Modeling Perceived Relevance for Tail Queries without Click-Through Data

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Abstract Click-through data has been used in various ways in Web search such as estimating relevance between documents and queries. Since only search snippets are perceived by users before issuing any clicks, the relevance induced by clicks are usually called perceived relevance which has proven to be quite useful for Web search. While there is plenty of click data for popular queries, very little information is available for unpopular ones. These tail queries take a large portion of the search volume but search accuracy for these queries is usually unsatisfactory due to data sparseness such as limited click information. In this paper, we study the problem of modeling perceived relevance for queries without click-through data. Instead of relying on users’ click data, we carefully design a set of snippet features and use them to approximate the perceived relevance. We study the effectiveness of this set of snippet features in two settings: (1) predicting perceived relevance and (2) enhancing search engine ranking. Experimental results show that our proposed model is effective to predict the relative perceived relevance of Web search results. Furthermore, our proposed snippet features are effective to improve search accuracy for longer tail queries without click-through data.

1 Introduction

Designing effective ranking functions to satisfy all kinds of information needs of end users is admittedly difficult. A practical approach used by commercial search engines is to collect all possible useful signals or features and combine them together using techniques such as learning to rank [4,37]. Beyond the regular text matching features (e.g., TF-IDF), click-through data has been studied extensively [22,12,21,24]. Noticeable usages of click-through data include propagating semantic information between queries and documents [5,26,34,4], estimating document relevance [22,12,16,36,10], defining features in learning to rank [2,21], etc. All the existing works have demonstrated the unique values of click-through data in improving search engines from many perspectives. A main advantage of click-through data is that it contains users’ implicit perceived relevance feedback.

A well-known challenge in leveraging click-through data is that click-through information is very noisy and biased by many factors such as presentation order and appearance [23,11,35]. Many studies such as [12,15,19,10,23,20] have attempted to address the position bias to extract the relevance between documents and queries which is hidden in the clicks. Since only search snippets are perceived by users before issuing any clicks, the relevance induced by clicks are usually called perceived relevance. In general, when there are sufficient clicks information for a query, existing approaches can estimate the perceived relevance reliably which has been proven to be quite effective to improve Web search.

While there are plenty of click information for popular or head queries, unfortunately, very little information is available for tail ones and existing methods either can not be applied to or can give unreliable estimation for tail queries due to limited click data. According to a recent study [31], queries submitted to Web search engines follow a heavy-tailed power-law distribution. Thus a large fraction of queries are issued very infrequently,
forming the well-known “long tail” [3]. Naturally, the useful signals for such tail queries are very scarce in search logs. As a result, the benefit of click-through data is mainly for popular head queries and current search engines usually perform poor for tail queries [14]. A recent study [18] shows that almost every individual user has both head and tail requests for Web search. Thus, poor search results on tail queries can not only make most of users unsatisfactory for their immediate requests, but also deteriorate their overall perceptions of a search engine. Interestingly, [18] has also shown that there is a second-order effect that satisfactory results for tail requests can significantly boost the head requests due to increased user satisfaction and resulting repeat patronage. However, search accuracy for these queries is usually unsatisfactory due to data sparseness. Thus it remains a challenge to improve search quality for tail queries.

The importance and uniqueness of tail queries has been noticed recently. Existing works on tail queries mainly focus on aspects such as query classification [6], query advertisability [27], and query suggestions [32]. Surprisingly, there are few works on directly improving search accuracy for tail queries, which is the most important aspect of a search engine. In this paper, we propose a self-reinforcement way for tail queries. Motivated by the perceived relevance in click-through data, our main idea is to capture the perceived relevance based on search result snippets without requiring any click-through data. Search result snippets are valuable resources for the following reasons: (1) Search result snippets are highly correlated with click data and thus the underlying perceived relevance. (2) The snippets are summaries of the documents which are the most relevant passages deemed by the snippet generation methods. Passage level relevance [8] can be modeled by matching queries with search snippets.

Specifically, we define a set of snippet features whose goal is to capture the perceived relevance from multiple perspectives, including language attractiveness, URL attractiveness, and query-snippet matching attractiveness. All of these features do not need any user click data and can be computed solely based on queries and snippets. We study the effectiveness of this set of snippet features in two settings: (1) predicting perceived relevance and (2) enhancing search engine ranking. For (1), we first estimate perceived relevance for queries which have sufficient clicks using an existing dynamic Bayesian network model. We then train a machine learning model to predict the estimated perceived relevance. For (2), however, it is not straightforward to incorporate these features into a search process since most of the features can be only computed after the query-dependent snippets are generated. We thus propose two strategies to leverage these snippet features. Our first strategy is to combine the predicted perceived relevance scores with the original ranking scores to rerank search results. Our second strategy is to expand the original ranking features by adding the snippet features to learn a new ranking function. We show that both strategies can be naturally incorporated into a search process in different application scenarios.

