Generating recommendations for entity-oriented exploratory search

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Abstract

We introduce the task of recommendation set generation for entity-oriented exploratory search. Given an input search query which is open-ended or under-specified, the task is to present the user with an easily-understandable collection of query recommendations, with the goal of facilitating domain exploration or clarifying user intent. Traditional query recommendation systems select recommendations by identifying salient keywords in retrieved documents, or by querying an existing taxonomy or knowledge base for related concepts. In this work, we build a text-to-text model capable of generating a collection of recommendations directly, using the language model as a “soft” knowledge base capable of proposing new concepts not found in an existing taxonomy or set of retrieved documents. We train the model to generate recommendation sets which optimize a cost function designed to encourage comprehensiveness, interestingness, and non-redundancy. In thorough evaluations performed by crowd workers, we confirm the generalizability of our approach and the high quality of the generated recommendations.

1 Introduction

During interactive search, the system user may issue queries that are under-specified, ambiguous, or open-ended. For instance, a user interested in finding a new movie might search for “Action films”, or a computer vision researcher interested in learning more about NLP might search for “Pretrained NLP models”. These forms of interaction are examples of exploratory search (Marchionini, 2006).

In this work, we focus specifically on queries whose answer is a (potentially large) list of entities – for example, “Rush Hour” is one of the thousands of answers to the query “Action movies”.

Displaying the entire answer list is unlikely to satisfy the user’s information needs. Instead, systems for query recommendation (also known as query refinement) can assist users by offering a set of followup queries that clarify and focus the user’s search, progressively “drilling down” on the topics and entities they find most interesting (Figure 1).

Classic recommendation approaches for exploratory search include search results clustering (Carpineto et al., 2009) and faceted search (Hearst, 2006). Both approaches rely on a collection of retrieved documents as a source of potential recommendations; faceted search additionally requires an external category system or taxonomy as a scaffold for recommendation selection. Relying on an exist-

∗Work primarily completed while interning at Google.
ing taxonomy can work well when the input query corresponds to a category in the taxonomy (Figure 1a), but will not readily generalize to novel queries not present in the taxonomy (Figure 1b).

In this work, we train a transformer language model to generate a set of recommendations directly, without relying on any additional resources at inference time. Our approach is motivated by findings across a number of NLP tasks that pre-trained language models (Raffel et al., 2020; Devlin et al., 2019; Brown et al., 2020) can store world knowledge in their parameters, acting as “soft” knowledge bases (Petroni et al., 2019; Roberts et al., 2020; Jiang et al., 2020).

Our approach enjoys two notable advantages. First, it is flexible: by using a language model as our knowledge source, we are able to generate recommendations for queries that are not covered by an existing taxonomy. Second, it is global: as we will show, language models can be trained to offer a set of recommendations that provides a summary of the full space of entities answering the input query, rather than extracting keywords from a handful of documents retrieved by an IR system.

To develop a recommendation generation system, we propose methods to (1) construct a collection of query / recommendation set pairs to use as training data, and (2) formulate recommendation set generation as an NLP task. To construct a training dataset, we leverage the YAGO3 (Mahdisoltani et al., 2015) knowledge base, treating YAGO entity types as queries. YAGO types are based on the Wikipedia category system, which provides a rich, crowdsourced taxonomy of real-world entity types. Given a YAGO type \( q \), we consider all subtypes of \( q \) in the taxonomy as potential training recommendations; for example, Figure 1a shows four subtypes of the YAGO type “Action films”. To select the best \( k \) subtypes to use as a recommendation set for model training, we propose a method which we call “Query Recommendation via Entity Space Partitioning” (QRESP). QRESP identifies the collection of subtypes whose answers come closest to partitioning the entities of type \( q \) into \( k \) disjoint, equal-sized subsets. We argue in §3 and §4 that this is a desirable property for a recommendation set. In §5, we perform A / B tests (randomized side-by-side comparisons) to confirm that, given an input query \( q \), human annotators prefer the recommendation set selected by QRESP over a collection of \( k \) randomly-chosen subtypes of \( q \).

We cast recommendation generation as a “text-to-text” task, using T5 (Raffel et al., 2020) as our base model. The task input is the user query, and the output is the recommendation set, represented by concatenating the individual recommendations separated by a sentinel token. As we show in §6, this simple approach to recommendation set generation leads to outputs that are more comprehensive and less redundant than those obtained by sampling \( k \) separate recommendations from the output distribution of a model trained to generate recommendations individually.

We evaluate our system on held-out entity types from the YAGO taxonomy, as well as on queries from Natural Questions (Kwiatkowski et al., 2019) and the TREC 2009 Million Query Track (Carterette et al., 2009). We find that human annotators prefer recommendations from our system over a baseline trained to generate randomly-chosen entity subtypes, suggesting that our model is able to learn a generalizable notion of recommendation quality. We close by briefly exploring a promising direction for future research, using the RELIC entity typing model (Ling et al., 2020) to perform post-hoc filtering of model outputs and further improve recommendation quality.

2 Related work

Entity-oriented exploratory search

Entity-oriented exploratory search is situated at the intersection of two well-studied search paradigms. Entity-oriented search occurs whenever the user intent is to learn about specific entities or entity categories. Prior research has found that between 40-70% of all web queries are entity-oriented (Guo et al., 2009; Lin et al., 2012; Pound et al., 2010), and 10% specifically target a list of entities (Chakrabarti et al., 2020). Exploratory search encompasses a wide variety of search activities; White and Roth (2009) define a search session as exploratory when the user is unfamiliar with the domain of their search, or unsure about their search goals and how best to achieve them. Given the inherent open-endedness of exploratory search, query recommendation systems have the potential to substantially improve the user search experience.

Query recommendation for exploratory search

We review two classic approaches for recommendation selection during exploratory search. Search results clustering (Carpineto et al., 2009) offers
recommendations by retrieving a collection of documents in response to an input query, clustering them (traditionally, using word count-based statistics), and assigning a name to each cluster by identifying a salient phrase that appears frequently in the given document cluster (Zamir and Etzioni, 1999; Osinski and Weiss, 2005). More recently, seq2seq models have been trained to generate recommendations which summarize the content of the retrieved documents (Medlar et al., 2021).

Faceted search (Tunkelang, 2009) organizes retrieved documents according to a faceted concept hierarchy, which is used as a source of recommendations. The hierarchy can be created by the system designers (Yee et al., 2003), adapted from an existing crowd-sourced category hierarchy like the Wikipedia category system (Li et al., 2010), or constructed automatically using NLP methods (Stoica et al., 2007). Our goal in this work is to achieve a “soft” form of faceted search, where a transformer language model replaces a fixed taxonomy or faceted category system.

Query recommendation, refinement, and clarification A number of related tasks in the NLP and IR communities involve generating queries or questions in order to clarify user intent or incorporate relevant context. In the NLP community, researchers have trained generation models resolve ambiguity in information-seeking questions (Min et al., 2020) and to incorporate dialogue context (Elgohary et al., 2019; Anantha et al., 2021). Whereas our focus is on open-ended queries with potentially hundreds or thousands of answers, these works generally aim to distinguish between a small handful of potential answers.

In the IR community, researchers have designed models to offer clarifying questions in response to open-ended user queries (Aliannejadi et al., 2019). Recent work has used a taxonomy of clarification types to generate question templates, which are used to train neural models capable of generating clarifying questions (Sekulic et al., 2021; Zamani et al., 2020). We share the motivation of using language models to generalize from a fixed taxonomy, but our focus is on generating recommendations rather than clarifying questions.

Finally, previous work has leveraged query logs as supervision to train models for query recommendation, using modeling techniques including Markov chains (Boldi et al., 2008; Bonchi et al., 2012) and neural seq2seq models (Dehghani et al., 2017; Sordoni et al., 2015).

Applications of the Wikipedia category system We rely on the Wikipedia category system as our source of training data. Previous work has utilized it as a source of supervision for NLP tasks including textual entailment (Chen et al., 2020), semantic parsing (Choi et al., 2015), and category name generation (Zhang et al., 2020).

