Optimizing Whole-Page Presentation for Web Search

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Modern search engines aggregate results from different *verticals*: webpages, news, images, video, shopping, knowledge cards, local maps, etc. Unlike "ten blue links", these search results are heterogeneous in nature and not even arranged in a list on the page. This revolution directly challenges the conventional "ranked list" formulation in ad hoc search. Therefore, finding proper *presentation* for a gallery of heterogeneous results is critical for modern search engines.

We propose a novel framework that learns the optimal *page presentation* to render heterogeneous results onto search result page (SERP). Page presentation is broadly defined as the strategy to present a set of items on SERP, much more expressive than a ranked list. It can specify item positions, image sizes, text fonts, and any other styles as long as variations are within business and design constraints. The learned presentation is content-aware, i.e. tailored to specific queries and returned results. Simulation experiments show that the framework automatically learns eye-catchy presentations for relevant results. Experiments on real data show that simple instantiations of the framework already outperform leading algorithm in federated search result presentation. It means the framework can *learn* its own result presentation strategy purely from data, without even knowing the "probability ranking principle".

CCS Concepts: • **Information systems** → **Combination, fusion and federated search**; **Presentation of retrieval results**; • **Computing methodologies** → *Learning to rank*; *Reinforcement learning*;

Additional Key Words and Phrases: Whole-page optimization, page presentation, user satisfaction

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1 INTRODUCTION

A decade ago, search engines returned "ten blue links". Result presentation was straightforward: ranking webpages by estimated relevance. It naturally saves user effort as she scans down the list, hopefully hitting the desired information at top ranks. This "probability ranking principle" was long envisioned in the 1970s [54], and later confirmed by eye-tracking studies [27, 28] and search log analysis [18, 34].

Today's search engines return far richer results than "ten blue links". Aside from webpages, results can also include news, images, video, shopping, structured knowledge, and local business maps. Each specific corpus is indexed by a *vertical* search engine; they are *federated* to serve the user's information need. Unlike "ten blue links", vertical search results have different visual appearance, layouts and sizes. They span across multiple columns on the page, not restricted in the mainline list (Figure 1).

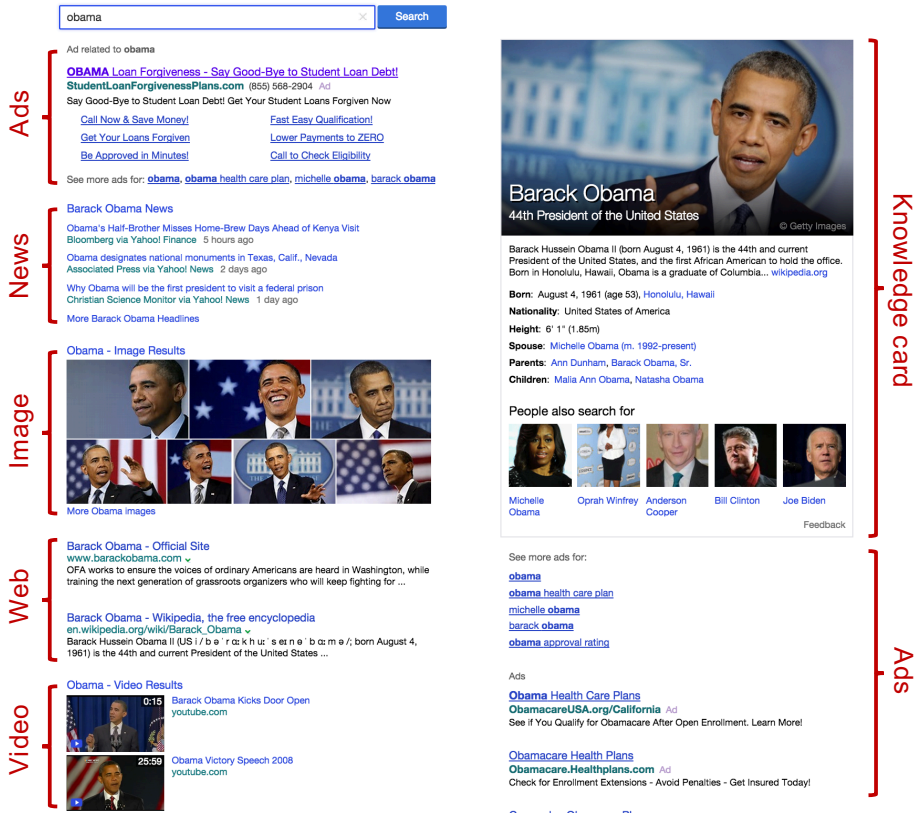


Fig. 1. Yahoo search engine result page for the query "obama". Accessed on July 12, 2015.

Federated search results have been transforming user interaction patterns on search result pages (SERPs). Human eyeballs are spontaneously attracted by graphical results, causing a significant attention bias known as the *vertical bias* [13, 38, 44]. More interestingly, blue links surrounding a vertical result are also examined with increased probability [13]. In the presence of vertical results, user satisfaction towards an entire SERP cannot be reliably inferred from preference judgments for pairs of results [5].

These observations indicate that users do *not* sequentially scan results returned by federated search. Although the conventional "ranked list" formulation can still be used for federated search result presentation [3, 4], it is essentially a first-order approximation of the problem.

In this paper, we propose a novel framework that learns the optimal presentation for heterogeneous search results on SERP. Page presentation is broadly defined as the strategy to present a set of heterogeneous items on SERP, much more expressive than a ranked list. It can specify item positions, image sizes, text fonts, or any other styles as long as changes of these elements are allowed by business constraints [1] and page design templates. The goodness of a presentation is measured by user satisfaction metric: better presentation will make the user happier. The framework first learns a scoring function that maps search results and their presentation on SERP to user satisfaction metric. Then, given search results of a new query, the framework computes a presentation that maximizes user satisfaction.

The framework is quite general. First, practitioners can flexibly define the scope of page presentation. It can encode item positions (both horizontal and vertical) as well as element styles, such as image sizes and text fonts. It naturally encompasses ranked list as a special case. Second, different application scenarios can adopt different user satisfaction metric. It is not limited to click-based metric, but can also take other interactive behaviors into account, such as dwelling time and time-to-first-click. Lastly, the framework can potentially be instantiated in other interactive search scenarios, such as presenting search results on mobile and tablet devices, displaying multimedia feeds in online social networks, and arranging items on retailing websites.

We conduct experiments on both synthetic and real data to demonstrate the potential power of the proposed framework. Simulation experiments show that the framework can adapt to different types of attention bias and learn to present relevant results to catch user's eyeballs. This means our approach directly targets the new challenge brought by federated search, where users may not scan the results sequentially, and results are not in a ranked list. In real data experiments, simple instantiations of the framework outperform the leading algorithm in federated search result ranking. This is encouraging, because ranking algorithms use the probability ranking principle in its result presentation, while our framework does not even know the existence of it. Nevertheless, it *learns* its own result presentation principle purely from data and is able to deliver the state-of-the-art performance.

Our main contribution is summarized as follows:

- We formulate a new problem, *whole-page presentation optimization*, which extends the homogeneous document ranking in ad hoc search (Section 2).
- We propose a solution framework that computes the optimal presentation for federated search results (Section 3 and 4).
- Experiments on synthetic and real data demonstrate that the proposed framework is promising in solving the new problem (Section 5 and 6).
- We reformulate the problem in reinforcement learning, which provides a unified perspective. It not only explains the original approach as a special reinforcement learning algorithm, but also inspires new policy-based approaches that are efficient at runtime (Section 7).

Part of the results were reported in our recent work at WSDM 2016 [64]. For those who have read the conference version, this extension includes a case study following the real data experiment (Section 6) and a comprehensive literature review of related topics (Section 8). The reinforcement learning reformulation and policy learning approach (Section 7) are completely new.

[1]For example, sponsored results must be placed on the top.

2 PROBLEM FORMULATION

The problem statement of page presentation optimization is as follows: "given search results to be displayed on a page, to find the optimal presentation that maximizes user satisfaction". We assume the following setting: search engine returns a set of results upon receiving a query, and renders the items on SERP according to some presentation strategy. As the SERP is shown to the user, she interacts with it and get certain degree of satisfaction. Now let us define some important concepts in our setting:

Definition 2.1 (Page Content). Page content is the set of search results to be displayed on a page. Each search result is an **item**. Upon receiving user's query, search engine backend returns a set of k items. Each item is represented as a vector $\mathbf{x}_i$ [2]. Note that different users and different queries will produce different sets of items, so $\mathbf{x}_i$ also encodes information from actual users and queries. Page content is represented as concatenation of k item vectors: $\mathbf{x}^\top = (\mathbf{x}_1^\top, \cdots, \mathbf{x}_i^\top, \cdots, \mathbf{x}_k^\top)$. The domain of $\mathbf{x}$ is defined by all possible page content returned by the backend, denoted as $\mathcal{X}$.

