Assessing top-

k preferences

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Assessors make preference judgments faster and more consistently than graded relevance judgments. Preference judgments can also recognize distinctions between items that appear equivalent under graded judgments. Unfortunately, preference judgments can require more than linear effort to fully order a pool of items, and evaluation measures for preference judgments are not as well established as those for graded judgments, such as NDCG. In this paper, we explore the assessment process for partial preference judgments, with the aim of identifying and ordering the top items in the pool, rather than fully ordering the entire pool. To measure the performance of a ranker, we compare its output to this preferred ordering by applying a rank similarity measure. We demonstrate the practical feasibility of this approach by crowdsourcing partial preferences for the TREC 2019 Conversational Assistance Track, replacing NDCG with a new measure that can reflect factors beyond relevance. This new measure has its most striking impact when comparing traditional IR techniques to modern neural rankers, where NDCG can fail to recognize significant differences exposed by this new measure.

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1 INTRODUCTION

Preference judgments [7, 16, 30, 32, 38] have long been proposed as an alternative to graded relevance judgments for the offline evaluation of search and related ranking tasks, including recommendation and question answering. Instead of independently judging individual items according to defined relevance criteria, assessors make preference judgments on pairs of items by comparing them side-by-side to determine the better of the two. If we allow ties, preference judgments impose a weak ordering on a set of items. To evaluate the performance of a ranker on a query, we can directly compare this weak ordering to the actual ranking generated for that query. If we employ a rank similarity measure for this comparison, it provides a measure of the ranker’s performance [13]. This approach contrasts with the more established approach of converting independently assigned relevance grades into gain values to compute measures such as NDCG [4, 20] and ERR [10].

Compared with independent relevance judgments, assessors make preference judgments faster and more consistently [7]. Preference judgments also make it easy to incorporate factors beyond relevance into offline evaluation [12]. For example, for e-commerce search, these factors might include price and quality. For a news search vertical, these factors might include recency, so that an assessor comparing two equally relevant news stories could choose the latest update. If two news articles are equally relevant and timely, an assessor might prefer a shorter, more focused,
article over a longer article containing extraneous information. Preference judgments can also take personalization into account, so that locally available items could be preferred for an e-commerce search, or concordant political views could be preferred for a news search.

Preference judgments face two criticisms. First, even if we assume transitivity, a set of \( n \) items requires \( O(n \log n) \) judgments to produce a total order. If we don’t assume transitivity, a set of \( n \) items may require \( O(n^2) \) preference judgments. In contrast, if we have dedicated and reliable assessors, traditional graded relevance requires exactly \( n \) judgments. Second, while NDCG and similar graded relevance measures are well established for offline evaluation in both industry and academia, widely accepted evaluation measures for preference judgments have not yet emerged [7, 37].

In prior work, we addressed the first criticism by proposing evaluation by partial preferences [13]. We focus preference judgments on identifying and carefully ordering the best items for a query, perhaps no more than four or five. Since these are the items that are most likely to be seen by a searcher [21], these are the items a ranker should return as the top results, ranked consistently with preferences. These will have the most impact on perceived search quality, and it’s important to get them right. The remaining items can be grouped into larger equivalence classes, exactly as they are for graded measures, so that they still contribute to the measurement of ranker performance, but with less impact than the best items.

To address the second criticism, we measure a system’s performance by its maximum similarity to an ideal ranking [12]. Partial preferences impose a weak ordering on a collection. We interpret this weak ordering as a set of ideal rankings for a query. For the best items, preference judgments can precisely define this ideal ordering. For the larger equivalence classes, any ordering of the items in the class is equally good, although we do not include the class of non-relevant items in our ideal rankings. We then apply a rank similarity measure to compare these ideal rankings to an actual ranking generated the system we wish to measure. As our performance measure, we take the maximum similarity between the members of the ideal set and the actual ranking.

We call this process of computing maximum similarity to a set of ideal rankings computing the compatibility of the actual ranking. When compared to traditional graded relevance measures, compatibility allows us to more precisely specify the ideal response expected from a ranker, and to compare this ideal response with its actual response. We provide further details regarding compatibility in Section 3.1. As part of computing compatibility, we use Rank Biased Overlap [33] (RBO) to compute similarity between ideal and actual rankings. The properties of RBO make it ideally suited for this purpose, and we provide further details regarding RBO in Section 3.2.

This thread of research [12, 13] was directly motivated by our experience implementing offline evaluation metrics for a social media site. Even under carefully composed assessment guidelines, multiple items may appear to be perfect, but when these items are placed side-by-side, a clearly desirable ordering becomes apparent. For example, on social media sites popular entertainers may have multiple official accounts. As well, there may be multiple high quality and carefully curated fan accounts. On Twitter, there are at least two verified accounts for Taylor Swift, @taylorswift13 with 86M followers and @taylorswiftnation13 with 1M followers. As well, there are multiple fan accounts with over 100K followers. When independently assessed, any of these accounts could reasonably be labeled as perfect for the query "taylor swift", particularly when seen outside the context of the others. When placed side-by-side, and considering factors such as the number of followers, we might rank @taylorswift13 first, @taylorswiftnation13 second, with the various fan accounts after that.