We evaluate the usefulness of our defined snippet features based on a large set of queries and snippet features from a commercial search engine. Experimental results shows that the defined snippet features can give good prediction of perceived relevance and it can also improve the search accuracy significantly.

2 Related Work

The long tail view was first coined in [3] and has been observed for many diverse applications like e-commerce and Web search [18]. Our work is more related to the long tail study in Web search. For example, [14] compared head queries and tail queries in terms of search accuracy and users search behaviors. [6] proposed robust algorithms for rare query classification. [27] studied the advertisability of tail queries in sponsored search and proposed a word-based approach for online efficient computation. [32] studied query suggestions for rare queries but their approaches still assume that there is click information to leverage. In contrast, our work is on directly improving the search accuracy, which is the most important aspect of a search engine, for tail queries without any click-through data.

In the past, snippets have been used by many different purposes such as query classification [6] and measuring query similarity [30]. In particular, our work is related to [2]. In [2], some snippet features such as overlap between the words in title and in query are used, together with user behavior and click-through features. The main finding of their study is that click features are the most useful for general queries. In our work, we focus on tail queries which do not have any click information. We define a more comprehensive set of snippet features and discuss different application scenarios to efficiently leverage these snippet features.

Our work is related to click models and a number of recent studies has been conducted to analyze click data [22,12,10,16,20]. For example, [22] examined several rule-based methods to extract the relative preference between a pair of documents from click data. Recently, all clicks in a search session are modeled together and thus the dependency among clicks in different positions can be modeled. For example, cascade model [12]
assume that user sequentially examine results and stop as soon as a relevant document is clicked. 10 and 19 analyze click data based on different Bayesian generative models and perceived relevance is estimated by fitting the models to observed click data. 21 further extends these models to consider intent diversity. A recent approach 10 uses a session utility model to estimate the “intrinsic relevance” of each clicked document. Both 10 and 16 argued the difference between “perceived relevance” and “true relevance.” The main resources they relied on to estimate true relevance of a click are the session activities after the click. Usually, a document which is clicked last is given a higher relevance score. In our work, we choose to model perceived relevance since there are no actual click information for tail queries and it is hard to model what happened afterwards. Furthermore, all these works only leverage the click information and have not considered search result snippets.

Our work is also related to click prediction works 1, 15. 1 used an existing hierarchy to propagate clicks to rare events. 15 used past clicks to predict future. 28 proposed a feature-based method of predicting the click-through rate for new ads. To the best of our knowledge, few works have been conducted to predict click-based perceived relevance for tail queries in Web search. Furthermore, compared with 28, which only uses query-dependent features, we explore a more compressive feature set with both query-dependent and query-independent features.

3 Perceived Relevance and User Clicks

Click-through data has been extensively studied recently 22,12,10,24. A common observation is that click data contains users’ perceived relevance feedback and this information is quite effective to improve Web search. However, click data is noisy and biased by many factors such as presentation order and appearance. 28,11,35. Many studies such as 12,19,10,23 have attempted to address the position bias to extract the relevance between documents and queries which is hidden in the clicks. Technically, perceived relevance is usually captured by the click probability given the corresponding search result has been examined by end users. By definition, perceived relevance is independent of position bias. In the following, we give a brief review of the Dynamic Bayesian Network (DBN) model which can effectively extract the perceived relevance from a click session 10.

The DBN model is based on the cascade model proposed in 12. The cascade model assumes that a user examines the search results sequentially from top to bottom and decides whether to click a search result. After a document $u$ is examined, it is either clicked with probability $a_u$ or skipped with probability $(1 - a_u)$ where $a_u$ denotes the degree of attractiveness or perceived relevance. The cascade model assumes that a user who clicks never comes back and a user who skips always continue. A click on the $i$-th document means that the user skips all the documents ranked above and the user is satisfied by the $i$-th document

$$P(C_i = 1) = a_i \prod_{u=1}^{i-1} (1 - a_u)$$

All above assumptions clearly oversimplify the problem. The model suffers indeed from only being able to consider sessions with exactly one click.

