Gustavo Penha<sup>1</sup>, Enrico Palumbo<sup>2</sup>, Maryam Aziz<sup>3</sup>, Alice Wang<sup>3</sup>, Hugues Bouchard<sup>4</sup>

Spotify

<sup>1</sup>Netherlands, <sup>2</sup>Italy, <sup>3</sup>USA, <sup>4</sup>Spain {gustavop,enricop,maryama,alicew,hb}@spotify.com

## ABSTRACT

An important goal of online platforms is to enable content discovery, i.e. allow users to find a catalog entity they were not familiar with. A pre-requisite to discover an entity, e.g. a book, with a search engine is that the entity is *retrievable*, i.e. there are queries for which the system will surface such entity in the top results. However, machine-learned search engines have a high retrievability bias, where the majority of the queries return the same entities. This happens partly due to the predominance of narrow intent queries, where users create queries using the title of an already known entity, e.g. in book search "harry potter". The amount of broad queries where users want to discover new entities, e.g. in music search "chill lyrical electronica with an atmospheric feeling to it", and have a higher tolerance to what they might find, is small in comparison. We focus here on two factors that have a negative impact on the retrievability of the entities (I) the training data used for dense retrieval models and (II) the distribution of narrow and broad intent queries issued in the system. We propose CtrlQGen, a method that generates queries for a chosen underlying intentnarrow or broad. We can use CtrlQGen to improve factor (I) by generating training data for dense retrieval models comprised of diverse synthetic queries. CtrlQGen can also be used to deal with factor (II) by suggesting queries with broader intents to users. Our results on datasets from the domains of music, podcasts, and books reveal that we can significantly decrease the retrievability bias of a dense retrieval model when using CtrlQGen. First, by using the generated queries as training data for dense models we make 9% of the entities retrievable-go from zero to non-zero retrievability. Second, by suggesting broader queries to users, we can make 12% of the entities retrievable in the best case.

## **1** INTRODUCTION

In online content platforms, users can search for catalog entities<sup>1</sup> that they are already familiar with, for example, they issue queries with the title of a track to listen to next or of a book they would like

WWW '23, May 1-5, 2023, Austin, TX, USA

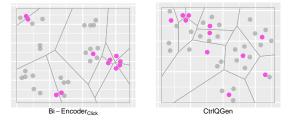


Figure 1: TSNE reduction of queries and entities when embedded with a Bi-Encoder trained with query logs and clicked entities (left), and synthetic queries from our proposed method CtrlQGen (right). The left model surfaces the same four entities for most queries while six entities are never retrieved as the most similar entity. The right model distributes the queries better, i.e. has less retrievability bias.

to read. This type of search based on bibliographic data (e.g. title, artist, author, etc) to find entities [7] has been referred to as *narrow* intent queries [27]. However, user information needs are diverse and can be more complex depending on their current mindset [33].

When users have an exploratory mindset, they have a higher tolerance and are prone to explore different alternatives through *broad* queries. Non-focused information needs are generally complex and require multiple interactions. Many users solve such information needs outside the search engine of the platforms, by asking broad queries to other users in forums such as subreddits<sup>2</sup> as existing search systems are ineffective for broader intents.

Broad intents are an opportunity to surface under-served entities that would not be discovered otherwise without affecting user satisfaction [57]. While approaches to promote the discovery of entities have been studied from the perspective of recommender systems [1, 42], they do not generalize to search engines where there is an input query. A prerequisite to improving the discoverability of entities through search is that the entity is retrievable. Azzopardi and Vinay [5] defined the *retrievability of a document as how many queries lead to the entity being surfaced in the top-k results.* 

For example, if we assume that the users will only interact with the top-1 ranked entity of the list, the dense retrieval model used to embed queries and entities in the left Voronoi plot of Figure 1 would make one of the five leftmost entities appear for every query (they are closest neighbors in the embedded space). These entities would have a high concentration of retrievability, i.e. retrievability bias, compared to the remaining entities which have no query close