Maximum similarity to an ideal ranking represents a radical simplification of existing offline evaluation practice. Essentially we reduce offline evaluation to the problem of answering the
question: "What would an ideal system do?" Once we determine the ideal ranking for a query—or rather a set of equally ideal rankings—we apply a rank similarity measure to determine the compatibility of an actual ranking generated by a ranker to this ideal. As an offline evaluation measure, compatibility is particularly suited to partial preferences, since the weak ordering induced by partial preference can be directly interpreted as a set of ideal rankings.

In the current paper, we extend our prior work to consider assessment methods for partial preferences. Starting from a pool of items, we examine methods for narrowing this pool to the top-k items, identifying and ordering these items, while minimizing the cost and effort required. We compare two methods. The first assumes dedicated and motivated assessors, employing a tournament structure. The second crowdsources preference judgments through Mechanical Turk. For both methods, we start with an initial graded assessment as a first step in narrowing the pool.

We focus our effort on partial preferences for a question answering task — the TREC 2019 Conversational Assistance Track\(^1\) (CAstT) [14]. For this task, questions were collected into conversations of between 7 and 12 questions each. Answers were drawn from a collection of passages derived from various Web sources, including Wikipedia. For each of the 479 test questions, participating systems returned a ranked list of passages intended to answer the question. Submitted runs were pooled to a depth of 10, and 173 of the questions were judged on a 5-point relevance scale. NDCG@3 formed the primary evaluation measure for the track. Through the application of preference judging, we aim to identify and order the top-five answers for these 174 previously judged questions.

The questions from the TREC CAstT Track provide some excellent examples of the problem that initially motivated us. Figure 1 shows four passages that receive the top relevance grade ("fully meets") for the question *What is taught in sociology?* (#79.1). When viewed in isolation, any of these passages could reasonably be judged to answer the question, but when placed side-by-side differences become clear. The first two passages provide direct answers, while the third passage contains extraneous information and the fourth is merely a disjointed list of topics.

Code and preference judgements are available at https://github.com/claclark/compatibility. As part of institutional ethics review, permission was given to include crowdsourced preference judgments in this release without identifying information.

2 PREFERENCE JUDGMENTS

As far back as 1990, Rorvig [30] argued for the superiority of preference judgments as a tool for estimating document utility, as opposed to graded or binary relevance judgments, explicitly recognizing that this utility may reflect differences beyond relevance. That paper raises the transitivity of preferences as a necessary requirement for this utility estimation, and it reports experiments demonstrating that document preference judgments do exhibit the required transitivity. Rorvig also outlines a procedure for constructing a test collection based on preference judgments, while noting that this test collection "would cost a great deal more to build than current collections," due to the large number of judgments required. Frei and Schäuble [16] also sidestep absolute relevance in favor of relative comparisons between items, arguing that human assessors make relative comparisons more easily and consistently.

In a 1995 paper, Yao [38] proposed preferences judgments as a solution to the difficulties already then encountered in attempts to define and interpret ordinal relevance scales, which in some cases might suggest, for example, “that a document with grade 2 is equivalent to two documents with grade one.” Under Yao’s proposal, preference judgments define a weak ordering on the collection, where items may be tied. Just as we propose in this paper, this weak ordering might be derived from direct pairwise comparisons or from ordinal relevance grades, avoiding the need to interpret

\(^1\)www.treccast.ai
Sociology is the study of social life and the social causes and consequences of human behavior. In the words of C. Wright Mills, sociology looks for the public issues that underlie private troubles. Sociology differs from popular notions of human behavior in that it uses systematic, scientific methods of investigation and questions many of the common sense and taken-for-granted views of our social world.

What is Sociology? Sociology is the study of human social relationships and institutions. Sociology’s subject matter is diverse, ranging from crime to religion, from the family to the state, from the divisions of race and social class to the shared beliefs of a common culture, and from social stability to radical change in whole societies.

Jennifer Conn used Snape’s and Quidditch coach Madam Hooch’s teaching methods as examples of what to avoid and what to emulate in clinical teaching, and Joyce Fields wrote that the books illustrate four of the five main topics in a typical first-year sociology class: “sociological concepts including culture, society, and socialisation; stratification and social inequality; social institutions; and social theory.”

relevance grades as relevance values. Effectiveness is then measured by computing the distance between this weak ordering and a ranking generated by a search system. Yao defines axioms required for this distance metric, including the usual mathematical properties required of any distance metric. Our compatibility measure, defined in Section 3, follows this suggestion, using rank similarity measures to compare ideal and system rankings.

