \log \pi_\theta(a_k|s_k)(R - V^\pi_\theta(s_1|\mu))) \)
15: \( \mu \leftarrow \text{Adam}(\mu, (R - V^\pi_\theta(s_k|\mu))V_\mu V^\pi_\theta(s_k|\mu)) \)
16: end for
17: end for
18: until \( T > T_{max} \)

Thus our state memorizes the decisions made before during an episode. At each step \( k \), the reward is calculated based on \( I^\phi(\cdot|k) \), i.e., at each step it is pre-evaluated for the decisions made so far, assuming the remaining decisions are all ones by default. For each reward \( r_k \), we decompose it into the effectiveness part \( T(s_k, a_k) \) and the efficiency part \( G(s_k, a_k) \), i.e., \( r_k = T(s_k, a_k) + G(s_k, a_k) \). For the efficiency part, we simply add a penalty when keeping the \( k \)-th factor as
\[
G(s_k, a_k) = \begin{cases} 
0 & \text{if } a_k = \text{Skip} \\
-\lambda n_{ic_k} & \text{if } a_k = \text{Keep}
\end{cases}
\]
This part is consistent with the Equation 10. For the effectiveness part, we choose to give a constant penalty if the ranking loss under \( \phi' \theta \) exceeds a pre-defined threshold as
\[
T(s_k, a_k) = \begin{cases} 
-r_c & D^{O_1}(\sigma_{1i}||\sigma_{1i}') > \beta \\
0 & \text{otherwise}
\end{cases}
\]
rather than \( -D^{O_1}(\sigma_{1i}||\sigma_{1i}') \) itself shown in Equation 10. By such design we could help the critic distinguish bad and good ranking result much easier. Moreover, we could avoid generating poor ranking performance with a large penalty \( r_c \).

5.4 Learning the Policy

After transforming the original problem into a reinforcement learning one, we could then apply any reinforcement learning methods. In this paper, we choose the well-known policy gradient method with actor-critic models as described in [21] and we call it RankCFS. It is worth noting that, the difficulty of the original optimization problem does not decrease with the introduction of reinforcement learning techniques. The RL-based approach here acts as a solver whose solution space contains the optimal, and provides an efficient searching path to the optimal through trial-and-error methods.

Algorithm 1 shows the training details. The data of page views in the on-line search system \( D = \{(u, q, O_i)\}_{i=1}^N \), the reward discount factor \( \gamma \), the parameters used in the reward definition \( \beta, \gamma, r_c \) and the maximal number of training step \( T_{max} \) are given as the input of the algorithm. The parameter of the actor network \( \theta \) is the output of the algorithm. We firstly initialize the parameters of the actor and critic network, as well as the step counter \( T \), as in Line 1 and 2. The training phase starts with the iteration of the each page view, with which an episode will be generated during the Line 6-10. Then standard policy gradient is conducted in Line 14-15, where the tuple \((s_k, a_k, r_k, s_{k+1})\) is organized in the backward way so the discounted cumulative reward \( R \) can be updated incrementally as in Line 13. The training process ends when the number of steps exceeds the given threshold \( T_{max} \).

6 EXPERIMENTAL RESULTS

In this section, we provide empirical results of our approaches in off-line evaluation and commercial on-line evaluation. We show the results of off-line settings in order to provide a way to justify our algorithm. Then, we test our method in a real on-line commercial web search engine to reveal the performance improvement with respect to the resource consumption. At last, we demonstrate the performance of our method in Singes’ Day shopping festival.

6.1 Off-line Comparison

In this subsection, we compare our method with norm elimination method, \( l_1 \)-based feature selection, tree-based feature selection and F-test feature selection in an off-line evaluation setting.

Norm Elimination is that we remove those factors whose absolute values of weights are less than a positive constant \( \epsilon \).

\( l_1 \)-based feature selection is a model-based feature selection method such that it selects factor according to the \( l_1 \) regularizer. The basic idea is that to eliminate those factors whose corresponding \( l_1 \) coefficients are zero. Since this method must be based on a


Tree-based feature selection is similar to the $l_1$-based feature selection and the difference is that we replace the Lasso model with a non-linear regression tree model.

F-test feature selection is a model-free feature selection method that selects top $k$ factors based on F-test scores.

Rank Contextual Factor selection (RankCFS) algorithm is out actor-critic method which is capable of adjusting the usage of factor by contexts.