10 extends the cascade model and proposes a Dynamic Bayesian Network (DBN) model to simultaneously model the relevance of all documents in the search results. The DBN model introduces the notion of satisfaction to separately model the relevance of the landing page and perceived relevance on the search results page (attractiveness). Formally, we use binary random variables $E_i, A_i, S_i$ and $C_i$ to denote examination, attractiveness, satisfaction, and click of $i$-th document. A session is generated by the following procedure, assuming $E_1 = 1$ and all other default values are 0:

- For each position $i$, sample an attractiveness probability $a_i$ from a Beta prior distribution.
- For each position $i$, sample a satisfaction probability $s_i$ from a Beta prior distribution.
- Repeat for each position $i$
  - Sample $A_i = 1$ with probability $a_i$. Set $C_i = A_i$ if $E_i = 1$
  - If $C_i = 1$, sample $S_i = 1$ with probability $s_i$. Otherwise set $S_i = 0$
  - If $S_i = 1$, set $E_{i+1} = 0$. Otherwise, sample $E_{i+1} = 1$ with probability $\gamma$.

The parameter $\gamma$ is the perseverance parameter and a user may give up the search with probability $1 - \gamma$ before satisfied. Assuming users always examine the first position, attractiveness, indeed is a prediction of the CTR at position 1. Given a set of click sessions in search logs, we can find a maximum a posterior (MAP) estimation of $a_i$ and $s_i$ by an EM algorithm 10. The obtained $a_i$ denotes the degree of attractiveness of $i$-th document.

In general, when there are sufficient click information for a query, existing approaches such as DBN can estimate the perceived relevance reliably. However, the existing click-based methods only rely on the click information in search logs but totally ignore the search snippets. While there are plenty of click information for popular or head queries, unfortunately, very little
information is available for tail ones and existing methods either can not be applied to or can give unreliable estimation for tail queries due to scarce click data. In the next section, we describe our approach to capturing perceived relevance using search snippets.

4 Capture Perceived Relevance for Tail Queries

Tail queries pose a big challenge to leverage the click-based methods. Since the ultimate goal of the click-based methods is to capture the perceived relevance and search results snippets are the main information sources before a user issues a click, we thus try to capture perceived relevance for tail queries based on search snippets in this section.

4.1 A Motivating Experiment

Our hypothesis is that there is a strong correlation between perceived relevance and snippets in a Web search result page. We test this hypothesis using a simple experiment as follows. In this experiment, we collected a set of tuples \((q, u_1, u_2)\) where \(u_1\) and \(u_2\) are any two URLs that appear in the same search result page for the query \(q\) during some period of time. We then computed the number of missing query tokens in titles. We examined how likely \(u_1\) is clicked more frequently than \(u_2\) when \(u_1\) has fewer missing query tokens than \(u_2\). In other words, we want to estimate the probability

\[
P_0 = \text{Prob}(u_1 \text{ is clicked more frequently than } u_2 \\
| \text{miss}(t_{u_1}) < \text{miss}(t_{u_2}))
\]

where \text{miss}(t_u) is the number of missing query tokens in the title \(t_u\) for \(u\). We balanced our samples to eliminate potential position bias by ensuring that \(u_1\) is presented higher than \(u_2\) in half of our examples. The estimation of \(P_0\) in our data was 0.74, which is much larger than 0.5 and shows positive correlation. Furthermore, we observed a stronger click preference if the title matching has larger difference for the two URLs.

\[
P_1 = \text{Prob}(u_1 \text{ is clicked more frequently than } u_2 \\
| \text{miss}(t_{u_1}) + 1 < \text{miss}(t_{u_2})) = 0.83.
\]

This result demonstrates that the snippets with more missing query tokens in their titles tend to receive fewer clicks than those with fewer missing query tokens. This makes sense intuitively since a page with title matched well with queries is more likely to be more relevant. Note that the title matching is only a single feature among many possible signals that may influence user clicks. To model the click behaviors more accurately, we need to seek a more comprehensive set of such snippet features to capture the perceived relevance more precisely.

4.2 Search Snippet Features

Our goal is to develop a comprehensive set of snippet features that capture the attractiveness of results. We define our features from the following perspectives: language attractiveness, URL attractiveness, and query-snippet matching attractiveness. All the features are summarized in Table 1 and we describe them separately in the following.

4.2.1 Language Attractiveness

We model the language attractiveness by two sets of features: readability and word-level attractiveness. (1) Recent studies such as [11] show that the readability

| Language Attractiveness Features |
|----------------------------------|
| Readability Features             |
| NumChars | Number of characters in snippet |
| NumWords | Number of words in snippet      |
| NumSegments | Number of period/ellipsis-separated segments |
| NumWordInitCap | Number of words with initial capitals in snippet |
| FracWordInitCap | Fraction of words with initial capitals in snippet |
| NumCapChar | Number of capital characters in title or URL |
| FracCapChar | Fraction capital characters in title or abstract |

| Word-level Attractiveness |
|---------------------------|
| FracAttrWord | Fraction of attractive words |

| Matching Attractiveness Features |
|----------------------------------|
| NumMatch | Number of all matches in snippet |
| NumUniqMatch | Number of unique matches in snippet |
| NumApoxMatch | Number of approximate matches in snippet |
| FracMatch | Fraction of matches in snippet |
| FracApoxMatch | Fraction of approximate matches in snippet |
| NumBckMatch | Number of words before the first match |
| NumBtwMatch | Number of extra words between matches |
| IsExactMatch | Is whole query string exactly matched |
| IsOrderMatch | Are matches in the exact order |
| IsSegMatch | Are all matches occur in a single segment |