More recently, Carterette and Bennett, along with various collaborators, published a series of papers aiming to establish preference judgments as a practical approach to offline search evaluation [5–9, 11, 39]. Carterette et al. [7] provides evidence that preference judgments are generally transitive, so that \(O(n^2)\) judgments are not required for a pool of \(n\) items. They further recognize that prejudging non-relevant documents allows these documents to be excluded from the pool for preference judging, further reducing effort. Carterette et al. [5] describe the creation of one of the few test collections based on preferences. Along with Carterette and Bennett [6], these papers propose evaluation measures based on the discordant pairs in an actual ranking.

Zhu and Carterette [39] crowdsource preference judgments for search page layouts, providing advice that informs our current effort. Chandar and Carterette [8] employ preference judgments to generate an ideally diverse ranking. Chandar and Carterette [9] extend this work to define an evaluation measure for novelty and diversity based on preference judgments. Chen et al. [11] present an active learning approach to inferring a ranking from crowdsourced preference judgments.
Radinsky and Ailon [29] refer to the practice of inferring preferences from individual relevance judgments — both to train rankers and for evaluation — as the "IR detour". Through experiments on human subjects they conclude that "the validity of taking the IR detour is questionable." They propose an active learning method for reducing the number of preference judgments. In particular, they propose focusing preference judgments on identifying the top-$k$ items, although they do not explore this proposal in detail. They also provide an overview of some of the earlier work in the large body of literature related to preference judgments for learning-to-rank. This literature includes research specifically focused on top-$k$ learning-to-rank methods [25, 28, 34].

Another large body of literature explores methods for crowdsourcing relevance judgments [1, 2, 26], including preference judgments. Maddalena et al. [27] crowdsourced relevance magnitudes through a process in which assessors view a series of documents and estimate relevance relative to the previously seen document. Their results call into question the standard practice of converting relevance grades into gain values for the purpose of computing NDCG. Hui and Berberich [18, 19] explore the transitivity of crowdsourced preference judgments and propose an algorithm based on a randomized quicksort to reduce judging effort by allowing ties. Yang et al. [37] compare preference, absolute and ratio judgments through a large crowdsourced experiment, concluding that crowdsourced preferences provided similar outcomes as dedicated assessments when comparing rankers.

Bashir et al. [3] propose methods for converting preference judgments to relevance scores by adapting the ELO ratings used for chess and other games. Kim et al. [23] provide evidence that preference judgments can capture differences beyond traditional topical relevance, such as authority and recency. Hassan Awadallah and Zitouni [17] employ a classifier to reduce the effort associated with preference judgments. Kuhlman et al. [24] explore interaction methods for collecting preference judgments. Kalloori et al. [22] augment star ratings with preference judgments in a recommender system.

In a recent SIGIR 2020 paper, Sakai and Zeng [32] propose and explore two broad families of measures intended to support preference judgments. The first family is based on counts of concordant pairs, generalizing and extending ideas proposed by Carterette et al. [7] and Carterette and Bennett [6]. The second family converts preference judgments to gain values for use with traditional graded relevance measures. A unique aspect of these measures is that they work directly from a collection of preference judgments, and do not require assumptions of transitivity. As part of this work, the authors released an exhaustive set of preference judgments for an NTCIR task. Overall, the work demonstrates several important advantages of preference judgments, especially their closer agreement with SERP preferences, but questions remain regarding the costs and sensitivity of measures based on preference judgments.

Given the quality and breadth of this prior research, it is perhaps surprising that preference judgments are not yet standard for offline search evaluation. Many of the key ideas we employ in this paper have been explored, or at least proposed, in this prior work. We view the primary contribution of this paper and our related papers [12, 13] as consolidating and simplifying this prior work to establish the practical utility of preference judgments. In particular, we focus preference judgments on the top items to maximize impact while minimizing judging effort. In addition, we further establish maximum similarity to an ideal ranking as a simplified framework for offline evaluation, accommodating traditional relevance grades, preference judgments, and factors beyond relevance.
3 COMPUTING COMPATIBILITY

3.1 Compatibility

Computing compatibility requires two choices: 1) a choice of rank similarity measure to compare rankings, and 2) a definition of an ideal ranking, which might be a single ranking or a set of equally ideal rankings. For rank similarity we use RBO because its properties make it ideally suited for comparing rankings (see Section 3.2). For the experiments in this paper, we define the ideal rankings for a query by a set of equivalence classes, or "effectiveness levels", where each effectiveness level contains one or more items.

Let \( \{L_1, L_2, \ldots, L_T\} \) be the set of effectiveness levels for a query. The effectiveness levels are ordered so that \( L_1 < L_2 < \ldots < L_T \), with \( L_T \) being the top level. Unlike traditional graded relevance, the number of levels \( T \) can vary from query to query. We define an extra level \( L_0 \) containing all items not appearing in another level. We define an ideal ranking as any ranking containing all the items in \( L_T \), in any order, followed by all the items in \( L_{T-1} \), in any order, and so on down to \( L_1 \). The items in \( L_0 \) are not included.