3 Task definition

We present the task of recommendation generation for entity-oriented exploratory search, and describe the criteria used to assess recommendation quality.

3.1 Query recommendation for entity-oriented exploratory search

We aim to generate recommendations which facilitate entity-oriented exploratory search, helping the user “drill down” on entities of interest (Figure 1).

Formally, the task input is a query \( q \). We assume that the answer to \( q \) is a list of entities; following Chakrabarti et al. (2020), we call this a list-intent query. Equivalently, the query \( q \) specifies an entity type. We refer to the list of entities answering \( q \) as the answers to \( q \), or \( A(q) \). The task output is a collection of \( k \) recommendations \( R(q) = \{ q_1', \ldots, q_k' \} \). We refer to \( R(q) \) as a recommendation set – or “RS” for short – and each individual member of \( R(q) \) as a recommendation. Each recommendation \( q_i' \) should itself be a list-intent query. In addition, each answer to \( q_i' \) should also be among the answers to \( q \); \( A(q_i') \subseteq A(q) \). In other words, each \( q_i' \) should specify a subtype of \( q \). As a concrete example, every movie that is an answer to the query “martial arts films” is also an answer to the more general query “action films”.

3.2 Desiderata for recommendation sets

The query recommendation task is inherently open-ended, and there may be many reasonable RSs (recommendation sets) for any given query. In this work, we think about recommendation generation from the standpoint of entity discovery: given an input query \( q \), can we design a recommendation system such that any entity \( e^* \in A(q) \) is discoverable after a few rounds of interaction with the system? From this standpoint, the best-possible recommendation set would partition the entities \( A(q) \) into \( k \) disjoint, equally-sized subsets, such that each answer \( e_j \in A(q) \) is an answer to exactly
Action films
Martial arts films
Superhero films
Action comedy films
Buddy cop films
Action thriller films
Swashbuckler films
Buddy cop films
Rush Hour
Pirates of the Caribbean

Figure 2: An entity-space view of a recommendation set for the query “Action films”. Rectangles indicate recommendations, and black circles indicate entities. The four rectangles with solid borders correspond to the four recommendations shown in Figure 1. The rectangles with dashed borders show two other action movie subgenres that were not included in the recommendation set, since they are redundant and/or do not cover many films. Collectively, the four selected recommendations provide a good approximation to a partition of the answer space, but it is not perfect. For instance, the movie “Rush Hour” is both an action comedy film and a martial arts film, while “Pirates of the Caribbean” is a swashbuckler film and is not covered by any of the selected recommendations.

one recommendation $q_i' \in R(q)$. This would ensure that any entity in $A(q)$ is discoverable after at most $\log_k(|A(q)|)$ recommendations\(^1\). We refer to a recommendation set satisfying this criterion as ideal.

In practice, it will almost never be possible to generate an ideal RS, since each recommendation must specify a semantically meaningful category expressed via natural language. Figure 2 provides an example showing how the recommendations for the query “Action movies” from Figure 1 provide a good approximation to an ideal RS. We will formalize this notion in §4.

3.3 Evaluation criteria

While the goal of efficient entity discovery motivates the modeling approach we present in §4, the modeling outcome of most importance is whether the recommendations presented by the system are considered useful by system users. We assess usefulness using A/B tests, where annotators compare two competing recommendation sets $R_A(q)$ and $R_B(q)$ on a number of attributes. The evaluation process takes place in two stages.

Stage 1: Validity of individual recommendations First, the annotator confirms that the individual recommendations making up $R_A(q)$ and $R_B(q)$ conform to the task definition, checking for:

1. Fluency: Each recommendation must be fluent and grammatical.
2. Relevance: Each recommendation must specify a subtype of $q$. Non-fluent recommendations are automatically judged as not relevant.

Table 1a provides some examples of queries that pass and fail these requirements. If fewer than half of the recommendations from either RS satisfy the criteria, annotation stops here.

Stage 2: Overall recommendation set quality If the majority of recommendations in $R_A(q)$ and $R_B(q)$ are judged as valid, the annotator compares the two RSs as a whole, based on four attributes:

1. Comprehensiveness: Does $R(q)$ provide a good overview of the entities answering the original query $q$?
2. Interestingness: Do the recommendations in $R(q)$ provide new information about the different kinds of entities answering $q$, or are they generic and uninteresting?
3. Non-redundancy: Does each recommendation in $R(q)$ specify a unique entity type, or are some of them redundant?
4. Overall usefulness: Overall, how useful are the recommendations $R(q)$ for learning more about the entities answering $q$?

Table 1b provides examples. For each attribute, the annotator selects whether $R_A$ is better, $R_B$ is better, or whether the two RSs are equal. Details of the annotation process are provided in §5.2.

4 Recommendation selection using QRESP

Our goal is to build a system capable of generating recommendation sets that are close to ideal, in the sense described in §3.2. Our approach to this challenge is as follows: (1) Leverage an existing

\(^1\)Using this scheme, each entity $e_j \in A(q)$ can be represented by a $k$-ary prefix code indicating the sequence of recommendations used to arrive at the entity. Assuming that all entities in $A(q)$ are equally likely to be the “target” entity $e^*$, choosing recommendations which partition the entity space into equal-sized subsets induces an optimal prefix code (Cormen et al., 2009, Chapter 16.3). Future work could extend this framework to model entity popularity, assigning shorter codes (i.e., shorter sequences of recommendations) to more frequently searched-for entities.
**Query:** Action films

| Recommendation set | Fluent | Relevant |
|--------------------|--------|----------|
| Martial arts films | ✓      | ✓        |
| Romance films      | ✓      | X        |
| Martially films arts of | X | X |

(a) **Stage 1 evaluation** screens out individual recommendations which are not fluent and relevant.

| Query: Action films |
|---------------------|
| Recommendation set  | Comprehensible | Interesting | Non-redundant |
| 1 Action comedies, Action thrillers, Martial arts films, Spy films | ✓ | ✓ | ✓ |
| 2 Action films set in [Asia, North America, Africa, Europe] | ✓ | X | ✓ |
| 3 Kung Fu films, Karate films, Boxing films, Wrestling films | X | ✓ | ✓ |
| 4 Karate films, Films about karate, Boxing films, Films with boxing | X | ✓ | X |

(b) **Stage 2 evaluation** assesses the quality of recommendation sets as a whole. Row (2) is comprehensive since many action films take place on one of the listed continents, but is not interesting since many queries can be categorized by continent. Row (3) is not comprehensive, since it covers martial arts films but not other action films. Row (4) is redundant.

Table 1: Example evaluations on the criteria presented in §3.3. In human evaluations, Stage 2 annotation involves comparisons between two recommendation sets, rather than binary ✓/✗ decisions made for a single set in isolation; we show binary decisions for illustration.

To select \( k \leq K \) sub-types to form our final recommendation set. We use the entities in the YAGO knowledge base that are instances of type \( q \) as the answers to \( q \), or \( A(q) \). For a concrete example of a query \( q \), its candidates \( C(q) \), and its answers \( A(q) \), see Appendix B. We defer dataset details to §5, and focus here on the method for selecting an RS \( R(q) \) from \( C(q) \). We refer to this approach as Query Recommendation via Entity Space Partitioning, or QRESP.

**Cost function** Let \( e_j \) denote a particular entity in \( A(q) \), and let \( n = |A(q)| \). Given a pool of candidate recommendations \( C(q) \), let \( \mathcal{R}(q) \) indicate the collection of all size-\( k \) subsets of \( C(q) \). Given a possible recommendation set \( R(q) \in \mathcal{R}(q) \), and a recommendation \( q_i \in R(q) \), let \( a_{ij} = 1 \{ e_j \in A(q'_i) \} \).