For $l_1$-based feature selection, Tree-based feature selection and F-test feature selection, we adopt their implementations in scikit-learn [24]. We implement RankCFS with Tensorflow [1]. For the optimal ranking model in the off-line evaluation, we select one of linear ranking models of Taobao.com and treat it as a black box so that the input and output of the ranking model are merely considered during the experimental process. We set the constant $c = 0.1$ in the Norm Elimination method; the constant that multiplies the $l_1$ term $\alpha$ equals 0.05 in the Lasso model; We choose the default ExtraTreeRegressor in scikit-learn package as our tree model; The actor and critic are construct by two deep neural networks (DNN) with three fully connected layers, respectively. The DNN structures of actor are 266×128×128×20 and ones of critic are 266×128×128×1. We adopt relu as the activation functions for the hidden layers, Adam as our optimizer and the learning rates of actor and critic are 0.0001 and 0.001, receptively.

We sample a data set with 100, 000 examples as mentioned above, then train the $l_1$-based, Tree-based and F-test approaches on 50, 000 examples and test then on the rest of 50, 000 \(^4\). For the $l_1$, Tree-based and F-test methods, the feature selection are determined after the training, that is, we use a fixed feature selection policy during the testing stage. Since our method requires to consider the computational costs of factors, the computational cost vector $c$ is obtained from the on-line operational environment of Taobao.com.

We test our methods on 5, 000 page views and each page view contains 10 items so that there are 50, 000 testing examples. Then, we evaluate the averaged pairwise loss defined in Equation 9 and factor usage over page views. Figure 4-6 show our experimental results. Generally, the Norm Elimination method removes those factors whose absolute values are small under different contexts, therefore indicators such as loss, factor usage may vary over page views. Figure 4 demonstrates that our RankCFS with the threshold $\beta \geq 0.05$ outperforms all other methods in terms of pairwise loss. And in Figure 6, it shows that the averaged factor usage of RankCFS algorithm is also close to the lowest Tree-based method. Figure 6 demonstrates the weighted factor usage, in which the weights are the corresponding computational costs. This metric is more accurate to describe the factor usage in terms of efficiency due to the variety in computational costs among factors. For example, it only considers absolute values of weights in the Norm Elimination method, while RankCFS tends to eliminate those factors with high computational costs. Although, RankCFS $\beta = 0.05$ and Tree-based method have similar averaged factor usage, RankCFS $\beta = 0.05$ has much lower weighted factor usage. It is the evidence that our approach relieves the computational burden in an intelligent way and save more computational resources. Empirically, our method

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\(^4\)It is not necessary to train Norm Elimination method since it only removes those factors whose absolute values of weights are less than a positive constant $c$.

\(^5\)10, 000 page views and 10 items in each page view.

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**Table 1: Results Summary**

| Algorithm               | Averaged Pairwise Loss | Averaged Factor Usage | Weighted Factor Usage |
|-------------------------|------------------------|-----------------------|-----------------------|
| F-test $k = 8$          | 0.47                   | 8                     | 72.44                 |
| F-test $k = 11$         | 0.40                   | 11                    | 84.63                 |
| F-test $k = 14$         | 0.29                   | 14                    | 107.93                |
| Norm Elimination        | 0.35                   | 7.41                  | 78.84                 |
| Lasso                   | 0.31                   | 8                     | 71.16                 |
| Tree-based              | 0.3                    | 7                     | 63                    |
| RankCFS $\beta = 0.05$ | 0.21                   | 7.01                  | 51.06                 |
| RankCFS $\beta = 0.15$ | 0.27                   | 9.07                  | 67.40                 |
| RankCFS $\beta = 0.25$ | 0.25                   | 8.4                   | 63.72                 |

supervised machine learning model, we need to convert our ranking problem into a supervised one. We define the training data set as following: let the label $y_{i,j} = f(x_{1,i,j}, x_{2,i,j}, \ldots, x_{p,i,j}) = \sum_{k=1}^{p} w_k x_{i,k}^{(j)}$ and corresponding factor vector $x^{(j)}$, thus the set of training examples has the form $D_{tr} = \{x_{i,j}^{(j)}\}$ such that $j = 1, \ldots, n_i$ and $i = 1, \ldots, N$. Therefore, we can train a regressor via training set $D_{tr}$ and select the factors base on the trained model. We adopt the Lasso as our comparison method.
is capable of exploring better solution in a combinatorial solution space with less factor usage. The F-test method suffers high pairwise loss since it is a model-free method, it is not required to consider the ranking model we adopt. Overall, the experiments shows that our RankCFS algorithm successfully explores the function space and find an excellent approximation to the optimal ranking function. We summarized the complete experimental results in Table 1 with varieties in parameters. Note that RankCFS $\beta = 0.25$ outperforms RankCFS $\beta = 0.15$. It is possible that RankCFS $\beta = 0.15$ falls into a worse local optimal solution and fails to escape from it.