If we have graded relevance values, these effectiveness levels correspond exactly to them, with \( L_0 \) containing items that are non-relevant, spammy, unjudged, etc. If we have an ideal ranking exactly defined by a top-\( k \) ranking of items, then we have \( T = k \), with the first item alone in \( L_k \), the second item alone in \( L_{k-1} \), etc. We can also combine a top-\( k \) ranking with graded relevance by ordering the top-\( k \) items first and ordering the remaining items in the graded relevance levels below them. In this paper, we do all three.

Together, a set of equivalence levels defines a set of ideal rankings containing \( |L_T|! \times |L_{T-1}|! \times \ldots \times |L_1|! \) elements. If equivalence levels are based on graded relevance, the size of this set can be a million or more for a typical TREC task. For TREC 2019 CAsT questions, the size of this set ranges from 192 ideal rankings up to 26,842,725 ideal rankings, with an average above two million. In contrast, with a top-\( k \) ranking, the sole element in the set can precisely specify what the searcher should see.

Fortunately, regardless of the number of ideal rankings, we do not need to generate all of them to determine the ideal ranking. This maximum will be obtained by the ideal ranking that has all the items in each level ordered according to the actual ranking, maximizing the number of concordant pairs [12, 13]. For items not appearing in the actual ranking, they should be placed last in the level in any order. Once we have chosen a rank similarity measure and defined a set of ideal rankings, we compute compatibility as the maximum similarity between members of the ideal set and the actual ranking generated by a ranker we wish to measure.

3.2 Rank biased overlap

While in principle any rank similarity measure could be used to compute compatibility, we employ Rank Biased Overlap (RBO). By design, its properties make it ideally suited for this purpose. In creating RBO, Webber et al. [33] carefully identified and specified the requirements of rank similarity for what they call indefinite rankings, such as the output of rankers. For example, when comparing an actual ranking generated by a ranker to an ideal ranking, the top ranks matter more and should be given greater weight. The ideal ranking may be relatively short — just the top-5, for example — while the actual ranking may be much longer — up to 1000 passages for TREC CAsT experimental runs. Since all the items appearing in the ideal ranking may not appear in the actual ranking, RBO allows us to meaningfully compare rankings with differing length and content. While we could certainly employ or invent other rank similarity measures, they would still need to satisfy the requirements of Webber et al. [33]. Further discussion can be found in our related paper [13].
Ashvan top-

measure judgments sensitivity kendall’s \( \tau \)

NDCG@3 graded only 71.7% - -

compatibility graded only 71.0% 0.907 Fig. 2

" combined 76.5% 0.851 Fig. 7

" top-5 only 73.3% 0.814 Fig. 8

" best only 55.2% 0.775 Fig. 9

Table 1. Sensitivity and consistency of evaluation measures and judgment sets examined in this paper. NDCG@3 forms the baseline for all experiments and for Kendall’s \( \tau \).

Using RBO, we compute compatibility between an ideal ranking \( I \) and an actual ranking \( R \) as follows: Let \( I_{1:i} \) denote the top \( i \) items in \( I \), and let \( R_{1:i} \) denote the top \( i \) items in \( R \). We define the overlap between \( I \) and \( R \) at depth \( i \) as the size of the intersection between these lists at depth \( i \): \(|I_{1:i} \cap R_{1:i}|\). We define the agreement between \( I \) and \( R \) at depth \( i \) as the overlap divided by \( i \). RBO is then a weighted average of the agreement across depths from 1 to \( \infty \), as follows:

\[
RBO(R, I) = (1 - p) \sum_{i=1}^{\infty} p^{i-1} \frac{|I_{1:i} \cap R_{1:i}|}{i}.
\]

The parameter \( 0 < p < 1 \) represents searcher patience or persistence, with larger values representing more persistent searching. For practical purposes, the summation is computed down to sufficient depth so that \( p^{i-1} \) is close to zero and we reach the bottom of both the ideal and actual rankings. We go down to depth 1000 for this paper. Please see Webber et al. [33] for further discussion.

3.3 Consistency and sensitivity

Along with other analyses, we compare evaluation measures in terms of their consistency and sensitivity. By consistency we mean the degree to which evaluation measures recognize the same differences between rankers. By sensitivity we mean the ability of evaluation measures to recognize significant differences between rankers.

We measure consistency using Kendall’s \( \tau \). We measure sensitivity following the approach of Sakai [31], but using paired t-tests rather than bootstraps (see Yang et al. [37], for example). We take all pairs of experimental runs and compute a paired t-test between them under each measure. A pair with \( p < 0.05 \) is considered to be distinguished. Sensitivity is then:

\[
sensitivity = \frac{\# \text{ of distinguished pairs}}{\text{total pairs}}
\]

Please note that sensitivity reflects a property of the evaluation measure and that — because there is no Bonferroni or other correction — some of the distinguished pairs may not represent actual significant differences. Sensitivity is really a measure of “best case” performance of the evaluation measure, allowing us to compare one measure to another. Table 1 provides sensitivity and consistency values for key experiments in this paper.