<sup>&</sup>lt;sup>1</sup>Catalog entities are items from a platform that can be retrieved and/or recommended to users. For example, the book *"The Fellowship of the Ring by J.R.R Tolkien"* is an entity from an online book platform. We refer to such items as *entities* throughout the paper.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

<sup>© 2023</sup> Copyright held by the owner/author(s). Publication rights licensed to ACM. ACM ISBN 978-1-4503-XXXX-X/18/06...\$15.00 https://doi.org/10.1145/3543507.3583261

<sup>&</sup>lt;sup>2</sup>See for example https://www.reddit.com/r/musicsuggestions/ or /r/booksuggestions/.

in the embedding space. Retrievability bias limits exploration, as it becomes harder to discover new entities through search when they have low retrievability scores.

In this paper, we study the effect of *generating queries* on the retrievability of the system. Although the implications of query generation techniques for training document/passage dense models have been studied in detail [20, 35, 40, 61], little attention has been given to generating queries for *entities* and their impact on the effectiveness and *retrievability bias*. Dense models have shown promising results for different retrieval tasks [37], requiring a significant amount of in-domain supervision data for training [56]. Query generation approaches have shown to be effective in generating training data for domains with a scarcity of labeled data [15, 35, 40].

Unlike previous approaches to query generation which are agnostic to search intents, we propose CtrlQGen which controls for the underlying intent. By generating both narrow and broad queries for an entity we are able to (I) train the dense retrieval model for both types of intents and (II) suggest broader and more exploratory queries to users. With the use of weak supervision through the proposed *weak labeling functions*, CtrlQGen does not strictly require any training data to generate synthetic queries for a given entity.

With our empirical evaluation using three datasets in the domains of music, podcasts, and books we set out to answer the following research question: To what extent can we reduce the retrievability bias of entity search with automatically generated queries without significant impact in the effectiveness?

Considering that the retrievability of an entity depends on (I) the retrieval model which decides which entities are surfaced for each query and (II) the set of queries used for the estimation, we generate two retrievability debiasing hypotheses that focus on modifications to the retrieval model and the set of queries respectively. Our first hypothesis, **H1**, is that training dense retrieval models with CtrlQGen queries will lead to less retrievability bias compared to training with real queries and their respective clicked entities. The click data is prone to different biases, for example, many queries will be issued for the most popular entities, i.e. popularity bias, and after training the model on such data and this bias will be reinforced in later interactions with the system. Conversely, with CtrlQGen we can obtain pairs of query-entity to train the model for any given entity, which can be randomly sampled from the collection.

Our second hypothesis, **H2**, is that suggesting broad queries using CtrlQGen will lead to less retrievability bias. Narrow queries have by definition less relevant entities than broad queries. By assisting users in formulating their queries with the suggestion of broad queries we can potentially influence users' query behaviors and then have an impact on the query type distribution.

Our main findings and contributions are:

- We introduce CtrlQGen, a novel method to generate queries for a given entity conditioned on a desired underlying intent (narrow or broad). We demonstrate two ways of using the generated queries: as training data for dense retrieval models and as query suggestions.
- We find positive evidence for H1: dense models fine-tuned on synthetic queries have significantly less retrievability bias than models fine-tuned on click data. When using the queries from the proposed CtrlQGen we reduce the retrievability bias by 10% in terms of Gini scores on average when

compared to a model that uses the click data and make 9% of the Tracks collection of entities retrievable—go from zero to non-zero retrievability score.

• Regarding H2, we show that applying CtrlQGen for generating query suggestions can reduce the retrievability bias of the system up to 9% percent and increase the number of entities that have non-zero retrievability 11% for the Tracks collection when using a Bi-Encoder model that was trained with an unbiased set of queries.

Next, we describe the related work, followed by the proposed method in Section 3. Section 4 describes the experimental setup used to answer the research question, followed by our experiments in Section 5. We conclude the paper in Section 6.

## 2 RELATED WORK

We first discuss here related work on search for the domains considered here. Then we look into retrievability followed by a discussion on query generation techniques and their applications.