## 6.2 On-line Evaluation in Operational Environment

In this subsection and the following subsection, we present the experimental results of on-line evaluation in the real-world large-scale operational environment of Taobao.com with a standard A/B testing setting. For the on-line evaluation, we adopt the same learning structure with the off-line one, but with a more complex nonlinear optimal ranking model. The training is conducted with more than $1 \times 10^{9}$ training samples on a distributed streaming system in an on-line learning fashion. The system information of computers in the clusters on which we conducted our experiments is list in Table 2.

![Latency for regular operational environment](image)

(a) Latency for regular operational environment

![Latency for Singles’ Day](image)

(b) Latency for Singles’ Day

Figure 7: Latency in a real-world large-scale e-commerce search engine. Lower is better.

### Table 2: System information

| Hardware   | Configuration               |
|------------|-----------------------------|
| CPU        | 2x 16-core Intel(R) Xeon(R) |
| RAM        | 256 GB                      |
| Hyperthreading | Yes                         |
| Networking | 10 Gbps                     |
| OS         | ALIOS7 Linux 3.10.0 x86_64  |

The search engine of Taobao.com is a complex system, processing billions of items and hundreds of millions of user queries every day. As a core system in Taobao.com, the search engine needs to respond the user queries in a timely manner. The search traffic might increase significantly during some promotional campaign such as the Singles’ Day shopping festival. Therefore, the system efficiency is always an important issue. Furthermore, the system is still required to provide high quality search service to the users, leading to computational burden for the whole system.

We conduct a standard A/B test experiment in our operational environment, where roughly 6% of the random users are select for the testing. The parameter $\beta \in \{0.25, 0.15, 0.05\}$ and $\lambda \in \{0.9, 0.8, 0.7\}$ are tuned through the GMV and search latency. The goal is to minimize the impact on the GMV as much as possible, while reducing the latency as much as we can, comparing the control group. Figure 7a shows the best result with $\beta = 0.05$ and $\lambda = 0.9$. Our method saves approximately 40% average search latency, comparing to the control group. For the max search latency, our algorithm reduce roughly 25% latency. The system performance (GMV) is almost the same or little lower (0% to 0.5%) as the control group.

### 6.3 Singles’ Day Evaluation

Alibaba Singles’ Day shopping festival is one of the biggest shopping extravaganzas around the world and is the Chinese version of Black Friday. In 2017, by the end of day (November 11), sales hit a new record of $25.3$ billion, more than 40% higher than sales on Singles’ Day 2016 and it attracts over hundreds of millions users from more than 200 different countries. The infrastructure system manages to handle 0.325 millions orders per second at peak\(^3\). The e-commerce search system played a crucial role in this event.

In November 11th, the search traffic burden of the e-commerce search engine abruptly increases by multiple times as much as in a regular day. On the one hand, the e-commerce search engine faces the high traffic challenge, which might lead to system degradation. On the other hand, it is still crucial to provide high search accuracy even during shopping festival.

In the event, our method collaborates previous work [20] in order to maximize optimization at the search engine system level. The algorithm called CLOES mainly focuses on optimizing the number of items in the ranking process via cascading model, while our method concentrates on optimizing the set of ranking factors during the ranking process. Thus, both of approaches are able to apply on the search engine simultaneously. We use CLOSE approach as our control group, CLOES+RankCFS as the experimental group, in which the parameter $\beta = 0.05^5$. Figure 7b depicts the average latency change during the experiments, in which our method averagely saves 20% more latency on the basis of CLOES. And also, our method saves approximately 33% peak latency on the basis of CLOES. The system performance (GMV) is almost the same as the CLOSE method.

Our method and CLOES collaborate together in the very day of Singles’ Day 2017, and succeed in providing a much better search performance than previous year.

### 7 CONCLUSION AND FUTURE WORK

In this paper, we thoroughly investigate the effectiveness and efficiency issues in a real-world large-scale e-commerce search system

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\(^{3}\)https://techcrunch.com/2017/11/11/alibaba-smashes-its-singles-day-record/

\(^{5}\)Due to the limited on-line resources, we are only able to use CLOES as our control group.
and propose an intelligent optimization solution by reinforcement learning method. We formally defined the learning to rank problem in an e-commerce scenario and characterize the effectiveness and efficiency, which is a NP-hard problem. Then, we convert the problem into a reinforcement learning problem by the reward design and solve it by the actor-critic method. We empirically test our method in off-line and on-line evaluation scenarios, demonstrating our method is a practical solution in a real-world large-scale e-commerce search system. In future, we plan on finding other ways to optimize the system engine such as memory usage, load balancing, combined with search latency. Moreover, the DNN network representation in our current setting is not an end-to-end solution so that the end-to-end representation solution (i.e. pointer network [28]) will be considered.

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