3.4 Compatibility with relevance grades only

As detailed in Section 3.1 relevance grades alone can be used to define a set of ideal rankings, allowing compatibility to be computed. For the TREC 2019 CAsT task, there are four effectiveness levels. The top effectiveness level \( L_4 \) contains all passages judged “fully meets”, \( L_3 \) contains all passages judged “highly meets”, \( L_2 \) contains the “moderately meets” passages, and \( L_1 \) contains the “slightly meets” passages. Figure 2 compares compatibility and NDCG@3 on the 42 automatic runs from TREC 2019 CAsT. We compare with NDCG@3 because this is the primary evaluation measure.
Fig. 2. The relationship between NDCG@3 and compatibility on TREC 2019 Conversational Assistance Track automatic runs when ideal rankings are based on graded relevance values only. Even though compatibility does not convert relevance grades to gain values, the relationship is nearly linear, with Kendall’s $\tau = 0.907$.

reported for TREC 2019 CAsT [14]. The relationship between these measures is nearly linear, with relatively few inversions, especially in the higher scoring runs.

Since this comparison forms a baseline for later work, we tune the value of $p$ to provide the best match for RBO to NDCG@3 in terms of consistency and sensitivity. Tuning was entirely manual; we tried four or five values before settling on $p = 0.80$. This value provides approximately the same sensitivity as NDCG@3, as well as a relatively high Kendall’s $\tau$ of 0.907. Higher values of $p$ tend to increase sensitivity and decrease $\tau$, while lower values tend to decrease both sensitivity and $\tau$. In general, the value of $p$ can be adjusted to provide a close match with NDCG@n, in terms of consistency and sensitivity. For example, across multiple TREC Web Track tasks, $p = 0.95$ provides a close match with NDCG@20 [13].

4 IDENTIFYING THE TOP-K

Our goal is to identify the top-$k$ items for each query while minimizing effort. We follow a multi-step approach, depending on if the assessment will be completed by dedicated assessors or by crowdsourced assessors. We assume that dedicated assessors will be more focused and reliable than crowdsourced assessors, so we build more redundancy into the crowdsourced process. Our overall approach is to favor simplicity. It can be summarized as follows:

1. Perform an initial graded relevance assessment pass to “thin the herd”, producing a reduced candidate pool $C$, with $|C| \geq k$ to focus preference judgments on the most promising items (Section 4.1).
2. If dedicated assessors are to be used, we structure assessment as a single-elimination tournament (Section 4.2).
3. If crowdsourced assessors are to be used we follow a two-stage process, with the first stage reducing the size of the candidate pool and the second stage determining the final order (Section 4.3):
   a. While the size of the candidate pool is greater than some threshold $F$, where $|C| > F > k$, we generate random pairings of candidates, so that each candidate is paired
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Fig. 3. Relevance grades of passages selected for the candidate pool relative to the top relevance grade for the question.

with $P$ or $P + 1$ other candidates, where $F > P > k$. These pairings are then judged by crowdworkers, for some threshold $P > k$. Items losing more than a majority of pairings are eliminated, and we repeat.

(b) Once the size of the candidate pool is less than or equal to $F$, we pair all remaining candidates with all other remaining candidates, which are judged by crowdworkers. Items are then ranked by the number of pairs they win, and we cut to the top $k$. In the case of ties at rank $k$, we keep all candidates with the tied score, so that in some cases the size of the final ideal ranking will be larger than $k$.

For the experiments in this paper, we use $k = 5$, $F = 9$, and $P = 7$. The values for $F$ and $P$ were based on a pilot test, intended to keep our costs under $4,000.

4.1 Thinning the herd

We start with an initial graded relevance assessment, giving us an initial candidate pool of higher quality items and avoiding unnecessary preference judgments against lower quality items, particularly non-relevant items. These initial judgments could be crowdsourced or use dedicated assessors.

If we assume $g$ relevance grades, with $G_0, G_1, ..., G_g$ as the sets of items for each grade, we compute $C$ as follows:

\[
\begin{align*}
    i & \leftarrow g \\
    C & \leftarrow \emptyset \\
    \text{while } |C| < k \text{ and } i > 0: \\
    C & \leftarrow G_i \cup C \\
    i & \leftarrow i - 1
\end{align*}
\]

For the TREC 2019 CAsT task, experimental runs were pooled down to depth 10 for assessment. A total of 29,350 passages were judged on a 5-point scale, from “fully meets”(4) down to “fails to meet”(0). Of these, 8,120 passages were assigned a positive grade. Running the algorithm above on the passages with a positive grade gives an initial candidate pool of 2,673 passages. The number of candidates vary by question up to a high of 112 for question #67.8. Of the 173 questions, 57 had
Table 2. Upper bound estimates of extra judging effort to identify top-$k$ items for the TREC 2019 CAsT task with dedicated and reliable assessment.

| Topics | $k$ | official | extra | % extra |
|--------|-----|----------|-------|---------|
| 173    | 3   | 29,350   | 3,456 | +11.78% |
| "      | 5   | "       | 5,429 | +18.50% |
| "      | 10  | "       | 10,691| +36.43% |

an initial candidate pool with $|C| \leq F$, so that for crowdsourced assessments, these candidates immediately moved to the second stage. As shown in Figure 3, not all candidates came from the top relevance grade for that question. More than a third came from below the top grade, with a just over 1% coming from three levels lower. Since we are depending on the relevance grades to build the initial candidate pool, it is certainly possible that some of the top answers were missed by this process; we further discuss this possibility later in the paper.