Define \( c_j = \sum_{i=1}^{k} (a_{ij}) \), the number of recommendations in \( R(q) \) for which entity \( j \) is an answer. Let \( n_i = \sum_{j=1}^{n} (a_{ij}) = |A(q'_i)| \), the number of entities that answer recommendation \( i \). Then define

\[
S(R(q)) = \sum_{j=1}^{n} (c_j - 1) - \min_{i \in \{1, \ldots, k\}} n_i, \tag{1}
\]

and choose

\[
R(q) = \text{arg min}_{\mathcal{R}(q)} S(R(q)). \tag{2}
\]

QRESP chooses the \( R(q) \) that minimizes Eq. 1 over all possible \( \mathcal{R}(q) \). In Appendix A.1, we provide a proof that the RS selected by QRESP is the best achievable in the following sense: the scoring function \( S(R(q)) \) achieves its global minimum if and only if \( R(q) \) is ideal as defined in §3.2. Thus, selecting recommendations according to QRESP enables the most efficient entity discovery possible, given the subcategories \( C(q) \) available in YAGO.

Informally, the first term in Eq. 1 is minimized when each answer to \( q \) is an answer to exactly one of the \( q'_i \), encouraging comprehensiveness and non-redundancy. The second term encourages the smallest recommendation to have as many answers as possible. Combined with the first term, this rewards the selection of recommendations which all have a similar number of answers.

Finding the \( \text{arg min} \) in Eq. 2 involves a combinatorial optimization over \( \mathcal{R}(q) \). We solve this problem by converting Eq. 2 into an integer linear program (ILP), and applying an off-the-shelf solver; see Appendix A.2 for details.

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**Source taxonomy** We use the YAGO3 taxonomy (Suchanek et al., 2007; Mahdisoltani et al., 2015) (referred to simply as YAGO in what follows) as our source to construct a training dataset. The YAGO entity type system is adopted from the Wikipedia category system, a crowdsourced poly-hierarchy used to organized Wikipedia pages. We use types in the YAGO taxonomy as input queries \( q \). Given a type \( q \), we consider all sub-types of \( q \) in the taxonomy as recommendation candidates, denoted \( C(q) \). From this collection of \( K \) candidates, we aim to select \( k \leq K \) sub-types to form our final recommendation set. We use the entities in the YAGO knowledge base that are instances of type \( q \) as the answers to \( q \), or \( A(q) \). For a concrete example of a query \( q \), its candidates \( C(q) \), and its answers \( A(q) \), see Appendix B. We defer dataset details to §5, and focus here on the method for selecting an RS \( R(q) \) from \( C(q) \). We refer to this approach as Query Recommendation via Entity Space Partitioning, or QRESP.
5 Training data creation

We apply QRESP to the YAGO taxonomy to create a training dataset for query recommendation generation, and conduct A / B tests to confirm that recommendations selected by QRESP are preferred over entity subtypes randomly selected from $C(q)$.

5.1 Dataset creation

We apply QRESP to select recommendation sets from the YAGO taxonomy as follows. First, we filter out queries with fewer than 50 answer entities, as it may be difficult to offer interesting recommendations for these queries. We set the number of recommendations to $k = 5$ for all experiments.

Given a YAGO type $q$ with candidate subtypes $C(q)$, we use rule-based filters to remove candidates that differ from $q$ only by the addition of a date, a location, or modifiers like “male” or “female”, as these tend to lead to generic recommendations (see Appendix B for the full list of rules). We refer to the filtered collection as $C_{\text{Filter}}(q)$. Queries with fewer than $k$ subtypes post-filtering are removed from the dataset. For the remaining queries, we apply QRESP to the candidates $C_{\text{Filter}}(q)$ to select recommendations $R_{\text{QRESP}}(q)$. We refer to the resulting dataset as $D_{\text{QRESP}} = \{(q_i, R_{\text{QRESP}}(q_i))\}_{i=1}^N$.

We also construct two alternative datasets for comparison. For $D_{\text{Random}}$, we select recommendations for each $q$ by randomly choosing 5 subtypes from $C(q)$, without filtering. For $D_{\text{Random-F}}$, we choose 5 random subtypes from $C_{\text{Filter}}(q)$.

We hold out 282 query / recommendation instances to be used for model development in §6. We also remove all subtypes of development queries from the train set to prevent dev set information leakage. We choose types with at least 15 subtypes, each of which must have at least 200 answers.

Our training dataset consists of 8,958 query / RS pairs for $D_{\text{QRESP}}$ and $D_{\text{Random-F}}$, and 17,598 instances for $D_{\text{Random}}$. In Figure 3, we plot the costs $S(R(q))$ of the RSs in $D_{\text{QRESP}}$ versus those in $D_{\text{Random-F}}$. The results confirm that QRESP is able to identify RSs that have substantially lower cost than choosing randomly from $C_{\text{Filter}}(s)$.

5.2 Human evaluation

We conduct A / B tests to confirm that the cost function minimized by QRESP correlates with human judgements of recommendation quality. Details on the annotation process – including annotator screening, compensation, and inter-annotator agreement, are included in Appendix C. In general, rater agreement on the individual evaluation criteria ranged between 0.4 and 0.6 Cohen’s $k$, indicating moderate agreement (Landis and Koch, 1977); this is consistent with the subjectivity inherent in the task. The full user annotation guide is included in Appendix D.

We perform two sets of comparisons. First, we compare recommendations from $R_{\text{QRESP}}$ with recommendations chosen randomly, $R_{\text{Random}}$. In addition, we also compare $R_{\text{QRESP}}$ to $R_{\text{Random-F}}$, to confirm that the improved ratings are due to selection using QRESP, and not simply the filtering out of uninteresting candidates.

The results are shown in Table 2. RSs selected by QRESP are preferred by annotators 86% of the time over random RSs, and 73% of the time over random RSs post-filtering. $R_{\text{QRESP}}$ is preferred more frequently for comprehensiveness than for interestingness, which may be explained by the fact that Eq. 1 explicitly rewards comprehensiveness. Virtually all RSs are judged as relevant and fluent; this is expected, since the recommendations
We show that the notion of recommendation quality is also preferred over random recommendation sets on all criteria.

We train with a batch size of 32 for 8000 training steps, using the default T5 optimizer. We evaluate the perplexity of the recommendation generation model. Given a dataset $\mathcal{D}$ consisting of training pairs $(q_i, R(q_i))_{i=1}^{N}$, we provide $q$ as the input for T5 and train it to generate $R(q)$. We format $R(q)$ by concatenating the individual recommendations in alphabetical order, separated by a sentinel token. At prediction time, we provide $q$ as input and greedily decode. We train models on $\mathcal{D}_{\text{QRESP}}$, $\mathcal{D}_{\text{Random-F}}$, and $\mathcal{D}_{\text{Random}}$; we will refer to these as $\mathcal{M}_{\text{QRESP}}$, $\mathcal{M}_{\text{Random-F}}$, and $\mathcal{M}_{\text{Random}}$, respectively. We train with a batch size of 32 for 8000 training steps, using the default T5 optimizer.

As an additional baseline, we train a model $\mathcal{M}_{\text{Separate}}$ on $\mathcal{D}_{\text{QRESP}}$, which predicts a single recommendation $r_i$ at a time, rather than predicting a full recommendation set $R(q)$. At prediction time, given an input $q$, we sample 5 separate predictions from $\mathcal{M}_{\text{Separate}}$ and concatenate them to form $R(q)$.

6.2 Automated evaluations

In §5, we established that human annotators prefer recommendations from $\mathcal{D}_{\text{QRESP}}$ over those from $\mathcal{D}_{\text{Random}}$ and $\mathcal{D}_{\text{Random-F}}$. Therefore, for our automated evaluations, we treat RSs from the $\mathcal{D}_{\text{QRESP}}$ dev set as “silver” data against which to evaluate the predictions of our trained models. We evaluate using the following metrics:

1. **Sequence-based metrics**: We treat a generated RS as a text sequence with no additional structure, and compare it to the corresponding silver RS using BLEU and ROUGE-L (ROUGE-1 and -2 show the same trend).