Definition 2.2 (Page Presentation). Page presentation defines the way in which page content $\mathbf{x}$ is displayed, such as position, vertical type, size, and color. It is encoded as a vector $\mathbf{p}$. The domain of $\mathbf{p}$ is defined by all possible page presentations permitted by business and design constraints, denoted as $\mathcal{P}$.

Definition 2.3 (Search Result Page (SERP)). When page content $\mathbf{x}$ is put on page according to presentation strategy $\mathbf{p}$, a search result page (SERP) is generated. In other words, content $\mathbf{x}$ and presentation $\mathbf{p}$ uniquely determine a SERP. It is represented as a tuple $(\mathbf{x}, \mathbf{p}) \in \mathcal{X} \times \mathcal{P}$.

Definition 2.4 (User Response). User response includes her actions on SERP, such as number of clicks, positions of clicks, dwell time of clicks, and time to first click. This information is encoded in a vector $\mathbf{y}$. The domain of $\mathbf{y}$ is defined by all possible user responses, denoted as $\mathcal{Y}$.

Definition 2.5 (User Satisfaction). The user experiences certain degree of satisfaction as she interacts with the SERP. We assume that user satisfaction can be calibrated as a real value $v \in \mathbb{R}$: larger value of v means higher satisfaction.

The user response is a strong indicator for satisfaction. Intuitively, if a user opened the SERP, clicked on the top result right away, then spent long time dwelling on that result, she was highly likely to be happy with the result. With definitions above, we formulate our problem:

Page Presentation Optimization is to find the presentation $\mathbf{p} \in \mathcal{P}$ for a given page content $\mathbf{x} \in \mathcal{X}$, such that when the SERP $(\mathbf{x}, \mathbf{p})$ is presented to the user, her satisfaction score v is maximized.

If we define a scoring function $F : \mathcal{X} \times \mathcal{P} \to \mathbb{R}$ that maps a SERP $(\mathbf{x}, \mathbf{p})$ to a user satisfaction score v, then page presentation optimization problem can be formally written as $\forall \mathbf{x} \in \mathcal{X}$,

$$\max_{\mathbf{p} \in \mathcal{P}} F(\mathbf{x}, \mathbf{p}) \ . \tag{1}$$

The problem of page presentation optimization is both new and challenging. It is new because page presentation can be flexibly defined, which opens up possibility to learn brand-new ways to display information. Retrieval and recommender systems typically use a ranked list for displaying homogeneous content. As heterogeneous results are weaved onto webpages, it is critical to present them in a proper manner to maximize user's utility. The problem is challenging because it is rather unclear how to find the scoring function that maps the *entire* SERP (content and presentation) to user satisfaction. We propose our solution framework in the next section.

[2]Throughout the paper we use bold lowercase letters for column vectors.

3 PRESENTATION OPTIMIZATION FRAMEWORK

In this section, we propose to solve page presentation optimization using a supervised learning approach. We set up a general framework, including data collection methodology, design of scoring function $F(\cdot,\cdot)$, the learning and optimization stages. In the next section, we describe actual instantiations of the framework.

3.1 Data Collection Through Exploration

Supervised machine learning needs labelled training data. The caveat in data collection here is that normal search traffic cannot be used as the training data to learn the scoring function $F(\mathbf{x},\mathbf{p})$. This is because in normal search traffic, search engine has a deterministic policy to present page content $\mathbf{x}$, which is controlled by existing model/rules within the system. In other words, page presentation $\mathbf{p}$ is uniquely determined given page content $\mathbf{x}$. However, we expect the model F to tell us user satisfaction as we search through *different* page presentations. Confounding between $\mathbf{x}$ and $\mathbf{p}$ will bias the learned model, which will be a serious problem.

To eliminate confounding, we allocate "presentation exploration bucket" to do randomized experiments. For each request in the bucket, we organize page content with random page presentation. Here "random" means to uniformly draw presentation strategies within business and design constraints, such that user experience is not hurt too much. Further, the presentation exploration traffic is controlled within a very small amount so as not to affect overall quality of the search service. Data collected in this way allow unbiased estimation of the scoring function.

In cases that showing random exploration results to the users is not desired, it would also be possible to either hire human annotators to label the page, or collect data from multiple buckets with different fixed presentation strategy as every Internet company is doing for testing their UI changes. Since we have already developed a good data collection through exploration framework in our production system, we choose to take this approach for data collection.

3.2 Learning Stage

The core of page presentation optimization is to estimate the scoring function $v = F(\mathbf{x},\mathbf{p})$. We might consider two approaches:

(I) ***Direct approach:*** Collect page-wise user satisfaction ratings and directly model the dependency between SERP and user satisfaction. The dependency path is "$(\mathbf{x},\mathbf{p}) - v$".

(II) ***Factorized approach:*** First predict user response $\mathbf{y}$ on SERP, then find a function that measure user satisfaction from these responses. The dependency path is "$(\mathbf{x},\mathbf{p}) - \mathbf{y} - v$".

Approach (I) is straightforward. However it is very difficult, particularly at a large scale, to obtain explicit user rating s towards the *entire* SERP. To construct such data set, we would have needed substantial amount of observations and human annotation to overcome training data sparseness.

Approach (II) takes two steps. The first step is to predict user responses on a given page; the second step is to measure user satisfaction based on her page-wise response. Introducing user response variable $\mathbf{y}$ permits a separation of concerns. On the one hand, user response on a page is a direct consequence of interacting with the page. On the other hand, user satisfaction is typically estimated from user responses *only*, e.g. using total number of clicks, or long dwell time. In Approach (II), the complex dependency in $F(\cdot,\cdot)$ is decomposed into two relatively independent factors. Furthermore, on a practical note, Approach (II) is more realistic for current Web technology because user response on SERP can be easily collected via Javascript, whereas explicitly asking the users to evaluate the whole page is very uncommon. Therefore, we adopt the ***factorized approach***.

In factorized approach, the first step is to learn a *user response model*

$$\mathbf{y} = f(\mathbf{x},\mathbf{p}),\ \forall\, \mathbf{x} \in \mathcal{X}, \mathbf{p} \in \mathcal{P}.$$

This is a supervised learning task; the actual form of $f(\mathbf{x}, \mathbf{p})$ can be chosen flexibly. We can simply build one model for each component y_i in $\mathbf{y}$, or we can jointly predict all components of $\mathbf{y}$ using structured output prediction [9]. In any case, user's responses on the page depends on both the content (whether it is relevant, diverse, or attractive) and the presentation (whether it is close to the top, around a graphical block, or shown in big size).

The second step is a utility funciton which defines a *user satisfaction metric*

$$v = g(\mathbf{y}), \forall\, \mathbf{y} \in \mathcal{Y}.$$

Finding the right user satisfaction metric based on page-wise user responses is not the focus of this paper, and can itself be a substantial research topic in interactive information systems [30, 43, 56]. Indeed, practitioners often heuristically define the metric as aggregation of fine-grained user responses, such as click-through rates, long-dwell-time clicks, time-to-first-click.

Finally, our scoring function for the entire SERP is

$$v = F(\mathbf{x}, \mathbf{p}) = (g \circ f)(\mathbf{x}, \mathbf{p}) = g(f(\mathbf{x}, \mathbf{p})).$$

3.3 Optimization Stage

We compute the optimal presentation $\mathbf{p}^*$ given content $\mathbf{x}$ by solving the following optimization problem:

$$\max_{\mathbf{p} \in \mathcal{P}} g(f(\mathbf{x}, \mathbf{p}))\ .$$

Computational cost of this optimization problem depends on actual form of the objective function $F = g \circ f$ and the constraints on presentation $\mathbf{p}$. In the next section we show that for certain instantiations of f and g, $\mathbf{p}^*$ can be computed quite efficiently. In Section 7, we present a reinforcement learning solution where the optimization stage is replaced by a policy.

4 INSTANTIATIONS OF PRESENTATION OPTIMIZATION FRAMEWORK

This section describes instantiations of the framework, including feature representation, user satisfaction metric, two user response models and their learning and optimization stages. We conclude this section by showing that the framework encompasses learning to rank.

4.1 Features

Both content and presentation on a SERP are represented in a feature vector, which will be the input to user response models.

4.1.1 Content Features. Content features contain information of the query and corresponding search results, similar to those used in learning to rank. We adopt the same content features as used in [32] to facilitate direct comparison in experiments (Section 6):

- **Global result set features**: features derived from all returned results. They indicate the content availability of each vertical.
- **Query features**: lexical features such as the query unigrams, bigrams and co-occurrence statistics. We also use outputs of query classifiers, and historical session based query features, etc.
- **Corpus level features**: query-independent features derived for each vertical and web document such as historical click-through rates, user preferences, etc.
- **Search result features**: extracted from each search result. A list of statistical summary features such as relevance scores and ranking features of individual results. For some verticals, we also extract some domain specific meta features, such as if the movie is on-screen and

if the movie poster is available in the movie vertical, and the number of hits for the news articles from the news vertical in the last few hours.