## 2.1 Entity Search

A number of studies have explored user behavior when searching for specific entities such as music tracks, products, and books [7, 23, 27, 32]. While focused searches have the goal of finding a specific entity, non-focused searches involve broader intents, where the user is in an exploratory mindset [33, 51, 55].

The Social Book Search Lab CLEF [30] that ran from 2011 to 2016<sup>3</sup> enabled a number of studies in complex search for the book domain [13, 14, 17, 58, 59]. A richer document representation for books which contains for example reviews, tags, and controlled vocabulary was shown to have better retrieval effectiveness. It has also been shown in the music domain that multiple sources of data such as metadata, audio features, tags, and lyrics lead to better effectiveness for downstream tasks [29]. For podcast search, the TREC2020 podcasts track [28] revealed that adding the additional information of transcripts also leads to higher effectiveness when compared to using only the episode title and description.

Another external source of information for entities that was shown to be useful for downstream tasks [54] is the concept of lists, where users group together a number of entities that are similar in a way. In the music domain, this is often referred to as playlists. The creation of lists with curated entities is also common in the domains of books [39] and movies [25].

## 2.2 Retrievability

To estimate the retrievability of a document [4, 5] proposed to sum the popularity of the queries that retrieve the given document above a position that the user would actually look at (e.g. in the top-5 documents). Retrievability scores can be used to determine if a retrieval system has a concentration of retrievability, for example, to verify if certain types of documents are being surfaced more than others. For example, [50] showed that for a collection with datasets and articles, the retrievability bias was stronger for datasets when compared with articles.

<sup>&</sup>lt;sup>3</sup>The book corpus of the SBS tasks is no longer available.

WWW '23, May 1-5, 2023, Austin, TX, USA

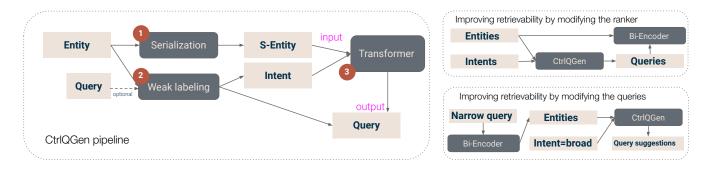


Figure 2: Left: Components of the CtrlQGen method. Each entity is serialized by concatenating the values of each metadata, e.g. *title: The Fellowship of the Ring [SEP] author names: J.R.R. Tolkien [...].* (2) Labeled data (*entity*; *query*; *intent*) is not strictly required, due to the use of weak labeling functions which output a query and intent for a given entity, e.g. (*The Fellowship of the Ring ; fantasy book*; broad). (3) Control over the underlying intent (narrow or broad) when generating the query via prompting, e.g. "*Generate a query with* narrow/broad *intent from: <serialized\_entity>*". Right: Different ways of using the proposed CtrlQGen to improve the retrievability of the search system: modifying the ranker by fine-tuning on synthetic queries and modifying the set of queries by suggesting broad queries for the narrow intent queries issued.

Even though a system with less retrievability bias does not necessarily mean that the system is more effective, studies have found a correlation between the two [9, 62, 63], suggesting that a measure of retrievability bias can potentially be used to select better retrieval systems. In order to reduce the retrievability bias of a system [8] proposed a query expansion technique with a novel document selection process for pseudo-relevance feedback in the domain of patent search. Chakraborty et al. [18] proposed to use retrievability of a document over a set of query variations to decide which documents to use for relevance feedback. Finding which queries lead to a document can be also used to improve search transparency [34].