2. **Set-based metrics**: We treat the generated RS as a set of $k$ recommendations, and evaluate the precision, recall, and F1 relative to the set of silver recommendations.

3. **Perplexity**: We evaluate the perplexity of the silver RSs, formatted as a sequence, under each generation model.

The results are shown in Table 4. Across all evaluations, $\mathcal{M}_{\text{QRESP}}$ outperforms the other systems. Training on randomly-chosen candidate subtypes ($\mathcal{M}_{\text{Random-F}}$ and $\mathcal{M}_{\text{Random}}$) decreases performance, particularly as measured by F1. We also observe

4We found that greedy decoding outperformed sampling-based decoding and beam search on automated evaluations.

Table 2: A / B tests comparing recommendation sets from $\mathcal{D}_{\text{QRESP}}$ against $\mathcal{D}_{\text{Random}}$ and $\mathcal{D}_{\text{Random-F}}$. $N$ indicates the number of annotated instances. For the “Fluent + Relevant” row, “Neutral” indicates either that both A and B passed, or neither did. “Prefers A” indicates that A passed, while B failed, and vice versa for “Prefers B”. The remaining rows only compare cases where both A and B were judged as fluent and relevant. The “non-redundant” evaluation was added after these rows and is left blank.

| N = 105 | Prefers A | Neutral | Prefers B |
|---------|-----------|---------|-----------|
| Fluent + Relevant | 3% | 95% | 2% |
| Comprehensive | 88% | 10% | 2% |
| Interesting | 71% | 26% | 3% |
| Non-redundant | - | - | - |
| Overall | 86% | 10% | 4% |

(a) $\text{QRESP}$ is preferred over random recommendation sets on all criteria.

| N = 105 | Prefers A | Neutral | Prefers B |
|---------|-----------|---------|-----------|
| Fluent + Relevant | 0% | 100% | 0% |
| Comprehensive | 75% | 15% | 10% |
| Interesting | 64% | 24% | 12% |
| Non-redundant | - | - | - |
| Overall | 73% | 17% | 10% |

(b) $\text{QRESP}$ is also preferred over random recommendation sets chosen from filtered candidates $\mathcal{C}_{\text{Filter}}$. For training queries come directly from the YAGO taxonomy. Overall, the results indicate that $\text{QRESP}$ captures human intuitions about recommendation quality. An illustrative example of RSs from all three systems is shown in Table 3. Additional examples can be found in Appendix B.

6 Recommendation generation

Having established that $\text{QRESP}$ is able to select high-quality recommendation sets from a pool of candidates, we finetune a pretrained language model to generate recommendations for queries not found in an existing knowledge base. We experiment with two evaluation datasets: held-out categories from the YAGO taxonomy, and a collection of list-intent queries selected from NaturalQuestions (Kwiatkowski et al., 2019) and the TREC 2009 Million Query Track (Carterette et al., 2009). We show that the notion of recommendation quality captured by $\text{QRESP}$ is generalizable to new queries: a model finetuned on $\mathcal{D}_{\text{QRESP}}$ outperforms models finetuned on $\mathcal{D}_{\text{Random}}$ and $\mathcal{D}_{\text{Random-F}}$ as measured by both automated metrics and human evaluations.

6.1 Model training

We use T5-3B (Raffel et al., 2020) as our base model. Given a dataset $\mathcal{D}$ consisting of training pairs $(q_i, R(q_i))_{i=1}^{N}$, we provide $q$ as the input for T5 and train it to generate $R(q)$. We format $R(q)$ by concatenating the individual recommendations in alphabetical order, separated by a sentinel token. At prediction time, we provide $q$ as input and greedily decode. We train models on $\mathcal{D}_{\text{QRESP}}$, $\mathcal{D}_{\text{Random-F}}$, and $\mathcal{D}_{\text{Random}}$; we will refer to these as $\mathcal{M}_{\text{QRESP}}$, $\mathcal{M}_{\text{Random-F}}$, and $\mathcal{M}_{\text{Random}}$, respectively. We train with a batch size of 32 for 8000 training steps, using the default T5 optimizer.

As an additional baseline, we train a model $\mathcal{M}_{\text{Separate}}$ on $\mathcal{D}_{\text{QRESP}}$, which predicts a single recommendation $r_i$ at a time, rather than predicting a full recommendation set $R(q)$. At prediction time, given an input $q$, we sample 5 separate predictions from $\mathcal{M}_{\text{Separate}}$ and concatenate them to form $R(q)$.

We found that greedy decoding outperformed sampling-based decoding and beam search on automated evaluations.
Query: Action films

Table 3: Recommendation sets from \( \mathcal{D}_{\text{QRESP}} \), \( \mathcal{D}_{\text{Random}} \), and \( \mathcal{D}_{\text{Random-F}} \). \( \mathcal{D}_{\text{Random}} \) includes many recommendations based on a time period or a country of origin, which does not provide interesting new information about the topic. \( \mathcal{D}_{\text{Random-F}} \) is overly specific (e.g. “The Purge films”), and thus does not provide as good an overview as \( \mathcal{D}_{\text{QRESP}} \).

Table 4: Automated evaluation of generation models, using \( \mathcal{D}_{\text{QRESP}} \) as “silver” evaluation targets. Evaluations are categorized into Sequence-based, Set-based, and Perplexity-based (Perpl.). On all evaluations, \( \mathcal{M}_{\text{QRESP}} \) outperforms models trained on randomly-chosen recommendations, or trained to generate recommendations separately rather than as a single sequence.

Table 5: Results of A / B tests on the YAGO human evaluation set. \( \mathcal{M}_{\text{QRESP}} \) is preferred over all baselines. \( \mathcal{M}_{\text{QRESP}} \) are much more likely to be comprehensive and interesting (Table 5a). On the other hand, the models are similar in terms of their non-redundancy, since \( \mathcal{M}_{\text{Random}} \) tends to offer overly-specific recommendations which provide a poor summary but do not overlap (Table 6).

6.3 Human evaluation

We conduct A / B tests on two datasets. First, we evaluate on the human evaluation set of YAGO types described in §5.1. This measures our models’ ability to generalize to new in-domain queries. Second, to measure the ability to generalize to out-of-domain queries, we evaluate on 93 real-world list-intent queries selected by one of the paper authors from the Natural Questions (Kwiatkowski et al., 2019) dataset and the TREC 2009 Million Query Track. The full list of queries is included in Appendix C. We refer to these datasets as YAGO and NQ+TREC, respectively.

Results on YAGO Table 5 shows the results of A / B tests comparing \( \mathcal{M}_{\text{QRESP}} \) against \( \mathcal{M}_{\text{Random}}, \mathcal{M}_{\text{Random-F}}, \) and \( \mathcal{M}_{\text{Separate}} \). Table 6 shows the predictions of each system on a single query. Compared to \( \mathcal{M}_{\text{Random}}, \) recommendations from

\( \mathcal{M}_{\text{QRESP}} \) outperforms \( \mathcal{M}_{\text{Random}} \) on all criteria. \( \mathcal{M}_{\text{QRESP}} \) is more comprehensive than \( \mathcal{M}_{\text{Random-F}} \). (b) \( \mathcal{M}_{\text{QRESP}} \) is less redundant than \( \mathcal{M}_{\text{Separate}} \).
Table 6: Recommendations of $\mathcal{M}_{\text{QRESP}}$ and three baselines on a YAGO evaluation query. The $\mathcal{M}_{\text{QRESP}}$ suggestions cover 5 common types of physicians.

| $\mathcal{M}_{\text{QRESP}}$ | Alternative medicine physicians, cardiologists, dermatologists, ophthalmologists, psychiatrists |
|-----------------------------|--------------------------------------------------------------------------------------------------|
| $\mathcal{M}_{\text{Random}}$ | Canadian dermatologists, German dermatologists, Norwegian dermatologists, Pediatricians, Women physicians |
| $\mathcal{M}_{\text{Random-F}}$ | Fictional physicians, Oncologists, Psychiatric physicians, Radiologists, surgeons |
| $\mathcal{M}_{\text{Separate}}$ | Atheist physicians, Baritone physicians, Fictional physicians, Military physicians, Neurologists |

| $\mathbf{N} = 93$ | $\mathbf{A = QRESP}$ vs. $\mathbf{B = Random}$ |
|-----------------|-------------------------------|
| Fluent + Relevant | 5% | 65% | 30% |
| Comprehensive | 45% | 30% | 26% |
| Interesting | 40% | 34% | 26% |
| Non-redundant | 23% | 51% | 26% |
| Overall | 43% | 28% | 30% |

Table 7: Human evaluations on NQ+TREC. $\mathcal{M}_{\text{QRESP}}$ recommendations tend to be more interesting and comprehensive when they are relevant (i.e. valid subtypes of the input query), but are more frequently judged as not relevant.