4.1.2 Presentation Features. Presentation features encode the way in which search results are displayed on SERP, which are novel features in our framework. Concrete examples include:

- **Binary indicators**: whether to show an item on a position. The scheme can encode positions in a wire-frame, such as a list or multi-column panels. Let there be k positions in the frame, and k items to be displayed. Let i be the index of items, j be the index of positions, $1 \le i, j \le k$. The presentation of item i, $\mathbf{p}_i$, is a 1-of-k binary encoding vector. If document i is placed at position j, then the j-th component of $\mathbf{p}_i$ is 1 and all others are 0. In this case we denote the value of $\mathbf{p}_i$ as $p_{ij} = 1$. The page presentation $\mathbf{p}^\top = (\mathbf{p}_1^\top, \cdots, \mathbf{p}_k^\top)$ consists of $k \times k$ binary indicator variables, essentially encoding the permutation of k objects.
- **Categorical features**: discrete properties of page items, e.g., multimedia type of an item (shown as text or image), typeface of a textual item;
- **Numerical features**: continuous properties of page items, e.g. brightness and contrast of a graphical item.
- **Other features**: e.g. certain interactions between page content and presentation may affect user response, such as "a textual item immediately above a graphical item".

We use two types of presentation features in real data experiments. We encode positions of items with binary indicators. For the local search results, we encode presentation size as a categorical feature ("single" vs. "multiple" entries).

4.2 User Satisfaction Metric

We assume that user satisfaction metric $g(\mathbf{y})$ is in the form of weighted sum of components in $\mathbf{y}$:

$$g(\mathbf{y}) = \mathbf{c}^\top \mathbf{y}.$$

In experiments, we use the click-skip metric for k items [32]:

$$g(\mathbf{y}) = \sum_{i=1}^{k} y_i,$$

where $y_i = 1$ if item i is clicked, and $y_i = -1$ if item i is skipped *and* some item below is clicked. A skip often indicates wasted inspection, so we set it to be a unit of negative utility. This metric strongly prefers adjacent clicks at top positions.

4.3 User Response Models

We use two models for predicting page-wise user response. The first model takes as features quadratic interaction between content and presentation. It permits an efficient optimization stage. The second model uses gradient boosted decision trees to capture more complex, nonlinear interaction between content and presentation. We expect it to generate improved performance.

4.3.1 Quadratic Feature Model. First, let us consider a simple instantiation of user response model that has efficient solution in the optimization stage. Since it uses quadratic interaction features between $\mathbf{x}$ and $\mathbf{p}$, we call it *Quadratic Feature Model*.

Assume there are k positions for k items. Page content $\mathbf{x}$ is the concatenation of k item vectors; page presentation is encoded using binary indicators, $\mathbf{p} \in \{0, 1\}^{k \times k}$, as defined in Section 4.1. The model also contains fully interaction between $\mathbf{x}$ and $\mathbf{p}$ as features. Let $\mathrm{vec}(\mathbf{A})$ denote the row vector containing all elements in matrix $\mathbf{A}$, taken column by column, left to right. The augmented feature

vector $\boldsymbol{\phi}$ for Quadratic Feature Model is:

$$\boldsymbol{\phi}^\top = (\mathbf{x}^\top, \mathbf{p}^\top, \mathrm{vec}(\mathbf{x}\mathbf{p}^\top)).$$

Let $\mathbf{y} \in \mathbb{R}^k$ be the user response vector; each component y_i is a user response (e.g. click or skip) on item i. A linear model f_i is used to predict each y_i in $\mathbf{y}$:

$$y_i = f_i(\boldsymbol{\phi}) = \mathbf{w}_i^\top \boldsymbol{\phi} = \mathbf{u}_i^\top \mathbf{x} + \mathbf{v}_i^\top \mathbf{p} + \mathbf{x}^\top \mathbf{Q}_i \mathbf{p}. \tag{2}$$

$\mathbf{u}_i$, $\mathbf{v}_i$, and $\mathbf{Q}_i$ are coefficients for content-only, presentation-only, and content-presentation quadratic interaction features, respectively. The coefficients $\mathbf{w}_i = \{\mathbf{u}_i, \mathbf{v}_i, \mathbf{Q}_i\}$ can be estimated using regularized linear regression. To avoid overfitting, we regularize the L_2 norm of $\mathbf{u}_i$ and $\mathbf{v}_i$, and further impose low-rank regularization on $\mathbf{Q}_i$ to handle the sparsity issue of quadratic features.

In total, we will have k such models, each predicting one y_i in $\mathbf{y}$. To group the k models in notation, let us write coefficients as $\mathbf{U} = (\mathbf{u}_1, \cdots, \mathbf{u}_k)^\top$, $\mathbf{V} = (\mathbf{v}_1, \cdots, \mathbf{v}_k)^\top$, $\mathbf{Q} = \mathrm{diag}(\mathbf{Q}_1, \cdots, \mathbf{Q}_k)$, and "copy" $\mathbf{x}$ and $\mathbf{p}$ k times to get the matrix $\mathbf{X} = \mathrm{diag}(\mathbf{x}^\top, \cdots, \mathbf{x}^\top)$ and the vector $\mathbf{t}^\top = (\mathbf{p}^\top, \cdots, \mathbf{p}^\top)$. To clarify dimensionality, if $\mathbf{x} \in \mathbb{R}^n$, $\mathbf{p} \in \mathbb{R}^m$, then $\mathbf{U} \in \mathbb{R}^{k \times n}$, $\mathbf{V} \in \mathbb{R}^{k \times m}$, $\mathbf{X} \in \mathbb{R}^{k \times nk}$, $\mathbf{Q} \in \mathbb{R}^{nk \times mk}$, and $\mathbf{t} \in \mathbb{R}^{mk}$. The user response model can be written as

$$\mathbf{y} = f(\mathbf{x}, \mathbf{p}) = \mathbf{U}\mathbf{x} + \mathbf{V}\mathbf{p} + \mathbf{X}\mathbf{Q}\mathbf{t}.$$

Denote user satisfaction metric as $g(\mathbf{y}) = \mathbf{c}^\top \mathbf{y}$. Then the scoring function $F = g \circ f$ is

$$\begin{aligned} F(\mathbf{x}, \mathbf{p}) &= g(f(\mathbf{x}, \mathbf{p})) \\ &= \mathbf{c}^\top \mathbf{U}\mathbf{x} + \mathbf{c}^\top \mathbf{V}\mathbf{p} + \mathbf{c}^\top \mathbf{X}\mathbf{Q}\mathbf{t} \\ &= \mathbf{c}^\top \mathbf{U}\mathbf{x} + \mathbf{a}^\top \mathbf{p} \end{aligned} \tag{3}$$

where $\mathbf{a} = \mathbf{V}^\top \mathbf{c} + \sum_{i=1}^k c_i \mathbf{Q}_i^\top \mathbf{x}$ is a known vector.

To this end, the optimization stage is to find the $\mathbf{p}$ that maximizes (3) subject to the constraints on $\mathbf{p}$. Since page content $\mathbf{x}$ is given, the first term in (3) is a constant and can be dropped. The second term $\mathbf{a}^\top \mathbf{p}$ is a linear term of $\mathbf{p}$. Since $\mathbf{p} \in \{0, 1\}^{k \times k}$ encodes a k-permutation, Each component in $\mathbf{a} \in \mathbb{R}^{k \times k}$ represents the gain of user satisfaction if item i is placed in position j, $1 \le i, j \le k$. Therefore, the optimization problem reduces to *maximum bipartite matching*, a special case of linear assignment problem. It can be efficiently solved by Hungarian algorithm [37] with time complexity $O(|\mathbf{p}|^3) = O(k^6)$. On a single-core computer with 2GHz CPU, the problem can be solved within 10 milliseconds for $k = 50$ items.

4.3.2 Gradient Boosted Decision Tree Model. In order to capture more complex, nonlinear interaction between content $\mathbf{x}$ and presentation $\mathbf{p}$, we replace the quadratic feature model f_i in previous section with a gradient boosted decision trees model h_i^{GBDT}. Gradient boosted decision trees (GBDT) is a very effective method for learning nonlinear functions [26].

Our feature vector is

$$\boldsymbol{\phi}^\top = (\mathbf{x}^\top, \mathbf{p}^\top),$$

and each user response y_i in $\mathbf{y}$ is predicted by a GBDT model:

$$y_i = h_i^{\mathrm{GBDT}}(\mathbf{x}, \mathbf{p}).$$

The user satisfaction metric is $g(\mathbf{y}) = \mathbf{c}^\top \mathbf{y} = \sum_{i=1}^k c_i y_i$.

In optimization stage, since each h_i is now a nonparametric model, we cannot get the analytical form of $F(\mathbf{x}, \mathbf{p}) = \sum_{i=1}^k c_i h_i^{\mathrm{GBDT}}(\mathbf{x}, \mathbf{p})$ in terms of $\mathbf{p}$. That is, the optimization over $\mathbf{p}$ is intractable. Nevertheless, in realistic settings, the search space of $\mathbf{p}$ is usually pruned down to tens of possible values by business and design constraints. We implement parallel enumeration to quickly find the optimal presentation that maximizes user satisfaction.