4.2 Dedicated assessment

If we have reliable and dedicated assessment, undertaken by a relatively small number of individuals who understand the task, we can use a single-elimination tournament structure, or heap, to determine the top-$k$ items with no more than $|C| + (k - 1) \lceil \log(|C|) \rceil$ preference judgments (not a tight bound). Using this formula, Table 2 provides an estimate of the preference judgments required for TREC 2019 CAsT for various values of $k$.

To provide a basis for comparison with crowdsourcing results, the authors applied this approach to identify a single top answer for each of the questions. Our initial goal was to identify the top-5, so we started the process with the full top-5 candidate pool described in Section 4.1. Over the course of several weeks, and requiring nearly 40 hours, we completed the first round of the single-elimination tournament. In total we made 4,125 preference judgments, including some false starts and repeats due to initial bugs in the judging interface. Since this process gave us a top answer for each question, which we could use to help validate the crowdsource assessment, we decided not to invest the extra time to identify the remainder of the top 5.

4.3 Crowdsourced assessment

As described above, crowdsourcing proceeds in two stages: a) a pool reduction stage, intended to reduce the size of the candidate pool below some threshold $F$, after which we b) compare all remaining candidates with each other, ranking the candidates according to the number of pairing in which they win and cutting to the top $k$. During the pool reduction stage each candidate is randomly paired with $P$ or $P + 1$ other candidates, with no repeated pairing. We use a brute-force algorithm to generate random graphs for this purpose. Candidates failing to win a majority of pairings are culled. If the size of the pool is still greater than $F$, we repeat the process. On the TREC 2019 CAsT candidate pool, each iteration of this process reduced the size of the pool by roughly half.

During the second stage all candidates are paired against each other, giving up to $F(F - 1)/2$ pairs. By fully judging all pairs, we hope to improve the consistency of the top-5. However, if these second-stage judgments are not fully transitive, ties can result. If the ties occur at rank $k$, we include all items tied at that rank. Otherwise, we cut to the top $k$. Ties also mean that some effectiveness levels will contain multiple items.

For the TREC 2019 CAsT passages, we used Amazon’s Mechanical Turk to recruit and pay crowdsourced workers. Workers were required to live in the U.S. and to have completed at least
1,000 HITs with an approval rating above 95%. Preference judgments were grouped into sets of 10, forming a single HIT for which we paid $2.00 to the worker, as well as a fee of $0.40 to Amazon. Each HIT also included three challenge questions, pairing a random passage from the candidate pool against a random non-relevant passage. HITs by workers failing a challenge question were discarded; these workers were paid but excluded from further work.

In total, crowdsourcing cost $3,879.60 for 15,349 preference judgments, including some pilot judgments and HITs excluded by the challenge questions. This corresponds to an average cost of just over $0.25 per preference judgment. Overall, preference judging required 52.3% additional judgments beyond the 29,350 initial graded judgments. Assuming the same average cost for a graded judgment and a preference judgment gives us a cost estimate of under $12K for the full assessment exercise.

Figure 4 provides an example of the judging interface. As was done for the official assessments, our assessments used the manually re-written questions supplied by the track, rather than the raw utterances from the conversations. Unlike the track assessment, questions were shown in isolation, rather than conversation order, a possible confound.

We kept the instructions simple, asking workers to identify the passage that "best answers the question." To break ties, we asked them to choose the one with the least extraneous information. All else being equal, we asked them to choose the one with the "best formatting", a phrasing we hoped would encourage them to choose on the basis of any passage-specific factors we they believed to be important. We deliberately did not allow assessors to indicate ties. As much as possible, we encouraged workers to indicate a preference, with the goal of making distinctions between the top answers. The simplicity and conciseness of these instructions can be compared with the assessment guidelines required for graded relevance assessment [14].