Results on NQ+TREC Table 7 compares $\mathcal{M}_{\text{QRESP}}$ against $\mathcal{M}_{\text{Random}}$ on the NQ+TREC queries. The results exhibit an interesting trend: RSs from $\mathcal{M}_{\text{QRESP}}$ are more likely to fail the initial screen for relevance and fluency. However, the RSs that pass the screen are preferred over RSs from $\mathcal{M}_{\text{Random}}$ in terms of comprehensiveness, interestingness, and overall quality. Metaphorically, $\mathcal{M}_{\text{QRESP}}$ tends to be overly “ambitious” while $\mathcal{M}_{\text{Random}}$ tends to be overly “cautious”. Table 8 offers some examples.

7 Recommendation correction

The results of the previous section suggest that $\mathcal{M}_{\text{QRESP}}$ has some difficulty generating relevant recommendations under domain shift. As a step toward addressing this challenge, we return to the idea that motivated QRESP: use the entities answering the candidate recommendations to guide the recommendation selection process. In §4, we made use of gold entities $A(q)$ found in a knowledge base. Here, we use an off-the-shelf machine learning model $A_{\text{ML}}(q)$ to predict answers for novel queries.

Question answering model: RELIC We use the RELIC model (Ling et al., 2020) as our QA system $A_{\text{ML}}$. RELIC uses a dual-encoder architecture consisting of (1) learned embeddings $f(e_i)$ for all entities in Wikipedia, and (2) an encoder $g(q)$ mapping an input query $q$ to a shared embedding space. RELIC encodes $q$ using $g(q)$, then ranks all entities $f(e_i)$ based on their cosine similarity to $g(q)$, and returns all entities with similarity higher than some threshold $t$ as answers to $q$. We finetune RELIC on the YAGO train set from §5.1, training for 310,000 steps with a batch size of 1024 and learning rate of $1 \times 10^{-4}$. A single training instance consists of a query $q_i$ paired with an answer $e_i \in A(q)$; all other entities in the batch are used as negatives. We set $t = 0.4$ based on performance on a held-out portion of the train set. This gives precision, recall, and F1 of 23.7, 51.9, and 32.6 respectively.

Identifying irrelevant recommendations A recommendation $q'_i$ is considered relevant if it is a subtype of $q$ – i.e. $A(q'_i) \subseteq A(q)$. In cases where we do not have access to “gold” answers, we can use predicted answers from $A_{\text{ML}}$ to identify recommendations likely to be judged as irrelevant. Since these predictions may be noisy, only keeping recommendations whose predicted answers $A_{\text{ML}}(q'_i)$ are a strict subset of $A_{\text{ML}}(q)$ is likely to be overly stringent. We err on the side of leniency, and predict a recommendation to be irrelevant if its answers have no overlap with the answers to the original query.

Table 9 shows confusion matrices comparing human relevance judgements with relevance predictions from $A_{\text{ML}}$ on YAGO and NQ-TREC. 42%
**Query:** Functions of government

| \(M_{\text{QRESP}}\) | Agricultural functions of the government, Defence functions of the government, Education functions of the government, Finance functions of the government, Foreign functions of the government |
| --- | --- |
| \(M_{\text{Random}}\) | Functions of the Canadian federal government, Functions of the government of Quebec, Functions of the government of Yukon, Functions of the government of the Northern Mariana Islands, Functions of the United States Congress |

(a) \(M_{\text{QRESP}}\) offers a list of five interesting, diverse government functions, while \(M_{\text{Random}}\) provides a generic list of five countries.

**Query:** Popular YouTube Channels

| \(M_{\text{QRESP}}\) | Celebrity YouTube channels, Music video channels, Religious YouTube channels, Religious television channels, Religious video channels |
| --- | --- |
| \(M_{\text{Random}}\) | American popular YouTube channels, Australian popular YouTube channels, British popular YouTube channels, Japanese popular YouTube channels, Pakistani popular YouTube channels |

(b) Three of the \(M_{\text{QRESP}}\) recommendations were judged irrelevant since they don’t mention YouTube specifically (they could refer to TV channels in general). \(M_{\text{Random}}\) makes five generic, but relevant, recommendations by once again listing five countries.

Table 8: Predictions on two queries from NQ+TREC. \(M_{\text{QRESP}}\) provides high-quality recommendations for the first query, but is slightly off-topic for the second one.

| Human | Predicted | Irrelevant | Relevant | Total |
| --- | --- | --- | --- | --- |
| Irrelevant | 91 | 128 | 219 |
| Relevant | 304 | 2642 | 2946 |
| Total | 395 | 2770 | 3165 |

(a) YAGO

| Human | Predicted | Irrelevant | Relevant | Total |
| --- | --- | --- | --- | --- |
| Irrelevant | 97 | 349 | 446 |
| Relevant | 104 | 1236 | 1340 |
| Total | 201 | 1585 | 1786 |

(b) NQ+TREC

Table 9: Confusion matrices comparing human vs. predicted judgements of recommendation relevance. The rows provide counts for recommendations judged (ir)relevant by human annotators. The columns show model predictions.

of YAGO recommendations marked irrelevant by humans were (correctly) flagged by \(A_{\text{ML}}\) as irrelevant, while only 10% of recommendations marked relevant by humans were (incorrectly) flagged by \(A_{\text{ML}}\). For NQ+TREC, these percentages are 22% and 7.8%, respectively. In both cases, there is a statistically significant association between the model’s predictions and human judgements \((p < 10^{-10}, \chi^2 \text{ test})\). However, the association is relatively weak, identifying recommendations judged irrelevant by human annotators at a performance of 29.6 F1 and 30.0 F1 for YAGO and NQ-TREC, respectively.

**Scoring full recommendation sets** We also experimented with using predicted answers from \(A_{\text{ML}}\) to score entire RSs according to Eq. 1. The resulting costs had little association with human judgements, likely due to the accuracy limitations of \(A_{\text{ML}}\) on this task.

**8 Conclusion**

In this work, we proposed the task of recommendation set generation for entity-oriented exploratory search. We developed a methodology \(\text{QRESP}\) to select high-quality recommendation sets for queries found in an existing taxonomy, and showed that our methodology has good agreement with human judgements. We then demonstrated that a text-to-text model trained on \(\text{QRESP}\)-selected data was able to generate high-quality recommendations for queries not found in an existing knowledge base.

In §6.3, we found that \(M_{\text{QRESP}}\) suffered a loss of performance under domain shift. This points to a need for domain adaptation techniques which do not require supervised query / recommendation set pairs for training. The recommendation correction approach outlined in §7 represents a promising path forward: as more accurate models for question answering and entity typing become available, they can be plugged into the framework developed in this work to offer corrections and further guide the recommendation generation process. This guidance could be accomplished using simple post-hoc filters, or using reinforcement learning techniques which leverage a QA model to provide feedback to the recommendation generation system.
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References

Mohammad Aliannejadi, Hamed Zamani, Fabio A. Crestani, and W. Bruce Croft. 2019. Asking clarifying questions in open-domain information-seeking conversations. *SIGIR*.

R. Anantha, Svitalana Vakulenko, Zhucheng Tu, S. Longpre, Stephen G. Pulman, and Srinivas Chappidi. 2021. Open-domain question answering goes conversational via question rewriting. In *NAACL*.