4.4 Special Case: Learning to Rank

When we restrict page presentation to be a ranked list, and assume that users are more satisfied if more relevant results are placed at top ranks, then presentation optimization reduces to the traditional ranking problem. We point out this connection to demonstrate the generality of the proposed framework.

The instantiation is as follows. We use binary indicators in Section 4.1.2 to represent the ranked list. Let user response $\mathbf{y}$ decompose into k components, each representing the user's utility of seeing result i at rank j_i. Let user response model $f(\mathbf{x}, \mathbf{p})$ decompose into k real-valued component, each only taking as input $\mathbf{x}_i$ and its rank j_i. So we have

$$\begin{aligned} f(\mathbf{x}, \mathbf{p}) &= f(\mathbf{x}_1, \cdots, \mathbf{x}_k, \mathbf{p}_1, \cdots, \mathbf{p}_k) \\ &= (f_1(\mathbf{x}_1, \mathbf{p}_1), \cdots, f_k(\mathbf{x}_k, \mathbf{p}_k))^\top \\ &= \left(f_1(\mathbf{x}_1, p_{1j_1} = 1), \cdots, f_k(\mathbf{x}_k, p_{kj_k} = 1)\right)^\top . \end{aligned} \tag{4}$$

Typically, the ranking function $h(\mathbf{x}_i)$ of result i is position-independent. It can also be interpreted as the score of result i seen on the top rank ($j_i = 1$). That means

$$h(\mathbf{x}_i) = f_i(\mathbf{x}_i, p_{i1} = 1).$$

Furthermore, traditional ranking problem assumes that the utility of a result is discounted by a factor w_j if it is ranked at position j. $w_j > 0$ is a decreasing function of j. E.g. in discounted cumulative gain (DCG),

$$w_j = \frac{1}{\log_2(1 + j)}.$$

The discounting assumption implies:

$$\begin{aligned} f_i(\mathbf{x}_i, p_{ij} = 1) &= w_j f_i(\mathbf{x}_i, p_{i1} = 1) \\ &= w_j h(\mathbf{x}_i). \end{aligned} \tag{5}$$

Combining (4) and (5), user response model is realized as

$$f(\mathbf{x}, \mathbf{p}) = \left(w_{j_1} h(\mathbf{x}_1), \cdots, w_{j_k} h(\mathbf{x}_k)\right)^\top,$$

where $h(\cdot)$ is the ranking function. User satisfaction is measured by the quality of ranked list, which *accumulate* the gain at each position:

$$g(\mathbf{y}) = \sum_{i=1}^{k} y_i = \sum_{i=1}^{k} w_{j_i} h(\mathbf{x}_i).$$

Clearly, maximum user satisfaction $g(\mathbf{y})$ is always achieved by *sorting the results by descending relevance scores*. This is the default presentation strategy of learning to rank.

5 SIMULATION STUDY

We demonstrate potential capability of presentation optimization framework by simulation. We use synthetic dataset so that we know the "ground truth" mechanism to maximize user satisfaction, and we can easily check whether the algorithm can indeed learn the optimal page presentation to maximize user satisfaction. We have two goals in this study:

(1) We show that the framework enables general definition of page presentation.
(2) We use both position bias and item-specific bias to show that the framework can automatically adapt to user interaction habits.

5.1 Overview

We first give a brief overview of simulation workflow. The simulated "presentation exploration bucket" will generate a page containing a set items with random presentation. Every time a new page is generated, each item is assigned some amount of reward (e.g. relevant information) drawn from an underlying distribution. The simulated "user" will have a certain type of attention bias: (1) position bias, in which more attention is paid to certain region of the page than elsewhere (Figure 2a); (2) vertical bias, or item-specific bias, in which more attention is attracted by a specific type of item and its surrounding area (Figure 2b).

(a) Position bias [50]

(b) Vertical bias [63]

Fig. 2. Different types of user attention bias.

An "interaction" happens when the "presentation exploration bucket" generates a page and the "user" examines it with attention bias. When the user examines an item, she receives the corresponding reward. User satisfaction towards the page is the sum of rewards. The page content, presentation, as well as the examined items and positions (user responses), become data that the framework learns from. Finally, we test if the framework successfully learned user's attention bias. Given a new set of items, we expect to see that the framework will place items with higher rewards to positions with more concentrated attention to achieve maximum user satisfaction. Therefore, to visualize the model's current belief in user attention bias, we can plot the distribution of item rewards on the page.

5.2 Data Generating Process

On the "search engine" side, a page (either 1-D list or 2-D grid) contains k positions. The page content $\mathbf{x} = (x_1, \cdots, x_k)^\top$, $x_i \sim \mathcal{N}(\mu_i, \sigma)$ represents intrinsic rewards of k items. We set $k = 10$ for 1-D list and $k = 7 \times 7$ for 2-D grid. μ_i's are random numbers drawn from in $[0, 1]$, $\sigma = 0.1$. The page presentation $\mathbf{p}$ is drawn from length-k permutations uniformly at random. The whole page is represented as $(\mathbf{x}, \mathbf{p})$.

On the "user" side, attention bias is simulated as follows:

Position bias: whether to examine position j is a Bernoulli random variable with parameter p_j. A real-life example is the top-down position bias, commonly observed when the user interacts with a ranked list.

Item-specific bias: whether to examine item i is a Bernoulli random variable with parameter p_i. A real-life example is the vertical bias, commonly observed when the user interacts with a page that contains vertical search results (images, videos, maps, etc).

Then, the "user" will "interact" with the page $(\mathbf{x}, \mathbf{p})$: k binary values are drawn from k Bernoulli distributions, and recorded as a user response vector $\mathbf{y} \in \{0, 1\}^k$. if item i is examined, $y_i = 1$, the user receives a reward x_i. The user satisfaction equals the sum of reward of examined items. We generate 100,000 pages to train the Quadratic Feature Model described in Section 4.3.

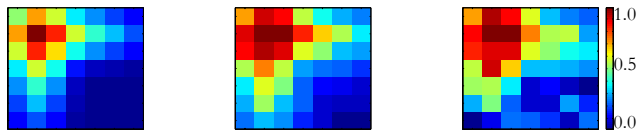
5.3 Results and Discussion

To visualize the learned optimal presentation, we pick a random $\mathbf{x}$ and compute the corresponding optimal presentation $\mathbf{p}^*$, then arrange the x_i's according to $\mathbf{p}^*$. A page is visualized as a heat map of x_i's rewards. Ideally, the items with higher reward ("better content") should be placed onto the position with higher probability of user attention.

Figure 3, 4, and 5 visualize the presentation results under various position biases. We can see that the algorithm indeed learns to put "better content" to positions with more user attention. Because the definition of page presentation is general, it is able to handle both 1-D list and 2-D grid. Furthermore, it can capture complicated distribution of position bias on a 2-D canvas: the top-left position bias in Figure 4, and the top-bottom position bias in Figure 5.

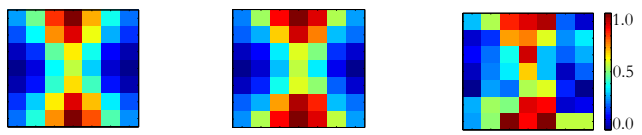
(a) Position bias (b) Ideal presentation (c) Learned presentation

Fig. 3. Top position bias and presentation on 1-D list.



(a) Position bias (b) Ideal presentation (c) Learned presentation

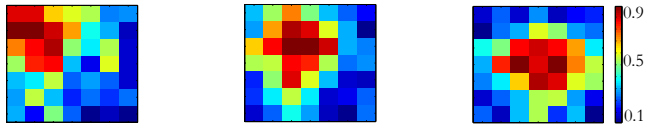
Fig. 4. Top-left position bias and presentation on 2-D canvas.



(a) Position bias (b) Ideal presentation (c) Learned presentation

Fig. 5. Two-end position bias and presentation on 2-D canvas.

Figure 6 visualizes the result under item-specific bias. This is an interesting case where an item on the page is very eye-catchy, and it also attracts user's attention to its surrounding items (e.g., an image attracts user's eyeballs on itself as well as its caption and description text). Also, suppose that for items farther away from that eye-catchy item, the user's attention drops further down. Then the optimal presentation strategy is to place the item on the *center* of the page, so that the whole page delivers the most reward. In Figure 6, we see that user satisfaction value r is highest when the item (the dark red region) is centered on the page.



(a) $\hat{v} = 4.07$ (b) $\hat{v} = 4.92$ (c) $\hat{v} = 5.41$

Fig. 6. Item-specific bias. $\hat{v}$: estimated user satisfaction by the quadratic feature model. When a specific item (e.g. image) attracts user attention to not only itself but also its surrounding results, then the page-wise reward is highest when the vertical is placed at the center of the page.

6 REAL DATA EXPERIMENTS

We demonstrate the effectiveness of page presentation optimization framework by conducting experiments on the real-world data set collected via a commercial search engine.