Table 1 Summary of the snippet features.
of snippets in a search result page can directly impact users’ click-through behavior. In this work, we define some readability features similar to those proposed in \cite{11,25,29} and also some new features based on our intuitive judgments and experiments. This set of features are mainly to model the syntactic information of titles and abstracts of the snippets. For example, the feature NumSegment measures the number of fragments separated by an ellipsis or a period in abstracts which in some sense reflects how easy the snippets can be read.

(2) The word-level attractiveness is to model the language in a semantic level. Previous researches \cite{11,25,13,25} also show that some terms in titles (e.g., “official” or “gallery”) specify a certain genre and influence user clicks noticeably. To identify these words, we use a t-test based on the URL attractiveness values estimated by the DBN model. Specifically, given head queries with attractiveness of URLs estimated by DBN, we form two sets of titles, $A$ and $U$, where $A$ includes the titles of the two most attractive URLs and $U$ includes the titles of the two most unattractive URLs of every query. An attractive words will have higher discriminative power between $A$ and $U$ and a less attractive word will have smaller difference between $A$ and $U$. For each word $w$, we perform a t-test on the mean difference between $w_A = \{I(w \in T) \mid T \in A\}$ and $w_U = \{I(w \in T) \mid T \in U\}$ where $I$ is an indicator function. Table 2 shows some examples of attractive words identified by our test with p-value $\leq 0.05$. Intuitively, a title with these words can attract users’ clicks for certain information needs.

### 4.2.2 URL Attractiveness.

URLs in snippets are also used by end users to select search results since URLs can implicitly tell users the reputation or quality of the landing pages \cite{29}. For example, a URL with “.edu” in its domain is a good indicator for academic-related queries. A long URL with high depth is probably less attractive than a URL with low depth if a user intends to find some broad information. We thus define the URL attractiveness features as shown in Table 1. All the URL features are query independent. For example, although a URL may not received any clicks for a tail query but it can be probably clicked again if it has received many clicks in the search logs. This is captured by our NumViews feature for URLs. Furthermore, we define a categorical feature TopLevelDomain in Table 1 to roughly capture the URL types. Table 3 lists the distribution of the highly clicked top-level domains identified in our search logs. The feature TopLevelDomain takes one of the 5 possible values in Table 5.

### 4.2.3 Matching Attractiveness.

Query-biased snippets are regarded as the most relevant part of the landing page by snippet generation methods \cite{33}. The matching fragments of a title, URL and abstract provides passage level relevance evidence between query and documents \cite{8} and also play an important role in users’ evaluation of the relevance of the landing page. We define a set of matching attractiveness in Table 1 in a similar way to the matching features between queries and whole documents. Our matching features cover string-level match, token-level match, matching positions (NumBtwMatch and NumBefMatch) and matching coherence and proximity (IsSegMatch and NumBtwMatch), etc. We also include approximate matches which are computed based on the edit distance between query tokens and words in snippets. This feature can capture the morphological variants and also acronyms. We discretize the approximate match in to binary values by thresholding. For example, FracApxMatch is computed as the fraction of query tokens which have approximate matches in titles or URLs.

\[
\text{FracApxMatch}: \frac{1}{|Q|} \sum_{q \in Q} \text{ApxMatch}(q, T \cup U)
\]

where $Q, T, U$ are a set of tokens in the query, title and URL respectively and

\[
\text{ApxMatch}(q, S) = \begin{cases} 
1 & \text{if } q \text{ approximately matches a token in } S \\
0 & \text{otherwise.}
\end{cases}
\]

The longer the token $q$, the more distance we allow in approximate matches. This feature has been shown to be an important feature in terms of discriminative power in prediction in our experiments.