## 2.3 Query Generation

Query generation techniques can be broadly categorized based on their input: documents or queries. For generating known-item queries for a given document, i.e. queries where the task is to find a previously seen document, techniques have been proposed that select a number of document terms based on different sampling methods [2, 3, 31]. Liu et al. [38] tackled a similar problem with the additional constraint that the generated queries are also informative. Generating queries for a given document using a seq2seq model was first proposed by [45]. Unlike sampling methods proposed for generating known-item queries, a seq2seq approach such as docT5query [44] is able to generate queries where its terms do not occur in the input document, being able to mitigate the vocabulary mismatch problem. Similarly, [35, 40, 61] generate queries based on documents using a transformer encoder-decoder model, but instead of using the queries for document augmentation, they employ the queries as additional training data for training bi-encoders, leading to significant gains in retrieval effectiveness-specially in crossdomain evaluation settings. It has also been proposed to replace the fine-tuned encoder-decoder model to generate queries with little supervision by doing in-context learning with models such as GPT-3 [15, 20]. Zhuang et al. [64] used generated queries with the goal of improving the effectiveness of the emerging differentiable search indexes. Another recent direction for query generation is to

incorporate explicit knowledge when generating queries, e.g. with the use of knowledge graphs [19, 26, 52].

Generating **queries for a given query** has also been shown to be useful in IR. For example by generating query suggestions or reformulations that help users explore and express their information needs [16, 43]. Another objective is to generate query variants that can be used to obtain more effective ranking models by combining such variants for the given query [11, 12], and also to better evaluate ranking models [6, 46, 65].

The closest to our problem is the generation of queries for product search. Lien et al. [36] used textual data from the reviews associated with the documents (products) to generate queries automatically for the following products: headphones, tents, and conditioners. In the domain of movies, Bassani and Pasi [10] generated queries automatically for a document (a movie) based on a number of predefined semantic components such as genre and year. We propose here a method to generate queries that can take advantage of manually created functions as a weak supervision signal, and also employ pre-trained language models. Unlike previous methods to generate queries, CtrlQGen does intent-aware generation, where it is possible to control for the underlying intent of the output query.

#### **3 CONTROLLABLE QUERY GENERATION**

In this section, we first describe the three main components of the proposed CtrlQGen followed by different applications for the generated queries. Figure 2 displays a diagram of the model, as well as two different ways to employ the synthetic queries. The serialization module is required to obtain a text representation for a given entity so that text-based models can use that as input. The second component is called weak labeling, which is able to bypass the need for a large amount of labeled data. Finally, the last component is the intent-aware generation, which is able to control for different types of intent (broad and narrow).

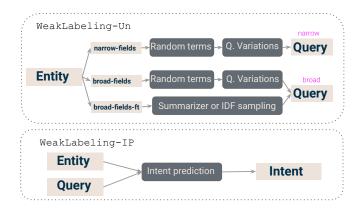
#### 3.1 Model Components

3.1.1 Serialization. This module takes as input an entity e and outputs a string representation of the entity:  $e_{serialized} = s(e)$ . The serialization function s concatenates every metadata column of the entity with their respective values, using a special token:  $s(e) = col_1 : val_1[SEP]col_2 : val_2[SEP]...[SEP]col_n : val_n$ . So for example the book with the title *The Fellowship of the Ring* becomes:

title: The Fellowship of the Ring [SEP] series name: The Lord of the Rings #1 [SEP] author names: J.R.R. Tolkien [SEP] publication year: 1954 [SEP] language: EN [SEP] genres: Fantasy, Classics, Fiction, Adventure, High Fantasy, ...[SEP] description: One Ring to rule them all, One Ring to find them ...[SEP] review: This book is full of wonder and adventure with fantastic writing ... [SEP] lists: fantasy, uk-and-ireland, witches-wizards, fiction, british, ...

3.1.2 Weak Labeling. In order to train CtrlQGen we require a dataset  $\mathcal{D} = \{(e_i, i_i, q_i)\}_{i=1}^M$  with training triplets of entity, intent, and query, which are the input, control variable, and output respectively. In each triplet, the query q has the underlying intent i (narrow or broad) when matching with the entity e. One option to acquire such data is to ask annotators to create narrow and broad queries for a given entity. Alternatively, we can employ weak labeling functions that generate such data based on heuristics.

We present here two flavors of weak labeling functions. The first is completely *unsupervised* (WeakLabeling-Un), and thus is able to generate both query and intents for any given entity. The second requires queries that are related to each entity and thus is based on *intent prediction* of the given query (WeakLabeling-IP).