6.1 Data Collection

We use a very small fraction of search traffic as the presentation exploration buckets. The data was collected through the year 2013. Vertical search results whose presentation are explored include *news*, *shopping*, and *local listings*. In the exploration buckets, the order of Web results are kept untouched and verticals are randomly slotted into allowed positions with uniform probability. Randomly generated SERPs are not influenced by any ranking algorithm in the system. As pointed out in Section 3.1, this is required to eliminate page content confounding when training models. The exploration SERP is then presented to the user who interacts with it in a normal fashion. Users response on the SERP, along with page-wise content information like the query, document features from backends, are logged.

6.2 Methods

We use two pointwise ranking models as baseline method. They are trained using the content features as described in Section 4.1. The first baseline method has been adopted in production (Logit-Rank) [32]. It estimates a logistic regression model for each vertical result (including web result):

$$y_i = \sigma(\mathbf{w}_i^\top \mathbf{x}_i),$$

where y_i is a binary target variable that indicates whether the result is clicked ($y_i = +1$) or skipped ($y_i = -1$) as described in Section 4.2, and $\sigma(\cdot)$ is the sigmoid link function rescaled to $[-1, 1]$.

The second baseline method uses gradient boosted decision trees to learn a pointwise ranking function (Gbdt-Rank). This is essentially replacing the logistic regressor in Logit-Rank with a GBDT regressor:

$$y_i = h_i^{\text{GBDT}}(\mathbf{x}_i).$$

We evaluate the two instantiations of presentation optimization framework described in Section 4.3: the Quadratic Feature Model (Quad-Pres) and the GBDT Model (Gbdt-Pres). They use page-wise information $(\mathbf{x}, \mathbf{p})$ to predict the user response *vector*, i.e. the vector of clicks and skips.

In implementation, we use Vowpal Wabbit [39] to learn logistic regression models, and XGBoost [14] to learn the gradient boosted decision tree models. The hyperparameters of the models are tuned on a small holdout data set.

Table 1. Match rate between random exploration presentation $\mathbf{p}$ and predicted optimal presentation $\mathbf{p}^*$. "Until WEB$_1$ " means that $\mathbf{p}$ and $\mathbf{p}^*$ encode the same presentation above the 1st webpage result.

	Until WEB$_1$	Until WEB$_2$	Until WEB$_3$
LOGIT-RANK	68.68%	46.76%	30.85%
QUAD-PRES	71.63%	50.68%	33.42%

6.3 Evaluation

We use half of the exploration SERP as training set (January – June), the rest as test set. It contains hundreds of millions of pageviews and was collected from real search traffic. Compared to standard supervised learning setup, it is difficult to do an unbiased offline performance evaluation because of the interactive nature of the task (see Section 4.3 in [32]). This is because the offline data $(\mathbf{x}^{(n)}, \mathbf{p}^{(n)}, \mathbf{y}^{(n)})$ is collected using a particular logging policy, so we only observe user response $\mathbf{y}^{(n)}$ for a specific page presentation $\mathbf{p}^{(n)}$. In offline evaluation, when the algorithm is given page content $\mathbf{x}^{(n)}$, it may output a presentation $\mathbf{p}^{*(n)} \neq \mathbf{p}^{(n)}$, for which we do not observe user response, hence cannot evaluate its goodness. To address this problem, we use an offline policy evaluation method proposed by Li et al. [40] for evaluating online recommendation systems. It is simple to implement and provides an unbiased performance estimate, thanks to data collected through random exploration. Given a stream of events $(\mathbf{x}^{(n)}, \mathbf{p}^{(n)}, \Pr(\mathbf{p}^{(n)}), \mathbf{y}^{(n)})$ collected through random exploration, where $\Pr(\mathbf{p}^{(n)})$ is the probability for the SERP $(\mathbf{x}^{(n)}, \mathbf{p}^{(n)})$ to be generated from uniform random exploration, the average user satisfaction for N offline events can be computed as

$$\bar{s} = \frac{1}{N} \sum_{n=1}^{N} \frac{g(\mathbf{y}^{(n)}) \mathbf{1}_{\{\mathbf{p}^{*(n)} == \mathbf{p}^{(n)}\}}}{\Pr(\mathbf{p}^{(n)})} ,$$

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function, and $g(\mathbf{y}^{(n)})$ is user satisfaction towards SERP n. This means the algorithm is evaluated on those exploration SERPs whose presentation *matches* what is chosen by the algorithm; otherwise the SERP is discarded in offline evaluation.

As the match goes deeper down the page, the match rate decreases (Table 1). If we require *exact match* between predicted $\mathbf{p}^{*(n)}$ and actual $\mathbf{p}^{(n)}$, a large fraction of test set will be discarded and the performance estimates tend to have large variance hence unreliable. Our evaluation only focuses on vertical results shown above the first, second, and third webpage result. Note that the first webpage result is *not* always on top rank; the top rank is frequently occupied by the vertical results.

6.4 Results and Discussion

Table 2 shows the average page-wise user satisfaction. It is encouraging to see that whole-page optimization methods outperform ranking methods, because ranking methods utilize probability ranking principle to rank results by relevance, which assumes a top-down position bias. QUAD-PRES and GBDT-PRES do not make this assumption, but *learns* its own result presentation principle purely from data. The reason that GBDT models work better than logistic regression models, mainly because logistic regression assumes linear decision boundary, while GBDT is capable of modeling nonlinear decision boundary.

Note that in our definition of user satisfaction metric $g(\mathbf{y})$, a skip causes negative utility ($y_i = -1$). The fact that QUAD-PRES and GBDT-PRES generally work better than the baseline methods is because they take into consideration the retrieved items, the page presentation, and their interaction on the entire SERP, not just a single result. The presentation-blind models LOGIT-RANK and GBDT-RANK always want to put on top the results that will most probably gets clicked. However, for certain queries people might intentionally skip the graphical results (e.g., when shopping ads are shown

Table 2. Average user satisfaction ($\times 10^{-3}$).

	Until Web_1	Until Web_2	Until Web_3
Logit-Rank	-0.25	1.79	1.89
Gbdt-Rank	2.18	3.68	2.22
Quad-Pres	0.62	6.39	5.37
Gbdt-Pres	**2.68**	**6.72**	**8.24**

but the search intent is in fact informational). In such cases, a click tends to happen *below* the top rank. In contrast, presentation optimization methods will consider both the result and its position on the page. That leads to more sensible arrangement of results. We see that Gbdt-Pres attracts more clicks and has less skips when we evaluate deeper down the SERP.

Table 3. CTR, match until Web_1

	News	Shopping	S. Local	M. Local
Coverage	0.46%	0.02%	0.02%	0.71%
Logit-Rank	21.05%	40.79%	11.58%	30.02%
Gbdt-Rank	23.28%	53.32%	38.26%	52.27%
Quad-Pres	21.97%	49.85%	47.16%	39.93%
Gbdt-Pres	22.34%	46.15%	48.12%	49.18%

Table 4. CTR, match until Web_2

	News	Shopping	S. Local	M. Local
Coverage	2.0%	0.11%	0.03%	2.3%
Logit-Rank	16.44%	23.71%	18.51%	8.92%
Gbdt-Rank	16.31%	30.39%	36.73%	23.11%
Quad-Pres	14.78%	13.57%	23.39%	27.53%
Gbdt-Pres	16.21%	40.83%	33.18%	35.23%

Table 5. CTR, match until Web_3

	News	Shopping	S. Local	M. Local
Coverage	3.8%	0.18%	0.11%	3.4%
Logit-Rank	14.52%	21.48%	13.80%	9.65%
Gbdt-Rank	12.51%	42.96%	24.93%	22.42%
Quad-Pres	11.45%	12.88%	15.47%	24.38%
Gbdt-Pres	14.11%	36.00%	24.72%	30.66%

Table 3, 4, and 5 shows the click-through rate (CTR) above Web_1, Web_2, and Web_3, respectively. "S. Local" means a single entry of local business result (such as restaurants); "M. Local" means multiple entries of local business results. They are the same vertical/genre results presented in different sizes. In terms of CTR, ranking methods have very strong performance because they are directly optimized for high CTR. However, whole-page optimization methods still achieve competitive or sometimes better CTR by taking into account page-wise information.

It is interesting to see that for News vertical, there is not much help to know about other results on the SERP, neither their presentation. In contrast, knowing page-wise results helps improve the CTR of top-ranked local listings by a large margin. A possible explanation is that news, more like general webpages, contain rich text information and their content relevance can be readily modeled by standard ranking functions. On the other hand, local listings are in drastically different nature compared to webpages and news, therefore knowing the complementary information from other webpage results helps predicting the click/skip patterns. We can also observe small improvements in CTR of the shopping results. Since the shopping results shown on the top are most likely to be skipped, the algorithm learns to become extremely conservative in showing shopping verticals on top. This leads to a much smaller coverage of shopping results in the entire traffic.