Our matching features can be also extended to an expanded set of queries for a given URL. Though we
have no click information for tail queries, we still have clicked information for a candidate URL. In our log, we
can have a set of queries which have led clicks to the
URL as the expanded set of queries. We can thus com-
pute the matching attractiveness of this set of queries
and use them as additional snippet features. Let $Q_{exp}(u)$
denote the set of queries for which the URL $u$ has been
viewed and clicked by users in our logs. Given a query
$q$ and a URL $u$, we define

$$\text{FracMatch}_{\text{Expanded}}(q, Q_{exp}(u))$$

where FracMatch denotes the fraction of query tokens
in the expanded query set. For example, given $q=\text{“puma concolor,”}$ the following URL:

URL: en.wikipedia.org/wiki/Mountain Lion
Title: Cougar -Wikipedia, the free encyclopedia

We have the expanded query set as \{cougar, mountain
lion, concolor\}. Although there is no matching between
the original query $q$ and the corresponding URL, i.e,
FracMatch($q$, $u$) = 0, we have FracMatch_{\text{Expanded}}($q$,
$u$) = 0.5. This makes sense because concolor is also
known as cougar or mountain lion, depending on re-

gions. This example shows that expanded query match
features can deal with some synonym or misspelling
problems effectively.

5 Leverage Snippet Features

Given a query, we use $x_i \in \mathbb{R}^d$ and $s_i \in \mathbb{R}^l$
to represent the original ranking features and the snippet
features for document $i$. A traditional ranking function $f_{\text{org}} : \mathbb{R}^d \rightarrow \mathbb{R}$ maps the original ranking features to a real
value and all the documents for a query is ranked by $f_{\text{org}}$ in
descent order. We leverage the snippet features to predict perceived relevance and enhance the search
result ranking.

5.1 Predict Perceived Relevance

We train an attractiveness function $f_{\text{attr}} : \mathbb{R}^l \rightarrow \mathbb{R}$
based on the snippet features $s_i$ and the attractiveness
score $a_i$ estimated using DBN model. We obtain our
training data by applying our feature definition and the
DBN model on a set of popular queries with suffi-
cient click information. Since $f_{\text{attr}}$ only relies on a set
of snippet features, it can be applied to tail queries.
We use the GBRank \cite{GBRank} method to find the optimal
$f_{\text{attr}}$ to minimize the following pairwise loss function.

Let $\mathcal{P} = \{(s_i, s_j, a_i - a_j)\}$. Our loss function is:

$$\sum_{\mathcal{P}} \max \left(0, (a_i - a_j) - (f_{\text{attr}}(s_i) - f_{\text{attr}}(s_j))\right)^2.$$ 

The function $f_{\text{attr}}$ can be used to predict the perceived
relevance between any query and URL.

5.2 Improve Web Search Ranking

In this section, we discuss how to leverage our snippet
features to enhance the ranking. We propose two
strategies and discuss their application scenarios in the
following.

5.2.1 Strategy I

To leverage the snippet features, our first strategy is to
use the predicted perceived relevance scores and com-
bine them with the original ranking scores to rerank the
top search results. Specifically, we propose the following
scenario to apply our strategy:

- An initial query is issued and the ranking function $f_{\text{org}}$ is used to select a few top results.
- The snippet generation method receives the selected
documents. It generates the snippets and also the
snippet features. Based on snippet features, $f_{\text{attr}}$ is
used to estimate the perceived relevance.
- The final ranking of search results is ranked based
on a linear combination of $f_{\text{org}}$ and $f_{\text{attr}}$:

$$f_t = \lambda \cdot f_{\text{org}} + (1 - \lambda) \cdot f_{\text{attr}}.$$ 

5.2.2 Strategy II

The first strategy is a simple linear combination of the
predicted scores. Our second strategy is to go to the
feature level and expand the ranking features $x_i$
by $s_i$. Thus we form a longer feature vector $[x_i, s_i]$ for
each document. We train a new ranking function
$f_I : \mathbb{R}^{d+l} \rightarrow \mathbb{R}$ on these concatenated vectors. Appar-
ently, it is difficult to directly apply such a strategy on
a search engine since the search snippets features can
be generated only after the snippets are generated. We
thus propose the following scenario in a feedback set-
ting to have two rounds of retrieval.

- An initial query is issued and the ranking function $f_{\text{org}}$ is used to return the search results and generate
snippets for the top ranked results.
- We provide users an additional button “Refresh to
Improve” which is intended to improve search re-
sults if a user is not satisfied with the current results
and clicks the button.

have no click information for tail queries, we still have clicked information for a candidate URL. In our log, we can have a set of queries which have led clicks to the URL as the expanded set of queries. We can thus compute the matching attractiveness of this set of queries and use them as additional snippet features. Let $Q_{exp}(u)$ denote the set of queries for which the URL $u$ has been viewed and clicked by users in our logs. Given a query $q$ and a URL $u$, we define

$$\text{FracMatch}_{\text{Expanded}}(q, Q_{exp}(u))$$

where FracMatch denotes the fraction of query tokens in the expanded query set. For example, given $q=\text{“puma concolor,”}$ the following URL:

URL: en.wikipedia.org/wiki/Mountain Lion
Title: Cougar -Wikipedia, the free encyclopedia

We have the expanded query set as \{cougar, mountain lion, concolor\}. Although there is no matching between the original query $q$ and the corresponding URL, i.e, FracMatch($q$, $u$) = 0, we have FracMatch_{\text{Expanded}}($q$, $u$) = 0.5. This makes sense because concolor is also known as cougar or mountain lion, depending on regions. This example shows that expanded query match features can deal with some synonym or misspelling problems effectively.