This study was approved by our institutional review board, who also approved the release of the preference judgments without personally identifying information. As required by our institution, the payment of $2.00/HIT was intended to provide compensation equal to or greater than minimum wage. Based on our dedicated assessment experience, we estimated a rate of one judgment per minute or higher, or roughly one HIT every 10 minutes. This rate translates to an estimated payment of $12.00 for an hour’s work, consistent with our local minimum wage.
5 Assesment Comparison

Having completed both a crowdsourced assessment for the top-5 answers and a dedicated assessment for the top answer (which we call the “local answer” for short) we can compare the two approaches. Figure 5 shows the result. For 63 questions (36%) the two assessment methods produced the same top answer. For 141 questions (82%) the local answer from the dedicated assessment appeared in the top-5 from the crowdsourced assessment. For example, of the passages in Figure 1 the first passage was selected by crowdworkers as the top answer. The second passage was ranked second by the crowdworkers, but was the top local answer. For 32 questions the local answer did not appear in the top five crowdsourced answers at all. In general, the crowdworkers appeared to prefer more direct answers, and appeared less tolerant of longer passages than the dedicated assessors.

Figure 6 compares the crowdsourced assessments with the original graded relevance assessments. Over 68% of the top-1 crowdsourced answers came from the highest relevance grade for the question, which varied from question to question. Over 61% of the top-5 crowdsourced answers came from the highest relevance grade. Nonetheless, the remaining answers came from lower relevance grades. Since we only added passages from lower relevance grades when they were needed to grow the candidate pool to sufficient size, this outcome suggests that our initial strategy for “thinning the herd” may have missed some answers that the crowdworkers would have placed in the top 5.

The values for \( F \) and \( P \) were chosen to keep us within an assessment budget of $4,000. After running a pilot study with 10% of the questions picked at random, we set \( F = 9 \) and \( P = 7 \), which kept us under budget. Nonetheless, even if we assume fully consistent crowdworkers, there is a small chance that some of the top-5 items might be missed. The worst case occurs with a candidate pool \( |C| = F + 1 = 10 \). In this case with \( P = 7 \) there is more than a 12% chance that the fifth-best answer will be paired with all the top-4 answers and would fail to win a majority of its pairings. However, once the size of the candidate pool \( |C| \leq F \), and we have moved to the second stage, all pairs are assessed, providing redundancy for the final top-5 ordering.

Overall, the assessment methods produced consistent, but not identical, results. By basing an initial pass on the original relevance grades, we may have missed answers that crowdworkers would have placed in the top 5. Larger value of \( F \) and \( P \) may have produced more consistent
6 IMPACT OF PARTIAL PREFERENCES

The plot in Figure 7 compares the performance of automatic runs submitted to the TREC 2019 CAsT Track under compatibility vs. NDCG@3. For this comparison, we create an ideal ranking by combining the crowdsourced top-5 answers with the original graded relevance judgments. The top-five answers fill equivalence levels $L_9$ down to $L_5$; graded relevance judgments fill equivalence levels $L_4$ down to $L_1$. This approach precisely specifies the top ranks, the ones most likely to be seen by the searcher, while still taking advantage of the relevance grades to compare rankers. As shown in Table 1 the sensitivity of compatibility using this ideal ranking is 76.5%, indicating that we are better able to recognize differences between rankers.

Compatibility provides insights not provided by NDCG. The top four runs (by either measure) represent the most successful of the numerous attempts by participants to apply BERT [15] for re-ranking answers. Under compatibility the separation between these four runs and the other runs is much more dramatic. The starred run (pgbert) produces the best score under compatibility and third-best score under NDCG. In addition to BERT for re-ranking, it applied a transfer learning approach for question re-writing [14]. Of the other three runs in the top four, one (pg2bert) is variant of the pgbert run from the same group. The other two (h2oloo_RUN2 and CFDA_CLIP_Run7) both apply doc2query for expansion, as well as BERT for re-ranking [35].

The circled run was the sole run in top ten to use only traditional IR methods. In particular, it was the only run in the top ten not to re-rank with BERT. Under NDCG, the starred run outperforms the circled run by +15%, which is not significant under a paired t-test ($p = 0.11$), even before Bonferroni or similar correction. Under compatibility, the starred run outperforms the circled run by +97%, with a p-value $< 10^{-6}$, which remains significant even after the conservative Bonferroni correction. Under NDCG, we might conclude that the modern NLP methods used for the starred run were providing only a modest and non-significant improvement over the traditional methods. Under compatibility, with an ideal ranking that precisely specifies the preferred answers, we see
the more dramatic improvements we might expect from these modern methods. The remainder of the top-ten runs, plus several other runs that also apply BERT, move ahead of this traditional run under compatibility, which drops from 7th to 15th place.

For Figure 7 we combined the top-5 crowdsourced answers with the graded relevance judgments. Instead, we might focus exclusively on the top-5 answers, recognizing that a searcher will rarely look beyond these results. Nothing beyond the top-5 counts, as if the search engine returned nothing after that point. The set of ideal rankings now consists of a single element — this single ranking of the top-5 answers — or perhaps a small number of equivalent rankings if crowdsourcing produced ties.