As the match goes deeper down the page, the local ranking algorithms show decreased performance in terms of CTR. This is because the local ranking methods tend to greedily put the high CTR items on top of the page, but ignores the content on the entire page. In contrast, the page presentation algorithms, especially GBDT-PRES, still get good CTR on News and Multi-local verticals, which takes larger coverage. This is attributed to the fact that they model user response over the entire page.

Figure 7 shows a real case where GBDT-PRES disagreed with GBDT-RANK (the algorithm then used in production) in serving a local search query. In this case, the user was searching for "`drinks near Columbus circle`". At the time of this study, the Yahoo search engine ranked local vertical results on the top, as shown in the screenshot. Columbus circle is a place in Manhattan, New York. The two vertical results, however, were not in Manhattan: one is in Brooklyn, New York, and the other is in the State of Connecticut. Our algorithm GBDT-PRES recommended to put the webpage result on top, which was indeed more relevant than the local listings. The page presentation algorithm made a better decision here because it was able to consider all candidate results on the SERP and weigh the benefits and risks of putting one on top of others.

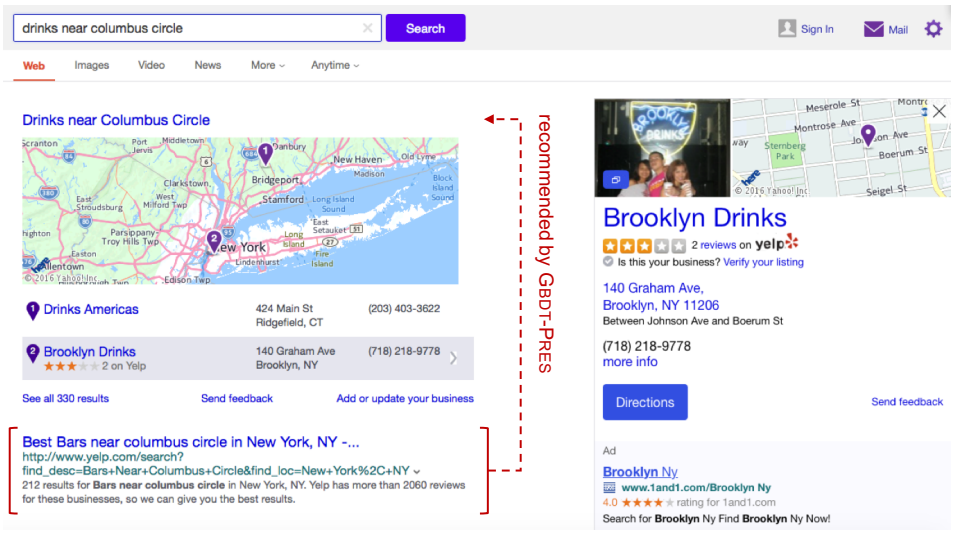


Fig. 7. Screenshot of the Yahoo search result page for the query "drinks near Columbus circle". Accessed early February, 2016. The two local listings did not satisfy the information need. Our algorithm GBDT-PRES recommended that the webpage result should be ranked on top of local listings.

7 RUNTIME-EFFICIENT PAGE PRESENTATION POLICY

In this section, we provide a new perspective on the problem of page presentation optimization through the lens of reinforcement learning. We show that the proposed approach in Section 3 is actually one of several possibilities for solving a reinforcement learning problem. Based on the new formulation, we provide a policy learning approach that solves the same problem and enjoys runtime efficiency. Finally, we demonstrate the effectiveness of the new approach through simulation experiments.

7.1 Reinforcement Learning Formulation

We briefly introduce the general reinforcement learning setup, and then recast page presentation optimization as a reinforcement learning problem.

In a **general reinforcement learning** setup, an agent acts in a stochastic environment by sequentially choosing actions over a sequence of time steps, in order to maximize a cumulative reward. It is formulated as a Markov decision process (MDP) with the following concepts.

(1) A *state space* $\mathcal{S}$.
(2) An *action space* $\mathcal{A}$.
(3) An *initial state distribution* $p(s_0)$, and a *state transition dynamics distribution* $p(s_{t+1}|s_t, a_t)$ satisfying the Markov property $p(s_{t+1}|s_0, a_0, \cdots, s_t, a_t) = p(s_{t+1}|s_t, a_t)$.
(4) A *reward function* $r : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$.
(5) A *policy* selects actions in a given state: $\pi_\theta : \mathcal{S} \to \mathcal{P}(\mathcal{A})$, where $\mathcal{P}(\mathcal{A})$ is the set of probability measures on $\mathcal{A}$ and $\theta \in \mathbb{R}^m$ is a vector of m parameters. $\pi_\theta(a|s)$ is the probability of taking action a in state s. A deterministic policy is a special case where an action a satisfies $\pi_\theta(a|s) = 1$ in any state s.
(6) The agent uses its policy to interact with the MDP to give a trajectory of states, actions, and rewards, $h_{0:T} = s_0, a_0, r_0, \cdots, s_T, a_T, r_T$ over $\mathcal{S} \times \mathcal{A} \times \mathbb{R}$. The cumulative discounted reward, or the *return*, is $R_\gamma = \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)$, where the discount factor $\gamma \in [0, 1]$ determines the present value of future rewards.
(7) The action-value function $Q^\pi(s, a) = \mathbb{E}\left[R_\gamma|s_0 = s, a_0 = a; \pi\right]$ is the expected return of taking action a in state s and then following policy π. $Q^*(s, a) = \max_\pi \mathbb{E}\left[R_\gamma|s_0 = s, a_0 = a; \pi\right]$ is the optimal action-value function.
(8) The agent's goal is to obtain a policy π which maximizes the *expected return*, denoted as $J(\pi) = \mathbb{E}\left[R_\gamma|\pi\right]$.

In **page presentation optimization**, the agent is the algorithm that determines the presentation of page content on a SERP for each incoming search query. Referring to the concepts and notations in Section 2:

(1) The page content $\mathbf{x}$ of a query is the state, and the state space is $\mathcal{X}$.
(2) The page presentation $\mathbf{p}$ is an action, and the action space is $\mathcal{P}$.
(3) The initial state distribution $p(\mathbf{x})$ is determined by the query distribution. As we do not model sequential interactions between the search engine and the user, there is no state transition dynamics.
(4) The reward function is the user satisfaction v on a given SERP, which we estimate by the scoring function $v = F(\mathbf{x}, \mathbf{p})$. Each point in the state-action space $\mathcal{X} \times \mathcal{P}$ is a SERP.
(5) A policy selects a presentation strategy $\mathbf{p}$ given page content $\mathbf{x}$. This is the page presentation optimization problem we formulated in (1).
(6) Since there is no state transition, the return $R_\gamma = v$, the discount factor $\gamma = 0$, and the effective time horizon $T = 0$.

(7) Since the policy does not take effect after the initial time step, the action-value function is equal to the reward function, $Q^{\pi}(s,a) = F(\mathbf{x},\mathbf{p}), \forall \pi$. Hence $F(\mathbf{x},\mathbf{p}) = Q^{*}(s,a)$.
(8) The expected return $J(\pi) = \mathbb{E}[v|\pi] = \mathbb{E}_{\mathbf{x}\sim p(\mathbf{x})}\left[\mathbb{E}_{\mathbf{p}\sim\pi(\mathbf{p}|\mathbf{x})}[F(\mathbf{x},\mathbf{p})]\right]$ is the average user satisfaction that the agent aims to maximize (the measurements in Table 2).

Therefore, the problem of page presentation optimization can be viewed as a reinforcement learning problem. The approach in Section 3 is in fact a Q-learning method. It first learns the optimal action-value function (in our case it coincides with the reward function/scoring function) $F(\mathbf{x},\mathbf{p})$ through supervised learning on exploration data. Then it derives a deterministic policy by choosing the action that maximizes the optimal action-value function: $\pi(\mathbf{p}|\mathbf{x}) = 1$ if $\mathbf{p}$ solves $\max_{\mathbf{p}\in\mathcal{P}} F(\mathbf{x},\mathbf{p})$, and $\pi(\mathbf{p}|\mathbf{x}) = 0$ otherwise.

A major drawback of this approach, as we have seen, is that it has to solve a combinatorial optimization problem for each query at runtime, which could become intractable for complex functional forms of $F(\cdot,\cdot)$. Fortunately, recasting the problem in reinforcement learning sheds new lights on runtime-efficient solutions. Below we describe policy learning as one such solution.

7.2 Policy Learning for Page Presentation

We seek for a new page presentation algorithm that is (1) efficient at runtime, (2) sufficiently expressive, i.e. capable of capturing sophisticated interactions between items on a page, and (3) trained offline using data collected through the exploration buckets. These requirements are critical for Web-scale online applications, because (1) runtime efficiency directly affects user experience, (2) different items may have dependencies when they are laid out on a SERP, and (3) updating the search algorithm offline reduces the risk of undesirable exploration behaviors.