5 Leverage Snippet Features

Given a query, we use $x_i \in \mathbb{R}^d$ and $s_i \in \mathbb{R}^l$ to represent the original ranking features and the snippet features for document $i$. A traditional ranking function $f_{\text{org}} : \mathbb{R}^d \rightarrow \mathbb{R}$ maps the original ranking features to a real value and all the documents for a query is ranked by $f_{\text{org}}$ in descent order. We leverage the snippet features to predict perceived relevance and enhance the search result ranking.

5.1 Predict Perceived Relevance

We train an attractiveness function $f_{\text{attr}} : \mathbb{R}^l \rightarrow \mathbb{R}$ based on the snippet features $s_i$ and the attractiveness score $a_i$ estimated using DBN model. We obtain our training data by applying our feature definition and the DBN model on a set of popular queries with sufficient click information. Since $f_{\text{attr}}$ only relies on a set of snippet features, it can be applied to tail queries. We use the GBRank \cite{GBRank} method to find the optimal $f_{\text{attr}}$ to minimize the following pairwise loss function.

Let $\mathcal{P} = \{(s_i, s_j, a_i - a_j)\}$. Our loss function is:

$$\sum_{\mathcal{P}} \max \left(0, (a_i - a_j) - (f_{\text{attr}}(s_i) - f_{\text{attr}}(s_j))\right)^2.$$ 

The function $f_{\text{attr}}$ can be used to predict the perceived relevance between any query and URL.

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5.2.1 Strategy I

To leverage the snippet features, our first strategy is to use the predicted perceived relevance scores and combine them with the original ranking scores to rerank the top search results. Specifically, we propose the following scenario to apply our strategy:

- An initial query is issued and the ranking function $f_{\text{org}}$ is used to select a few top results.
- The snippet generation method receives the selected documents. It generates the snippets and also the snippet features. Based on snippet features, $f_{\text{attr}}$ is used to estimate the perceived relevance.
- The final ranking of search results is ranked based on a linear combination of $f_{\text{org}}$ and $f_{\text{attr}}$:

$$f_t = \lambda \cdot f_{\text{org}} + (1 - \lambda) \cdot f_{\text{attr}}.$$ 

5.2.2 Strategy II

The first strategy is a simple linear combination of the predicted scores. Our second strategy is to go to the feature level and expand the ranking features $x_i$ by $s_i$. Thus we form a longer feature vector $[x_i, s_i]$ for each document. We train a new ranking function $f_I : \mathbb{R}^{d+l} \rightarrow \mathbb{R}$ on these concatenated vectors. Apparently, it is difficult to directly apply such a strategy on a search engine since the search snippets features can be generated only after the snippets are generated. We thus propose the following scenario in a feedback setting to have two rounds of retrieval.

- An initial query is issued and the ranking function $f_{\text{org}}$ is used to return the search results and generate snippets for the top ranked results.
- We provide users an additional button “Refresh to Improve” which is intended to improve search results if a user is not satisfied with the current results and clicks the button.
After the button is pressed, all the snippet features are generated for top results and the new ranking function \( f_{\text{snippet}} \) is used to generate a new search result page.

This strategy can be used without user interference by search engines. However, such a strategy may be risky for those queries for which the original ranking is already good enough. The button “Refresh to Improve” is a safe alternative when a user is not satisfied with the current results.

6 Experiments

We perform two types of experiments. First, we evaluate the performance of our attractiveness prediction. Then, we use the predicted attractiveness and the defined snippet features to improve the ranking accuracy.

6.1 Predict Perceived Relevance

6.1.1 Experiment Setup

We first test the predictive accuracy of our proposed prediction model for tail queries. A difficulty in this test is that we cannot obtain the “true” target attractiveness for tail queries: The estimation of attractiveness (by click models) is not reliable for tail queries due to the limited amount of click information. Thus, we need to simulate tail queries by sampling only a small subset of click logs of non-tail queries. Please note that the target attractiveness is obtained before the sampling.

We get click logs from a commercial search engine. The click log data is a set of sessions. A session is associated with a unique user and a unique query. It starts when a user issues a query and ends with 60 minutes idle time on the user side. Each session contains the list of URLs in the search results page and list of clicked URLs. We select queries with enough sessions to ensure the reliable target values. After this filtering, we obtain 40M sessions and 20K unique queries. Let this original set of sessions be \( S \). Then, \( S \) is split into the training set \( S_{\text{train}} \), the validation set \( S_{\text{validation}} \) and the test set \( S_{\text{test}} \). For all (query,URL) pairs in these sets, we obtain snippet features and target values (attractiveness computed by the DBN click model) for the DBN click model using the full data. We get \( S_{\text{test}}^{\text{tail}} \) by sampling 10 random sessions for each query in \( S_{\text{test}} \).