## Figure 3: Two variants of the weak labeling functions. While WeakLabeling-Un (top) outputs query and intents for a given entity, WeakLabeling-IP (bottom) outputs an intent label for a given pair of entity and query.

**WeakLabeling-Un**. The core intuition is that we can define a set of metatada columns that are inherently associated with narrow intent queries since they can identify the entity (*narrow-fields*), e.g. title and artists, and a set of metadata columns that capture characteristics of the entity that other entities might also have, e.g. genres,

and thus can be considered to be broad columns (*broad-fields*). In order to generate a set of queries and intents for a given entity we rely on randomly sampling terms from all possible combinations of the respective fields. So for example to generate a narrow intent query in the music domain, we could use either the title of a track, the album, the artist, or a combination of the three. After sampling terms from such the respective columns for the query, we apply a number of functions to generate query variations in a stochastic manner: shuffling words, adding misspellings, and removing prefixes<sup>4</sup>.

Specifically, when generating broad queries, we differentiate between metadata columns that are based on free text (*broad-fields-ft*), e.g. reviews, and the ones which are already category-like terms (*broad-fields*), e.g. genres. For the free text columns, in order to avoid selecting terms that are uninformative, we apply a sampling strategy that prioritizes terms with higher IDF. As another weak labeling function for the free text columns, we apply a text summarization model to select more informative terms.

**WeakLabeling-IP** In order to take advantage of existing data of entities and queries, e.g. query logs with clicked entities, this variant predicts if the query is broad or narrow based on its narrow and broad columns. If the similarity<sup>5</sup> of the query and the values of the narrow queries is higher than the similarity of the query with the values of the broad queries then the weak label will be narrow, otherwise broad. So for example, if the entity is a book with the title "*The Brothers Karamazov*", and the input query is "*Karamazov*", the label would be narrow whereas if the input query is "*russian theological fiction*" the label would be broad as it would be more similar to the categories of the book.

3.1.3 Intent-aware Generation. Given the training dataset  $\mathcal{D} = \{(e_i, i_i, q_i)\}_{i=1}^M$ , we train an encoder-decoder model *G* that receives as input the entity and the underlying intent to control for, and it outputs the query: G(e, i) = q. In order to achieve that we rely on adding the control variable as part of the language model prompt. We train the model with the following prompt: "Generate a query with narrow/broad intent from: <serialized\_entity>" and its respective query as the output. So for example the query "lord of th" with intent narrow would lead to the following training instance:

Input Generate a narrow query from: title: The Fellowship of the Ring [SEP] series name: The Lord of the Rings #1 [SEP] author names: J.R.R. Tolkien [SEP] publication year: 1954 [SEP] language: EN [SEP] genres: Fantasy, Classics, Fiction, Adventure, High Fantasy, ...[SEP] description: One Ring to rule them all, One Ring to find them ...[SEP] review: This book is full of wonder and adventure with fantastic writing ... [SEP] lists: fantasy, uk-and-ireland, witches-wizards, fiction, brittish, ...

**Output** lord of th

<sup>&</sup>lt;sup>4</sup>Since the datasets considered come from a large-scale online platform with *instant* search, many log queries are not complete and are just prefixes of the entity titles. This happens because the user might stop before the end of the query as the result could be already found in the list of results.

<sup>&</sup>lt;sup>5</sup>We employ here a transformer sentence representation and cosine similarity.

## 3.2 Applications

3.2.1 Synthetic training data. We can use the generated queries to train Bi-Encoder retrieval models, as shown on the right top part of Figure 2. For a randomly sampled set of entities  $\mathcal{E}'$  from the collection  $\mathcal{E}$  we apply CtrlQGen with both desired intents  $q'_{narrow} = G(e, \texttt{narrow})$  and  $q'_{broad} = G(e, \texttt{broad})$  for each e in  $\mathcal{E}'$ . After that, given a desired weight proportion of broad queries and narrow queries ( $P_{narrow}$ ,  $P_{broad}$ ) we can sample training instances from the synthetic generated queries Q' for training the Bi-Encoder. This gives us a dataset of pairs of synthetic queries and respective relevant entities that can be used to train Bi-Encoder models, controlling for the desired proportion of underlying intents.