A policy-based agent meets all the above requirements. The agent learns a policy $\pi_\theta(a|s)$ rather than a value function through experience. At runtime, it samples an action a from $\pi_\theta(a|s)$ given state s, without performing optimization in the action space. In reinforcement learning scenarios where the action space is high-dimensional or continuous, policy-based agent is often employed.

In our problem setting, the agent learns a policy $\pi_\theta(\mathbf{p}|\mathbf{x})$ from the exploration data. For a search presentation policy, it is more desirable to be deterministic than stochastic, because search engine users would prefer the search service to be predictable and reliable. We can write a deterministic policy as $\mathbf{p} = \pi_\theta(\mathbf{x})$. At runtime, given page content $\mathbf{x}$, the policy outputs a page presentation $\mathbf{p}$ that renders the content onto the page. To capture complex interactions between page contents, $\pi_\theta(\cdot)$ can take nonlinear functional forms.

Now we describe the design and training of the presentation policy.

7.2.1 Policy function design. The policy π_θ takes page content vector as the input and gives a presentation vector as the output. The output vector should encode a *permutation* of k items in $\mathbf{x}^{\top} = (\mathbf{x}_1^{\top}, \cdots, \mathbf{x}_k^{\top})$, along with other categorical and numerical properties (e.g. image sizes, font types). Instead of asking π_θ to directly output a k-permutation as a vector of $k \times k$ binary indicators (as in Section 4.1.2), we consider functions that implicitly outputs a k-permutation. At least two approaches can be considered:

(1) ***Generalized ranking approach***: π_θ outputs a sorting score for each item, which defines an order to arrange k items into k positions.
(2) ***Generalized sequence-to-sequence approach***: π_θ outputs a matching score for each item-position pair, which entails a bipartite matching between k items and k positions.

Note that in both approaches, the k positions can take arbitrary layout, not restricted to a one-dimensional list. Both approaches are viable if π_θ jointly considers all items and their dependencies.

In this paper, we consider the generalized ranking approach. We will explore the generalized sequence-to-sequence approach in our future work.

In the generalized ranking approach, each item i will have a sorting score $f_\theta(\widetilde{\mathbf{x}}_i)$. The sorting scores are produced by the same function f_θ. The feature vector $\widetilde{\mathbf{x}}_i$ is different for each item i and contains the entire page content feature $\mathbf{x}$. This can be achieved by prepending the dimensions of item i to the front of $\mathbf{x}$ and then setting the original dimensions of item i to zero. That is, $\widetilde{\mathbf{x}}_i^\top = (\mathbf{x}_i^\top, \mathbf{x}_1^\top, \cdots^\top, \mathbf{x}_{i-1}^\top, \mathbf{0}^\top, \mathbf{x}_{i+1}^\top, \cdots, \mathbf{x}_k^\top)$, for $i = 1, \cdots, k$. This allows the function f_θ to consider the entire page content but output a different score for each item. To capture complex interactions between items, each f_θ is a LambdaMART model (i.e. GBDT model) [11].

7.2.2 Policy training. There are multiple ways to train a policy in an offline fashion, including model-based methods [59] and off-policy actor-critic methods [20, 58]. Here we use a model-based method, which requires the reward function and the state transition dynamics to be learned first. In our setting, the reward function is the scoring function $F(\mathbf{x}, \mathbf{p})$, and there is no state transition. So we take two steps to train the policy π_θ:

(1) Learn the scoring function $F(\mathbf{x}, \mathbf{p})$ from exploration data, as in Section 3.2;
(2) Train the policy π_θ by maximizing the expected return $J(\pi_\theta) = \mathbb{E}_{\mathbf{x}\sim p(\mathbf{x})}[F(\mathbf{x}, \pi_\theta(\mathbf{x}))]$.

Note that neither Step (1) or (2) involves the optimization step $\max_{\mathbf{p}\in\mathcal{P}} F(\mathbf{x}, \mathbf{p})$. This is important as it allows us to choose complex functional forms for both F and π to capture intricate dependencies among page items[3].

In reinforcement learning literature, the policy is usually trained by following the *policy gradient* [60]. That is, π_θ can be gradually improved by moving θ along $\nabla_\theta J$. It is non-trivial to compute $\nabla_\theta J$ for deterministic policies [58], as is the case in our setting. Below we employ the idea of λ-gradients in LambdaMART to optimize the policy.

Since our policy π_θ generates a permutation by sorting, we can view $F(\mathbf{x}, \pi_\theta(\mathbf{x}))$ as a type of "listwise objective". Indeed, $\mathbf{x}$ contains k items and $\mathbf{p} = \pi_\theta(\mathbf{x})$ defines a permutation of them, though the layout may not be a "list". The difference between $F(\mathbf{x}, \pi_\theta(\mathbf{x}))$ and conventional listwise IR measures, such as NDCG and MAP, is that NDCG and MAP are based on per-item relevance judgments assigned by humans, while $F(\mathbf{x}, \pi_\theta(\mathbf{x}))$ is automatically learned from data. Optimizing $J(\pi_\theta)$ translates to optimizing the listwise objective $F(\mathbf{x}, \pi_\theta(\mathbf{x}))$. The listwise learning-to-rank method LambdaMART is well-suited in this scenario as it is empirically proven to optimize a wide range of IR measures [11, 24].

LambdaMART uses a succession of regression trees, each estimating the λ's. For a query q, $\lambda_i \in \mathbb{R}$ is a number assigned to a document d_i which indicates how much its current sorting score u_i needs to be changed to improve the NDCG of the ranked list retrieved by q. Therefore the λ's are the gradients of NDCG with respect to the sorting scores. They are computed by swapping two documents d_i and d_j in the predicted ranking, and then observing the change in NDCG [11]:

$$\lambda_{ij} = \frac{-\sigma}{1 + \exp\left(\sigma(u_i - u_j)\right)} \left|\Delta\text{NDCG}_{ij}\right| ,$$

$$\lambda_i = \sum_{j:rel(i)>rel(j)} \lambda_{ij} - \sum_{j:rel(i)<rel(j)} \lambda_{ij} ,$$

where ΔNDCG_{ij} is the change in NDCG after swapping d_i and d_j in the predicted ranking, and $rel(i)$ is the relevance grade of document d_i for query q. $\sigma > 0$ is a scaling hyperparameter.

[3]Unlike the Q-learning approach, now we do not need to decode $\mathbf{p}$ as a page presentation strategy from $F(\mathbf{x}, \mathbf{p})$. So $F(\mathbf{x}, \mathbf{p})$ can take any feature derived from $\mathbf{x}$ and $\mathbf{p}$ as input.

In our setting, each SERP is a generalized ranked list. The λ's can be computed by swapping *random pairs* of items in the predicted ranking, and then observing the change in F:

$$\lambda_{ij} = \frac{-\sigma}{1 + \exp\left(\sigma(u_i - u_j)\right)} \left|\Delta F_{ij}\right| ,$$
$$\lambda_i = \sum_{j:\Delta F_{ij}<0} \lambda_{ij} - \sum_{j:\Delta F_{ij}>0} \lambda_{ij} ,$$

where ΔF_{ij} is the change in $F(\mathbf{x}, \pi_\theta(\mathbf{x}))$ after swapping item i and j in the predicted permutation $\pi_\theta(\mathbf{x})$, which is determined by the sorting scores $u_i = f_\theta(\widetilde{\mathbf{x}}_i), i = 1, \cdots, k$.

This change generalizes the LambdaMART training algorithm into *bandit mode*: it does not need to observe the relevance judgments of individual results, but only the performance metric at the SERP level. The learning behavior is similar to a contextual bandit algorithm: given page content (the context), it learns by trying out different permutations of items (the arms) through random swaps[4], getting partial feedback, and gradually adjusting the model parameters in the direction of higher expected return.

7.3 Simulation experiments

We implement the above policy-based algorithm in the same simulation setup as Section 5. Our goal is to show that the policy-based approach can learn both 1-D and 2-D layouts, and it performs comparably as the original page presentation algorithms (the Q-learning approach).

Table 6 shows the user satisfaction of page presentation algorithms in both 1-D and 2-D scenarios. As the simulated user satisfaction is stochastic, we report the average and standard deviation of 1,000 runs for each setup.

- The IDEAL algorithm acts as in Figure 3(b) and 4(b). It puts the item with i-th highest reward to the position with i-th highest probability of examination. It gives the performance upper bound.
- The Q-LEARNING algorithm is QUAD-PRES[5]. It acts as in Figure 3(c) and 4(c) and is described in Section 4.3.
- We include two variants of the POLICY algorithm introduced in this section. They differ in the implementation of the scoring function F (cf. Section 3.2). One uses the *factorized approach*, where each item's reward is estimated with a GBDT model, and the page-wise user satisfaction is the sum of estimated item rewards, as defined in the simulation procedure. The other uses the *direct approach*, where a single GBDT model directly predicts the page-wise user satisfaction using the entire SERP information $(\mathbf{x}, \mathbf{p})$.
- The RANDOM algorithm shuffles items to positions at random. It gives the performance lower bound.