The evaluation is based on comparing pairwise attractiveness values predicted by our proposed model \( f_{\text{attr}} \) to the “true” pairwise attractiveness values derived from the DBN click model using the full session data: For two URLs, \( u_j \) and \( u_k \) for query \( i \), we predict that URL \( u_j \) is more attractive than URL \( u_k \) if

\[
f_{\text{attr}}(x_{i,j}) - f_{\text{attr}}(x_{i,k}) > \tau.
\]

Then, we test if \( a_{i,j} > a_{i,k} \) where \( a_{i,j} \) and \( a_{i,k} \) are the true target attractiveness values computed by the DBN click model using the full session data \( S_{\text{test}} \). Hence, this is a binary classification problem. With a different \( \tau \) values, we have a different levels of precision and recall. Thus, by varying \( \tau \), we can get a precision-recall curve.

Based on the test data, we compare the predictions given by the following:

- \( a^{\text{tail}} \): Attractiveness computed by the DBN click model using sampled session data \( S_{\text{tail}} \).
- \( f_{\text{snippet}} \): Function trained on only snippet features.
- \( f_{\text{snippet+click}} \): Function trained on both snippet features and clicks.

\( a^{\text{tail}} \) provides the baseline predictions: If \( a_{i,j}^{\text{tail}} - a_{i,k}^{\text{tail}} > \tau \), we predict that URL \( u_j \) is more attractive than URL \( u_k \).

We apply GBRank to train a function \( f_{\text{snippet}} \) on the pairwise training data

\[
P = \{(x_{i,j}, x_{i,k}, a_{i,j} - a_{i,k}) \mid i \in \{1, \ldots, N\}, j, k \in \{1, \ldots, 10\}, a_{i,j} > a_{i,k}\}
\]

where \( a_{i,j} \) and \( a_{i,k} \) are the attractiveness values computed by the DBN click model using the whole session data \( S_{\text{train}} \).

Once we train \( f_{\text{snippet}} \) on the training data, it can be used for new queries for which no click information is available. However, for tail queries for which some amount of click data is available, we can combine our attractiveness model and the click information. A straightforward way to combine the two is to have a linear combination of the two predictions:

\[
\lambda f_{\text{snippet}} + (1 - \lambda) a
\]

where \( a \) is the attractiveness computed by the DBN click model using the available click data and \( \lambda \) depends on the frequency of a query (the more frequent, the smaller \( \lambda \) becomes). However, we would have to tune \( \lambda \) manually or design a heuristic function for \( \lambda \). More principled way of combining the attractiveness model and click information is to use the click information as a feature and let the training procedure figure out the optimal combination. To this end, we generate another session data \( S'_{\text{train}} \) as follows. For each query in \( S_{\text{train}} \), we sample \( r \% \) of sessions where \( r \) is randomly selected to ensure that the sampled session data contains queries with various frequencies. Then, each feature vector \( x_{i,j} \) in our training data is expanded to include two additional features:
Then, we train a GBRank function \( f \) and \( f \) observations: We have the following tures ordered by their importance (See [17] for the defi-
information clearly outperforms either one. We summarize the precision-recall results of a combination of our attractiveness model and the click

6.1.2 Experimental Results

We summarize the precision-recall results of \( a_{\text{tail}} \), \( f_{\text{snippet}} \) and \( f_{\text{snippet+click}} \) in Figure 1. The result shows that the

6.2 Improve Ranking Relevance

We construct our data sets to test the effectiveness of our defined snippet features from a commercial search engine. The training examples are labeled using five values, \( \{0, 1, 2, 3, 4\} \), representing five levels of relevance. Our evaluation is based on NDCG

![Fig. 1 Precision vs. recall of 3 different ways of predicting attractiveness for tail queries. 'Summary' represents a function \( f_{\text{snippet}} \) trained on only snippet features. 'Click' represents predictions given by \( a_{\text{tail}} \), attractiveness computed by the DBN click model using a limited amount of click information. 'Summary and Click' represents a function \( f_{\text{snippet+click}} \) that combines both predictions.](image)

- \( a_{i,j} \): Attractiveness computed by the DBN click model using \( S_{\text{train}}' \)
- \( \text{session}_i \): The number of sessions for query \( i \) in \( S_{\text{train}}' \)

Note that we still use the true attractiveness \( a_{i,j} \) (computed by using the full data \( S_{\text{train}} \)) as targets. The new pairwise training data is

\[
P = \{(x_{i,j}, a_{i,j}', \text{session}_i), (x_{i,k}, a_{i,k}', \text{session}_i), a_{i,j} - a_{i,k}\}
\]

Then, we train a GBRank function \( f_{\text{snippet+click}} \) on this data.