3.2.2 Query suggestion. We can employ the CtrlQGen model to perform query suggestion, as shown on the bottom right part of Figure 2. Since the majority of the queries for entities have a narrow intent behind them, one approach to modifying the user's behavior is to suggest broader queries. In order to do that, we can employ the generated queries in the following manner. First, for a given input query *q*, we can obtain a list  $\mathcal{R}_q$  with the top-k entities ranked for it using a ranking model. For each entity in the top-k ranked list, we apply CtrlQGen to generate a set of broad queries Q' to recommend:  $Q' = \{G(e_i, \text{broad})\}$  for  $e_i$  in  $\mathcal{R}_q^6$ . The complexity of this approach is  $O(n^2 * d * k)$ , where *n* is the sequence length, *d* is the number of dimensions of the transformer model and *k* is the size of the list considered to generate suggestions.

Table 1: Datasets metadata and statistics. Metadata columns 1-3 are considered to be *narrow-fields*, whereas 4-9 are *broad-fields*. In the experiments the broad columns which are free-text (*broad-fields-ft*) are: Episode & show description and Transcript for Podcasts, and User reviews and Description for Books.

		Tracks	Podcasts	Books		
	(1)	Title	Title	Title		
Metadata	(2)	Album name	Show name	Series name		
	(3)	Artist names	Host names	Author names		
	(4)	Release year	Ingested date	Publication year		
	(5)	Language	Language	Language		
	(6)	Genres	Categories	Genres		
	(7)	Descriptors	Episode & show description	Description		
	(8)	Lyric	Transcript	User reviews		
	(9)	User Playlists	Topics	User lists		
# docs		682k	600k	617k		
# queries		100k	100k	100k		
Click # qrels train/val/test		75.9k/9.5k/9.5k	14.4k/1.8k/1.8k	117.5k/14.7k/14.7k		
Avg doc len		55.87	80.76	161.58		
Avg query len		1.96	3.06	4.47		

## 4 EXPERIMENTAL SETUP

In this section, we first describe the data used to test our hypotheses, followed by the implementation details of the methods and baselines as well as how we evaluate different approaches.

#### 4.1 Datasets

In order to test our hypothesis and compare different methods to generate queries we rely on three datasets: Tracks, Podcasts, and Books. For each dataset, we have a set of entities (>600k entities), a set of 100k queries, and a set of relevance judgements. Table 1 describes the statistics of the datasets and examples of entities.

While the queries and entities from **Tracks** and **Podcasts** were extracted from a large-scale online platform the **Books** dataset is a subset of the Goodreads public dataset from [60]<sup>7</sup>. The query sets from Tracks and Podcasts are a unique subset of randomly sampled entities and queries from the logs of a large scale online audio platform, where clicks for a given entity after issuing the query are considered to be the relevance signal in our experiments.

We also use the number of distinct users for which the query was issued by, and use them as  $o_q$  to calculate retrievability scores (see Section 4.3). Regarding the columns, as seen in Table 1, the ones with numbers 1–3 are considered to be *narrow-fields*, whereas 4–9 are *broad-fields*. The broad columns which are free-text (*broad-fields-ft*) are: *Episode & show description* and *Transcript* for Podcasts, and *User reviews* and *Description* for Books.

Since the Goodreads dataset does not have any set of queries available, we generate a set of queries automatically: 75% of the queries are narrow, generated by sampling words from the *narrow-fields*, and 25% of them are from *broad-fields* and consider that as the relevance labels. This specific split of narrow and broad queries was chosen to simulate actual user behavior observed in the other two datasets (Tracks and Podcasts) where narrow queries are the majority but in a less extreme fashion. We use the number of ratings the entities from Books have as a proxy for the number of users that would issue such queries ( $o_q$ ).