In both scenarios, Q-LEARNING performs almost as well as IDEAL. POLICY with factorized F performs comparably with Q-LEARNING in the 1-D case, and slightly worse than Q-LEARNING in the 2-D case. This is because we use a policy function $\pi_\theta(\mathbf{x})$ to approximate the global optimization procedure "$\text{argmax}_{\mathbf{p}\in\mathcal{P}} F(\mathbf{x}, \mathbf{p})$" in Q-LEARNING. It presents a trade-off between presentation quality and runtime efficiency.

The scoring function plays an important role in policy-based methods. In the direct approach, F loses the internal structure of the page-wise user satisfaction (the function g in Section 3.2), which

[4] As a mathematical fact, performing successive swaps starting from one permutation can reach any other permutation of k items [48].

[5] Since the performance of QUAD-PRES is already reaching the upper bound, we do not include GBDT-PRES here, which is inefficient at runtime.

Table 6. Average user satisfaction of different page presentation algorithms in two simulation scenarios. Standard deviations are shown in parentheses.

	1-D (top position bias)	2-D (top-left position bias)
Ideal	2.20 (0.78)	8.80 (1.63)
Q-Learning	2.18 (0.77)	8.43 (1.55)
Policy (factorized F)	2.18 (0.76)	7.90 (1.56)
Policy (direct F)	1.78 (0.56)	6.91 (1.44)
Random	1.41 (0.69)	5.36 (1.39)

is essential to generalizing well to unseen presentations and providing accurate feedback during policy training. The factorized approach preserves the structure in $F = g \circ f$, therefore it trains a better policy than the direct approach.

8 RELATED WORK

As a general framework for search result presentation, this work draws on many aspects of modern IR research. It extends the traditional "ranked list" formulation to the general notion of "page presentation" as a response to federated search, the defining feature of modern search engines. It aims to deliver optimal presentation by understanding and learning from interactive search logs.

8.1 Document Ranking in Retrieval

Document ranking has long been the core problem of ad hoc retrieval. In the traditional setup, given a query, the retrieval system returns a list of homogeneous documents ranked by decreasing probability of relevance. The presentation is optimal with respect to the user's effort when she sequentially and independently examines results from top to bottom [54]. Extensive research efforts have been dedicated to the design of relevance ranking algorithms, dating from vector space models [55] and language modeling ranking functions [68] to machine learning ranking [42] and top document reranking [12, 31, 51]. To evaluate a ranked list, traditional metrics such as mean average precision (MAP) and normalized discounted cumulative gain (NDCG) rely on human assessments, i.e. relevance judgments for query-document pairs.

Our framework extends homogeneous document ranking to heterogeneous content presentation. Document ranking is a special case when presentation is a ranked list. From an algorithmic perspective, we use *all* documents on SERP to determine the optimal presentation, which is in the same spirit of reranking/global ranking [31, 51]. The difference is that our framework allows much more general notion of presentation than a list. In fact, global ranking algorithms, and more broadly, structured prediction algorithms in machine learning literature [9], can be readily plugged into our framework as the user response model.

8.2 Federated Search

Federated search (or aggregated search) refers to searching through a collection of specialized search engines, or *verticals*, and aggregating the results on SERP. Usually, contents from different verticals are heterogeneous and visually rich. Federated search has two sub-tasks: vertical selection and result presentation [21, 45]. Given a query, the task of vertical selection is to accurately determine which candidate verticals provide potentially relevant results [6, 7]. After getting results from candidate verticals, the task of result presentation is to merge vertical results with general webpage results on the same page [4].

Our work is concerned with result presentation. Previous approaches formulate it as a ranking problem [4, 32, 49]. Specifically, [4, 32] employ pointwise ranking functions to rank results and blocks, while [4, 49] also construct pairwise preference judgments to train a ranking function. [15] considers 2-D grid presentation for image and shopping results. Our framework allows more flexible definition of presentation than ranked list and 2-D grid, e.g. arbitrary frames, image sizes, and text fonts.

Federated search results significantly change the landscape of SERP, which in turn calls for changes in evaluation methodology. Bailey et al. [8] propose the notion of *whole-page relevance*. They argue that the Cranfield-style evaluation is inadequate to quantify user's holistic experience on modern SERP, such as overall presentation and coherence. It proposes to evaluate whole-page relevance by assigning grades to various SERP elements. Whole-page optimization can incorporate other goals, such as the revenue of a search service provider in sponsored search [22] and online ads bidding [47]. Our framework is more general and can be applied in these problems by defining an appropriate user satisfaction metric, i.e. the optimization objective.

8.3 Understanding and Learning from User Interaction

User interaction behaviors on the SERP, such as clicks with long and short dwell time, query reformulations, and abandonments, often indicates the quality of search results. Understanding these behaviors is critical for delivering good search experience. Many search engines collect detailed user interactions on the SERP to evaluate and train relevance ranking algorithms [19].

Eye-tracking experiments [27, 28] and click log analyses [18, 34] observe that users follow sequential order in browsing blue-link-only SERPs. Lower-ranked results are examined with lower probability. These results confirm the probability ranking principle, encouraging search engines to put more relevant results on top. As visually rich, heterogeneous results appear on modern SERPs, users do not necessarily follow sequential order in browsing search results. Studies observe more interesting user interaction patterns, notably vertical bias [13, 38, 44] and presentation bias [67], essentially violating the assumptions of the probability ranking principle (PRP). Our experiments show that the proposed framework is able to learn the user's browsing habits without knowing the PRP.

Search engines collect user behaviors to *evaluate* the quality of search results. Traditional evaluation metrics such as MAP and NDCG are based on relevance judgments made by third-party assessors. When rating the relevance of results given a query, the assessors are out of the context of the actual user and may not be able to accurately interpret the user's information need when performing the search, especially when the query is context-sensitive [10]. In such cases, user satisfaction are better reflected in their behaviors. Extensive research has been devoted to developing user satisfaction metrics from their behaviors [16, 25, 29, 36, 65]. Our framework adopts a generic definition of user satisfaction, which can incorporate a wide range of user behaviors on the SERP.

Search engines also leverage user behaviors to *train* the search algorithms. However, due to position bias, vertical bias, and other factors, clicked results are not always relevant and non-clicked results may still be relevant albeit ranked at low positions. Therefore, click-through data are noisy and partial feedback of result relevance [34]. Various approaches have been proposed to leverage user behaviors to improve ranking algorithms. We can categorize these approaches into three lines.

(1) The first line of approach makes explicit assumption about user behavior patterns and how they indicate result relevance. User behavior signals are incorporated as additional features [2] and tasks [61, 70] to train existing rankers, interpreted as preference data to train pairwise rankers [33, 52]. Various click models are proposed to infer result relevance from observed

user clicks [13, 17, 23]. These approaches derive large amount of relevance information from search logs in an offline fashion. However, their assumptions may or may not hold as user interactions on SERP (and the search engine itself) evolve over time.

(2) The second line of approach empowers the search algorithm to perform online learning and adaptively optimize behavior-based metrics. This include interleaving experiments [53] and contextual bandit algorithms [40, 57, 66]. Online, interactive algorithms are also proposed to improve sequence of interactions between a search engine and the user [46, 69]. Online learning approaches can optimize behavior-based metrics without relying on strong assumptions of user behavior patterns. However, online bucket tests are expensive and random exploration may run the risk of undesirable results [41].

(3) The third and more recent line of approach combines the strengths of the previous two. It optimizes behavior-based metrics using already-collected exploration data in an offline fashion. This is in similar spirit to the off-policy learning scenario in reinforcement learning [59]. Crucially, it requires the exploration policy to record the probability of actions (e.g. putting an item in a position). This data will later be used to generate unbiased counterfactual evaluation of new rankers [1, 41] and seek for better rankers [35, 62].

Our work is in line with the third approach. We first learn an unbiased estimator of the user satisfaction metric (the scoring function F) from data collected by presentation exploration buckets, then optimize page presentation to maximize the metric. The main difference between these studies and our paper is in the problem formulation: we do not restrict the layout to be a ranked list, but rather consider the more general notion of page presentation.

9 CONCLUSION

This paper proposes a new problem in web search: *whole-page presentation optimization*. Modern retrieval systems return a collection of heterogeneous results, calling for more flexible presentation strategies than the conventional ranked list. This paper formulates the problem as a mathematical optimization problem, and proposes a framework that solves the problem in a data-driven fashion. This general framework is instantiated to enable more flexible and expressive definition of page presentation than ranked list. Simple instantiations of the framework are shown to outperform ranking-based methods in satisfying federated search users.

This study opens up many interesting avenues for the future work. We can instantiate the general presentation optimization framework properly on other heterogeneous content presentation scenarios, such as mobile and tablet search, where user's attention bias may be different from that on large screens. User response models can be instantiated in more sophisticated ways, e.g., modeling cursor position as conditional random fields over the SERP canvas. Finally, defining a proper quantitative metric for user satisfaction based on SERP-level, fine-grained user behaviors can be explored in human computer interaction research.

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