The result shows that the combination of our attractiveness model and the click information clearly outperforms either one.

After the training process, we obtain the list of features ordered by their importance (See [17] for the definition of importance of features). We have the following observations:

- For \( f_{\text{snippet+click}} \), the attractiveness and the number of sessions are among top three features in the importance list. When we look into the decision tree structure, we find that the two features function together: When the number of sessions is large (i.e. we have sufficient click information), the attractiveness computed by the DBN click model should be weighted more than snippet features. On the other hand, when we have a small number of sessions (i.e. tail queries), snippet features should play a more important role.

- Length of URL is the second most important feature for \( f_{\text{snippet}} \) and the forth for \( f_{\text{snippet+click}} \), which agrees with the results by [11].

- Features related to URL and title are more important than those for abstract.

\[
\text{NDCG}_k = \frac{1}{Z_k} \sum_{i=1}^{k} \frac{G_i}{\log_2(i + 1)}
\]

where \( G_i \) is the function of relevance grade of the document at rank position \( i \) and \( Z_k \) represents a normalization factor to guarantee that the NDCG\(_k\) for the perfect ranking (among the permutations of the retrieved documents) is 1.

We have a conventional data set which has the most informative 20 original ranking features, including some click-based features, to train a conventional ranking function. Since we aim at improving relevance for new or tail queries, we collect (query,URL) pairs which have no click related information from the above data set. We treat all the queries in the resulting data set as tail queries. Table 4 shows the distribution of the tail queries with respect to query length and their corresponding search accuracy using our baseline ranking function. Clearly, long queries cover a large portion of the tail queries. Furthermore, we can also see that while short tail queries can achieve reasonable accuracy, long queries usually have much worse search accuracy. This means that the baseline ranking function is less effective for longer tail queries. Thus, in the following experiments, we consider the queries with more than or equal to 3 tokens to help these more difficult tail queries. We split the data into training and test. In the training data, we have 202K (query,URL) pairs, resulting in 2M preference pairs. In the test data, we have 46K (query,URL) pairs and 545K preference pairs. Since no click information is available, all the queries in both training and test data can be regarded as unseen queries.
To obtain the training data to learn the attractiveness function $f_{attr}$, we use the data set used in the previous section. Each session contains the list of URLs in the search result page and list of clicked URLs. We select queries with enough sessions to ensure the reliable target values.

Figure 2 shows the accuracy comparison of the baseline ranking ($f_{org}$), strategy I ($f_I$), and strategy II ($f_{II}$) using NDCG$_5$ as the metric. For all these methods, we tune the GBRank parameters and $\lambda$ to be the optimal. From this figure, we can see that both our strategies can improve over the baseline ranking. For example, strategy II improve over the baseline by 0.8% relatively and this is statistically significant based on the Wilcoxon test ($p$-value < 0.01). Although strategy I is also able to improve over the baseline, the improvement is not statistically significant. Comparing the two strategies, strategy II is more effective than strategy I. This shows that the second strategy of directly training a new ranking function can better leverage the snippet feature signals.

In Figure 3 we show the impact of the parameter $\lambda$ in strategy I using both metrics NDCG$_5$ and NDCG$_{1}$ for higher ranked documents. This also means that the attractiveness scores from DBN is more accurate to predict higher ranked results and this is reasonable because the highly ranked documents is less influenced by the position bias.

Overall, we can see that both our strategies are effective to improve search accuracy. This confirm the effectiveness of our defined snippet features.

### 7 Conclusions and Future Work

In this paper, we studied how to model perceived relevance for tails queries without relying on any click-through data. We developed a set of snippet features to capture the attractiveness or perceived relevance of Web search results and proposed two novel strategies to leverage these snippet features to improve tail queries. We show that the two strategies can be naturally incorporated into a search process. We conduct experiments on a large data set from a commercial search engine. Our results confirm the defined snippet features are able to predict the perceived relevance effectively. Furthermore, the search accuracy of tail queries can be significantly improved by using the snippet features.

Our work is one of the few work on directly improving search accuracy for tail queries. In the future, one interesting direction is to provide a unified framework to jointly model both clicks and snippet features together so that information of head queries can be propagated to tail queries in a more principled way. A main challenge for tail queries is due to lack of users’ feedback and a possible direction is to leverage the relation
between queries such as a query graph to better capture the attractiveness of search results for tail queries.

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