Ksenia Bestuzheva, Mathieu Besançon, Wei-Kun Chen, Antonia Chmiela, Tim Donkiewicz, Jasper van Doornmalen, Leon Eifler, Oliver Gaul, Gerald Gamrath, Ambros Gleixner, Leona Gottwald, Christoph Graczky, Katrin Halbig, Alexander Hoen, Christoph Hojny, Rolf van der Hulst, Thorsten Koch, Marco Lübbeke, Stephen J. Maher, Frederic Matter, Erik Mühner, Benjamin Müller, Marc E. Pfetsch, Daniel Rehfeldt, Steffan Schlein, Franziska Schlösser, Felipe Serrano, Yuji Shinano, Boro Sofranac, Mark Turner, Stefan Vigerske, Fabian Wegscheider, Philipp Wellner, Dieter Weninger, and Jakob Witzig. 2021. The SCIP Optimization Suite 8.0. Technical report, Optimization Online.

Paolo Boldi, Francesco Bonchi, Carlos Castillo, Debora Donato, A. Gionis, and Sebastiano Vigna. 2008. The query-flow graph: model and applications. In *CIKM*.

Francesco Bonchi, R. Perego, Fabrizio Silvestri, Hossein Vahabi, and Rossano Venturini. 2012. Efficient query recommendations in the long tail via center-piece subgraphs. In *SIGIR*.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, T. J. Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeff Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *NeurIPS*.

Claudio Carpineto, Stanislaw Osinski, Giovanni Romano, and Dawid Weiss. 2009. A survey of web clustering engines. *ACM Computing Surveys*.

Ben Carterette, Virgiliu Pavlu, Hui Fang, and Evangelos Kanoulas. 2009. Million query track 2009 overview. In *TREC*.

Kaushik Chakrabarti, Zhimin Chen, Siamak Shakeri, Guihong Cao, and Surajit Chaudhuri. 2020. Table-qna: Answering list intent queries with web tables. *ArXiv*, abs/2001.04828.

Mingda Chen, Zewei Chu, Karl Stratos, and Kevin Gimpel. 2020. Mining knowledge for natural language inference from wikipedia categories. In *EMNLP findings*.

Eunsol Choi, Tom Kwiatkowski, and Luke Zettlemoyer. 2015. Scalable semantic parsing with partial ontologies. In *ACL*.

Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, and Clifford Stein. 2009. *Introduction to Algorithms, Third Edition*.

Mostafa Dehghani, Sascha Rothe, Enrique Alfonseca, and Pascal Fleury. 2017. Learning to attend, copy, and generate for session-based query suggestion. *CIKM*.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *NAACL*.

Ahmed Elghohary, Denis Peskov, and Jordan L. Boyd-Graber. 2019. Can you unpack that? learning to rewrite questions-in-context. In *EMNLP*.

J. Guo, Gu Xu, Xueqi Cheng, and Hang Li. 2009. Named entity recognition in query. In *SIGIR*.

Marti A. Hearst. 2006. Clustering versus faceted categories for information exploration. *Communications of the ACM*.

Zhengbao Jiang, Frank F. Xu, J. Araki, and Graham Neubig. 2020. How can we know what language models know? *TACL*.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur P. Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Lion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc V. Le, and Slav Petrov. 2019. Natural questions: A benchmark for question answering research. *TACL*.

J Richard Landis and Gary G. Koch. 1977. The measurement of observer agreement for categorical data. *Biometrics*.

Chengkai Li, Ning Yan, Senjuti Basu Roy, Lekhendro Lisham, and Gautam Das. 2010. Facetepedia: dynamic generation of query-dependent faceted interfaces for wikipedia. In *WWW*. 
A.1 Best achievable recommendations

In §4, we claimed that the cost function Eq. 1 optimized by QRESP achieves its minimum when, and only when, the recommendation set \( R(q) \) optimized by QRESP achieves its minimum when, and only when, the recommendation set \( R(q) \) optimizes the answer space \( A(q) \) into \( k \) disjoint, equal-sized subsets. We provide a proof here. For convenience, we assume that \( n = |A(q)| \) is divisible by \( k \), the number of recommendations. When this is not the case, the general proof idea is the same, except some recommendations will have one additional answer since it is not possible to evenly partition the \( n \) answers into \( k \) groups.

For convenience, we will use \( A \) as shorthand for \( A(q) \), \( A'_i \) for \( A(q'_i) \), and \( R \) for \( R(q) \). All other notation is shared with Eq. 1.

**Theorem** Recommendation set \( R = \{q_1', \ldots, q_k'\} \) minimizes \( S(R) \) if and only if the answers \( A'_i \) to the recommendations \( q'_i \in R \) partition \( A \) into \( k \) equally-sized sets. More precisely, for all \( e_j \in A \), there exists exactly one \( i \) such that \( e_j \in A'_i \), and \( |A'_i| = |A'_l| \) for all \( i, l \).

**Proof** For the forward direction, assume that \( R \) minimizes \( S(R) \).

**Claim 1** Each answer \( e_j \in A \) is included in at least one \( A'_i \).

**Proof of claim 1** Assume there is some \( e_j \) not included in any \( A'_i \). Then adding \( e_j \) to any \( A'_i \) would decrease \(|e_j - 1| \) in Eq. 1 from 1 to 0, and would either increase or not change \( \min_n n_i \). Overall, \( S(R) \) would decrease, contradicting the assumption that \( R \) minimizes \( S(R) \).
Basketball players
Guards, Forwards, Centers, Mens’
Michael Jordan, LeBron James,
Kobe Bryant, Magic Johnson, . . .

| Query q | Basketball players |
|----------|-------------------|
| Candidates C(q) | Guards, Forwards, Centers, Mens’ basketball players, Women’s basketball players, Basketball players in the United States, . . . |
| Answers A(q) | Michael Jordan, LeBron James, Kobe Bryant, Magic Johnson, . . . |

Table 10: An example of candidate recommendations (i.e. sub-types) C(q) and answers (i.e. instances) A(q) for the example query “Basketball players”. Some sub-types are specific to the domain (e.g. Guards and Forwards are specific positions played by basketball players), while others generically modify the query by adding a gender or country or origin.

c_j = \sum_i x_ia_{ij}. Let n_i = |A(q'_i)| and n_{max} = \max_i |A(q'_i)|. Then the optimization problem Eq. 2 can be re-written as:

\[
\begin{array}{ll}
\min & \sum_{i,j} y_{ij} - \xi \\
\text{s.t.} & c_j - 1 \leq y_{ij} \quad \forall j \\
& 1 - c_j \leq y_{ij} \quad \forall j \\
& c_j = \sum_i x_ia_{ij} \quad \forall j \\
& k = \sum_i x_i \\
& \xi \leq (1 - x_i)n_{max} + x_in_i \quad \forall i
\end{array}
\]

The x_i are binary optimization variables. The c_j, y_{ij}, and \xi are non-negative integer variables. The first two constraints “linearize” the absolute value from Eq. 1. The fourth constraint ensures that exactly k recommendations will be selected from C(q), and the final constraint forces \xi = \min_{i:x_i=1} n_i, which is equivalent to the second term in Eq. 2.

We use SCIP to perform the optimization (Bestuzheva et al., 2021). We initialize the solver with the greedy solution achieved by iteratively choosing the candidate recommendation which minimizes R(q).

A.2 Optimization

We convert the cost function Eq. 1 into an integer linear program. We use the same notation as in §4, with one change: in §4, we use i = \{1, \ldots, k\} to index the recommendations in a recommendation set R(q); here, we refer to recommendation candidates as q'_i \in C(q), for i = \{1, \ldots, K\}.

Let x_i = 1 [q'_i \in R(q)]; in other words, x_i indicates which candidates from C(q) are selected for R(q). Let a_{ij} = 1 [e_j \in A(q'_i)], and let

Claim 2 \max_{i,j} |n_i - n_j| \leq 1. In other words, no two answer sets differ in size by more than one.