As a minor point, under these circumstances ideal rankings are no longer indefinite in the sense of Webber et al. [33]. Under any circumstances, RBO always leaves a "residual", since rankings cannot practically be computed to infinity. This residual becomes vanishingly small as rankings become deeper. However, when $k$ is small this residual can be noticeably large, and if we limit ideal rankings to just the top-$k$, then they are not even theoretically indefinite. As a result, in this circumstance we apply a normalization for RBO, as follows:

$$NRBO(R, I) = \frac{RBO(R, I)}{RBO(I, I)}.$$ (3)

Unless the ideal ranking is relatively shallow, $RBO(I, I)$ is close to one, but if not, this formula provides a simple way to normalize out the residual.

While this normalization scales scores into the range $[0, 1]$, it does not matter from a statistical sense, since the same constant is applied to every run. Apart from lower values, plots are identical. However, if $k$ varies from query to query, this normalization would allow each query to contribute equally to the magnitude of the average score. While we do not vary $k$ in this way for the experiments in this paper, we can imagine this would be helpful in the case of Web search, for example, where different values of $k$ might be used for navigational vs. informational queries.

Figure 8 shows the relationship between NDCG@3 and compatibility when ideal rankings are based solely on crowdsourced top-5 answers. As shown in Table 1 the sensitivity of 73.3% is lower...
than with the combined ideal rankings of Figure 7, but higher than with graded relevance alone. The separation between the top-four runs and the rest of the runs remains.

To go one step further, Figure 9 shows the relationship between NDCG@3 and compatibility on when ideal rankings are based only on the single best local answer identified by the research team. Many runs now have compatibility values close to zero, even when NDCG@3 values are close to 0.2. Although sensitivity is now only 55.2%, the relative ordering of the top-four runs has not changed. Using only the single best crowdsourced answer produces a similar result (not shown).

7 CONCLUSION

It is widely recognized that offline evaluation should focus on the top ranks, those the searcher will most likely see. We often report measures of the form $\text{thing@}k$, for small values of $k$, with NDCG@3 providing a typical example. In effect, these measures evaluate rankers by asking the question: “What items did the ranker put in the top $k$ ranks?” In this paper, we turn this question around, asking instead: “Where did the ranker put the items that should be in the top $k$ ranks?” By doing this, we achieve an evaluation measure that is not only focused on the quality of the top ranked results, but which is also more sensitive to important differences between rankers.

It is only recently that neural rankers have begun to show significant improvements over traditional methods on IR tasks [36], and neural methods do not consistently provide the same dramatic improvements seen on many NLP tasks. We hypothesize that the lack of dramatic improvement may be due to the limitations of traditional IR evaluation methodologies, with their focus on relevance, which cannot capture important aspects of searcher preferences. In this paper, we propose partial preferences focused on the top ranks as a practical method for capturing these aspects.

While we have demonstrated that our assessment methods can be practically and affordably applied to an academic evaluation exercise, we have not as yet applied these methods in a commercial context. In addition, we have also not explored the cost-benefits tradeoffs of varying the judging parameters: $k$, $F$, and $P$. While our current method was kept as simple as possible to make easy for
Fig. 9. The relationship between NSCG@3 and compatibility on TREC 2019 Conversational Assistance Track runs when ideal rankings are based solely on the single best answer identified through dedicated assessment by the research team.

others to replicate, statistical and machine learning methods from the literature might be extended to partial preferences [3, 11, 17, 29], reducing assessment effort at the cost of complexity.

In this paper, we piggybacked our work on the existing TREC 2019 CAsT graded relevance judgments. Based on our experience, if top-\(k\) partial preferences was the end-goal from the start, it might be possible to simplify the initial graded relevance assessment to three grades: A: “answers the question” B: “provides related information”, C: “not relevant”. The grade-A passages would then become the initial candidate pool, unless its size is less than \(k\), in which case the grade-B passages would be included. While this process might produce a larger initial candidate pool and increase the total number of assessments, by simplifying the initial graded assessment stage it might speed the overall process, reducing total costs. The trade-off depends on the relative cost and consistency of graded vs. preference judgments, including any savings from reducing the complexity of graded assessment.

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## A SOFTWARE AND DATA RELEASE

Code and preference judgements are available at https://github.com/claclark/compatibility. Preference judgments are released without personally identifying information, for which we have University of Waterloo ethics approval.

The implementation of compatibility used for these experiments consists of a hundred-line Python program, which is backward compatible with the standard formats used by TREC for adhoc runs and relevance judgments. These relevance judgments are expressed as (topic-id, document-id, preference) triples (plus the required but unused “Q0” field).

Preferences can be any positive floating point or integer value. If one document’s preference value is greater than another document’s preference value, it indicates that the first document is preferred over the second. If preferences are tied, it indicates that the two documents belong to the same effectiveness level. The number of effectiveness levels for a topic is defined by the number of distinct preference values for that topic, and can vary from topic to topic. In this way, the program can be used directly with many existing TREC runs and qrels and extended by adding additional preference values.

By default the code computes NRBO, since this normalization is close to one unless the number of qrels is small. By default, we report $p = 0.95$, which provides a close match to NDCG@20, a primary measure for the older TREC Web Tracks. Overall the code should work “out of the box” for typical TREC tasks.