Proof of claim 2 Assume the contrary. Let \ell = \arg \min n_i. Then n_i - n_\ell \geq 2 for all i \neq \ell. Pick some i \neq \ell. Choose some e_j that is in A'_i but not A'_\ell, and reassign this entity to A'_\ell. This increases min n_i by 1, while not changing the first term in Eq. 1, contradicting the assumption that the original R was optimal.

Claim 3 Each answer e_j \in A is included in exactly one A'_i.

Proof of claim 3 Since Claim 1 shows that each e_j is included in at least one A'_i, it suffices to show that each e_j is included in at most one A'_i. Assume this is not the case and there are entities which are included in at least two answer sets. Let m = \sum_j |c_j - 1|, i.e. m is the total number of “excess” entities included in all answer sets. We can construct an alternative set of recommendations \tilde{R} with the same cost as R by assigning entities {e_{i(n/k)+1}, \ldots, e_{i(n/k)}} to \tilde{A}_i for i = \{1, \ldots, k\}, and then allocating the excess entities so that each \tilde{A}_i has the same size as the corresponding A'_i. This is guaranteed to be possible since, from Claim 2, the A'_i cannot differ in size by more than 1. Then, removing the duplicate entities from each \tilde{A}_i \in \tilde{R} decreases the first term in the cost of S(\tilde{R}) by m, while decreasing the second term by \lfloor m/k \rfloor < m. This implies S(\tilde{R}) < S(R), contradicting optimality of R.

Combining Claims 2 and 3 with the assumption that n is divisible by k, it follows that the answers to the recommendations R partition the answers A into equal-sized subsets, where each e_j \in A is included in exactly one A'_i. This proves the forward direction.

The reverse direction follows since all partitions of A achieve the same value of S(R), which has been established as the minimum.

B Dataset construction

B.1 YAGO3 examples

Table 10 shows an example of a YAGO category q, paired together with its sub-types C(q) and answers A(q). Table 11 shows a few examples of recommendations R_{QRESP}, R_{Random-F}, and R_{Random}.
Table 11: Additional example recommendations from $\mathcal{D}_{\text{QRESP}}$, $\mathcal{D}_{\text{Random}}$, and $\mathcal{D}_{\text{Random-F}}$.

### B.2 Filtering rules

We use the following heuristics to obtain $C_{\text{Filter}}(q)$ from $C(q)$. For each $q'_i$ in $C(q)$, we compare $q$ to $q'_i$. We remove $q'_i$ from $C_{\text{Filter}}(q)$ if it differed from $q$ by:

- The addition of an entity tagged by Spacy as DATE, GEP, NORP, or LOC. (e.g. “Politicians” $\rightarrow$ “American Politicians”).
- The addition of a phrase matching one of the following regular expressions:
  - `[0-9]{1,2}(st|th)(-| )century`
  - `1[0-9]{3}`
  - `[^0-9]`
  This filters out recommendations like “Politicians” $\rightarrow$ 19th century politicians.
- The addition of one of the following: male, female, men, women (e.g. “Politicians” $\rightarrow$ “Male politicians”).

### C Annotation process

Annotations were collected using the Amazon Mechanical Turk platform.

#### C.1 Annotators

Mechanical Turk crowdworkers were required to have Masters qualifications, and also required to pass a qualification quiz testing comprehension and good performance on the task. Roughly 25 workers took the qualification quiz; we selected the top 5 to perform annotations.

We maintained contact with annotators via email, fielding questions and discussing challenging cases. Annotators were paid per annotation (or HIT); we chose the HIT rate to target an hourly wage of between $15 / hour and $18 / hour.

#### C.2 Annotation procedure and agreement

Each example was annotated by two crowdworkers. For the Stage 1 evaluation (see §3.3), a recommendation is considered fluent if both annotators agree that it is fluent, and similar for relevance. For Stage 2 evaluation, if one annotator is neutral while the other prefers choice A, we mark choice A as preferred overall. If one annotator prefers A while the
other prefers B, we mark the example as neutral.

Table 12 shows measures of inter-annotator agreement as measured by Cohen’s $\kappa$, as well as the percentage of recommendations that passed Stage 1 quality filters. The $\kappa$ values range between 0.4 and 0.6, often considered to indicate “moderate” agreement (Landis and Koch, 1977).

C.3 Evaluation queries
The full list of human evaluation queries for YAGO and NQ+TREC is shown in Table 13.

D Annotation guide
The annotation UI is shown in Figure 4. The instructions summary is shown in Figure 5. Detailed instructions are shown in Figure 6.
| Academic journals | Action films | Activists | Albums | American activists | American artists | American military officers | American songs | Animals | Aviators | Baseball players | Battles | Battles of the Middle Ages | Birds | Boxers | Brazilian people | British musicians | Buildings and structures in England | Canadian people | Charitable organizations | Chinese people | Christian saints | Classical musicians | Comics characters | Companies based in Tokyo | Companies of the United States | Concertos | Dance music albums | Dictionaries | Electronic albums | Energy companies | Engineers | Engines | European films | Films | Finnish writers | Firearms | Foods | French novels | German films | History books | History museums | Indian films | Indian writers | Insect genera | Islands | Italian painters | Japanese songs | Lakes | Languages | Locomotives | Magazines | Manufacturing companies | Martial arts people | Media executives | Medical journals | Minerals | Mobile phones | Music award winners | Musicians | Newspapers | Non-fiction books | Novels | Operas | Organisations based in India | Organisations based in Singapore | Organizations based in the United States | Painters | Pakistani films | People associated with crime | People associated with religion | People from New York City | People in finance | Philosophers | Philosophical works | Physicians | Plays | Poets | Political organizations | Political parties | Proteins | Racing drivers | Radio stations | Researchers | Rock songs | Schools in London | Scientists | Ships | Singers | Social scientists | Songs | Sports competitions | Sports events | Sports leagues | Sports venues | Swimmers | Tools | Typefaces | United States federal judges | Vehicles | Video games | Weapons | Websites | Writers |
|-------------------------------------------------|----------------|-----------|--------|--------------------|----------------|--------------------------|----------------|--------|---------|----------------|--------|--------------------------|------|-------|----------------|----------------|--------------------------|-------------|---------------------|-------------|---------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Academic journals, Action films, Activists, Albums, American activists, American artists, American military officers, American songs, Animals, Aviators, Baseball players, Battles, Battles of the Middle Ages, Birds, Boxers, Brazilian people, Bridges, British musicians, Buildings and structures in England, Canadian people, Charitable organizations, Chinese people, Christian saints, Classical musicians, Comics characters, Companies based in Tokyo, Companies of the United States, Concertos, Dance music albums, Dictionaries, Electronic albums, Energy companies, Engineers, Engines, European films, Films, Finnish writers, Firearms, Foods, French novels, German films, History books, History museums, Indian films, Indian writers, Insect genera, Islands, Italian painters, Japanese songs, Lakes, Languages, Locomotives, Magazines, Manufacturing companies, Martial arts people, Media executives, Medical journals, Minerals, Mobile phones, Music award winners, Musicians, Newspapers, Non-fiction books, Novels, Operas, Organisations based in India, Organisations based in Singapore, Organizations based in the United States, Painters, Pakistani films, People associated with crime, People associated with religion, People from New York City, People in finance, Philosophers, Philosophical works, Physicians, Plays, Poets, Political organizations, Political parties, Proteins, Racing drivers, Radio stations, Researchers, Rock songs, Schools in London, Scientists, Ships, Singers, Social scientists, Songs, Sports competitions, Sports events, Sports leagues, Sports venues, Swimmers, Tools, Typefaces, United States federal judges, Vehicles, Video games, Weapons, Websites, Writers |
| (a) YAGO queries |
| 19th-century artists, Active volcanoes in the Philippines, African wool producers, Apple products, Architects in New Jersey, Arguments for the existence of God, Astronauts who stepped on the moon, BBC science news, BMW car models, Backward compatible games for XBox One, Baseball players featured on postage stamps, Battles of the revolutionary war, Best selling artists of all time, Billboard hot 100 number-one singles, Books in the New Testament, Branches of medicine, Bright stars in the sky, Cast of the movie “Now you see me”, Causes of the French Revolution, Census regions in the United States, Chief ministers of Indian states, Cities and towns in Northern California, Cities that have held the Olympic Games, Cities with high murder rates, Communist countries during the Cold War, Countries where US citizens can travel without a visa, Countries with French-speaking people, Democratic countries, Disney Pixar movies, Disney princesses, Division 2 colleges in the midwest, Earthquakes, Foods brought to the New World from Europe, Forbes list of largest companies in the world, Functions of all the body systems, Functions of the government, Games for super nintendo classic, Gods and goddesses of the world, Government monopolies in the United States, Greatest NBA players of all time, Hall of fame football players, Hotels near downtown Houston, Independent power producers in South Africa, Indian spices, James Bond movies, Jesuit universities in the United States, John D Rockefeller’s philanthropic projects, Languages spoken in India, Large charities, Largest cities in the world, Major exports of the United States, Malayalam movies, Most densely populated areas in the world, Most frequently used words in English, Most popular video games, Most spoken languages in the world, Movies Robert de Niro played in, National monuments in the United States, Natural air pollutants, Natural resources, Nobel Prize winners, Oil and gas companies in Kuwait, Oscar winners, PS4 games, Participants at the Battle of Wounded Knee, Places where carbon is stored on earth, Players who have a receiving touchdown in a superbowl, Political parties in India, Popular YouTube channels, Private medical colleges in Sindh, Public high schools in Brooklyn New York, Public sector mutual funds in India, Renewable energy companies, Rock and Roll Hall of Fame artists, Roles of local government in the Philippines, Romantic anime shows in English dub, Rulers of England, Satellites launched by India, Schools that offer architecture in Nigeria, Songs in West Side Story, Songs with California in the title, Sources of US oil, States in Nigeria, Stocks in the Dow Jones industrial average, Supreme court justices, Time Magazine person of the year winners, Trees with heart-shaped leaves, US presidents, Universities and colleges in Australia, Walt Disney films, World stock exchanges, Wrestling promotions in the United States, XBox 360 games |
| (b) NQ+TREC queries |

Table 13: Full list of queries used for human evaluation.
Topic exploration

Which group of queries provides a better overview for the topic? To learn more about one of the refinements, click it to see the results of a Google search.

Group A
Topic: Non-fiction books

| Refinement             | Fluent | Relevant |
|------------------------|--------|----------|
| Books about religion   | ☑      | ☑        |
| Philosophy books       | ☑      | ☑        |
| Reference works        | ☑      | ☑        |
| Science books          | ☑      | ☑        |
| Social sciences books  | ☑      | ☑        |

Group B
Topic: Non-fiction books

| Refinement                            | Fluent | Relevant |
|---------------------------------------|--------|----------|
| 2012 non-fiction books                | ☑      | ☑        |
| French non-fiction books               | ☑      | ☑        |
| LGBT non-fiction books                 | ☑      | ☑        |
| Military books                        | ☑      | ☑        |
| Non-fiction books about indigenous     | ☑      | ☑        |
| peoples of the Americas               |        |          |

Step 2
Perform step 2 only if the Step 2 header is green; skip if it is red and hit Submit. The header will turn green if you select at least 3 relevant and fluent refinements for both Group A and Group B.

If the header is green, compare the two groups using the sliders below. For short explanations of the different evaluation criteria, hover your mouse over the text above each slider.

Comprehensiveness
Group 1 is better

Informativeness
Group 2 is better

Non-redundancy

Overall Usefulness

Figure 4: Annotation UI and summary of annotation instructions.

Instructions

Summary | Detailed Instructions | Examples

Suppose you’d like to learn about a new topic.

To learn more, you may choose to view the results of searching for each of the queries in either Group A, or Group B.

You will indicate which group of refinements you think is better, in two steps:

- **Step 1:** Indicate which refinements in each group fluent and relevant.
- **Step 2:** If at least 3 refinements in each group are fluent and relevant, compare the two groups to decide which is more comprehensive, informative, and non-redundant. Then, choose which group you prefer overall.

For more information on these scoring criteria, see the detailed instructions.

**NOTE:** The topic and refinements are displayed as hyperlinks. Clicking on the links will perform a Google search in a new tab. If you aren’t familiar with one of the refinements, but think it might be relevant, click the link to learn more about it.

Figure 5: Annotation UI and summary of annotation instructions.
Instructions

| Summary | Detailed Instructions | Examples |
|---------|-----------------------|----------|

You will be shown a topic, and two different groups of search terms, each containing 5 refinements that you could use to help you learn more about the topic. You will rate the quality of these refinements in two steps. We’ll use “Musicians” as a running example of a topic we’d like to learn more about.

**Step 1: Indicate which refinements in each group are fluent and relevant**

You will see a check box next to each refinement. You should check these boxes if the refinement is:

- **Fluent**: A refinement is fluent if it looks like grammatical English.
  - **Not fluent**: “Musicians” -> “Singers”.
  - **Relevant**: A refinement is relevant if it describes a concept that is a more specific version of the original topic. Only fluent refinements should be counted as relevant.
  - **Not relevant**: “Musicians” -> “Singers”. Singers are a specific type of musician.
  - **Relevant**: “American Musicians” -> “Musicians from New Jersey”. Musicians from New Jersey are a particular group of musicians from America.
  - **Not relevant**: “American Musicians” -> “Canadian musicians”.

You will continue to Step 2 only if there are least 3 relevant and fluent refinements for each group; otherwise you're done.

**Step 2: Compare the refinements in Group A and Group B**

In Step 1, you looked at properties of individual refinements. In this step, you will compare the refinements in Group A vs. those in Group B overall, based on the following criteria:

- **Comprehensiveness**: Do the queries in the group provide a good overview of the topic?
- **Informativeness**: Do the queries provide useful information about the topic?
- **Non-redundancy**: Are all the refinements unique, or are there some refinements that express the same idea?
- **Overall usefulness**: Overall, which group is more useful in learning more about the topic?

**Example refinements**

Here are some example refinements, together with judgements on the three of the four criteria shown above.

- “Musicians” -> “[Classical musicians], “Rock and roll musicians”, “Jazz musicians”, “R&B musicians”, “Hip-hop musicians”.
  - Comprehensive, since it provides a good overview of different musical genres that musicians might fall into.
  - Informative, since it provides interesting information about different musical genres.
  - Non-redundant, since it covers different musical genres.

- “Musicians” -> “[Vocalists], “String instrumentists”, “Percussionists”, “Ham instrumentists”, “Composers”.
  - Comprehensive, since it provides a good overview of different types of instruments musicians might play.
  - Informative, since it provides information about different types of instruments.
  - Non-redundant, since each refinement covers a different instrument group.

- “Musicians” -> “[Tubaists], “Violinists”, “Pianists”, “Cellists”, “Timpanists”.
  - Not comprehensive, since many musicians play instruments other than the ones in this list.
  - Informative, since it does provide information on different types of musical instruments.
  - Non-redundant, since no instruments are repeated.

- “Musicians” -> “[Musicians from Europe], “Musicians from Asia”, “Musicians from North America”, “Musicians from South America”.
  - Comprehensive, since most musicians are from one of these continents.
  - Not informative, since you can always categorize people by the continent they’re from; these refinements provide no information unique to musicians.
  - Non-redundant, since no continents are repeated.

- “Musicians” -> “[Male musicians], “Musicians who are men”, “Female musicians”, “Musicians who are women”, “Musicians who do not identify as male or female”.
  - Comprehensive, since all musicians fall into one of these categories.
  - Not informative, since any group of people could be categorized this way.
  - Redundant, since male and female musicians are each repeated twice, with slightly different wording.

Figure 6: Annotation UI and summary of annotation instructions.