4.1.1 Broad queries datasets. Since the majority of the queries from Tracks, Podcasts and Books are narrow, we also employ two smaller additional sets of queries and relevance labels that have an underlying broad intent. They are Tracksbroad and Podcastsbroad, containing a total of 1309 and 500 queries. The Tracksbroad is a sample of queries from the logs that have a high predicted probability of being broad based on the interaction signals the user had after issuing the query. If the user interacts with entities such as playlists and hubs more than tracks and albums they are more likely to be issuing a broad query. Based on this set, we get the clicked entities where the query does not match the title, artist, or album of the entity, avoiding cases where the query seems broad but is in fact a narrow interaction, e.g. query "pop" and clicking a track with the title "POP!". For Podcasts  ${\tt broad},$  there is no parallel for the Tracks playlists so we employ a set of manually curated pairs of broad queries and entities. Annotators were instructed to write a query relevant to the podcast episode while avoiding exact matches and matching diverse metadata fields.

## 4.2 Implementation Details

4.2.1 Query generation models. As baselines for generating synthetic queries, we first use **QGen**, a common approach to generate queries from documents used in this manner in different previous work [35, 40, 44, 61]. We rely on fine-tuning T5 [47] (*t5-base*) on

 $<sup>^{6}</sup>$ In our experiments this set of queries Q' is appended, according to a percentage of acceptance, to the set of log queries Q in order to calculate the retrievability bias.

<sup>&</sup>lt;sup>7</sup>https://github.com/MengtingWan/goodreads

a subset of Click train set with 10k pairs query-entities. The second baseline for generating queries requires very little supervision signal: InPars [15]. The model uses in-context learning, i.e. few examples in the prompt of the document and expected query, and large language models. For a fair comparison, we randomly sample examples to use in the prompt every time we are generating the output queries, this way InPars has access to the same amount of training pairs of query and entities as QGen<sup>8</sup>. We rely on the open *bigscience/bloom-760m*<sup>9</sup> release to do so<sup>10</sup>. For the **CtrlQGen** implementation we also rely on the T5 (t5-base) model. When generating the queries with T5, for both QGen and CtrlQGen we employ *do\_sample*=True and *top\_k*=10.

4.2.2 Retrieval models. For BM25 [49] we resort to the default hyperparameters and implementation provided by the PyTerrier toolkit [41]. For the zero-shot Bi-Encoder models, we rely on the SentenceTransformers [48] model releases<sup>11</sup>. The library uses Hugginface transformers for the pre-trained models such as BERT [21] and MPNet [53]. Specifically, we employ the pre-trained model all-mpnet-base-v2. When fine-tuning the Bi-Encoder models on the Click or synthetic datasets, we rely on the *MultipleNegatives*-RankingLoss, which uses in-batch random negatives to train the model. We fine-tune the dense models for a total of 10k steps. Thus, all dense models were trained on the same amount of (synthetic or not) queries. We use a batch size of 8, with 10% of the training steps as warmup steps. The learning rate is 2e-5 and the weight decay is 0.01. We refer to the Bi-Encoder model trained on Click data as  ${\tt Bi-Encoder}_{\tt Click}$  and a <code>Bi-Encoder</code> model trained on the queries from CtrlQGen as **Bi-Encoder<sub>CtrlQGen</sub>**.

#### 4.3 **Evaluation Procedure**

To evaluate the effectiveness of the retrieval systems we use the recall at 100, R@100. The choice for R@100 is due to the objective of increasing the retrievability of items considering the first 100 options<sup>12</sup>. We perform Students t-tests at the confidence level of 0.95 with Bonferroni correction to compare the difference between models with statistical significance.

To evaluate how biased the retrieval system is in terms of retrievability, we first estimate the retrievability of an entity e as defined by [5]:  $r(\mathbf{e}) = \sum_{\mathbf{q} \in \mathbf{Q}} o_{\mathbf{q}} \cdot f(k_{eq}, c)$ , where **Q** is the set of queries<sup>13</sup>,  $o_q$  is the weight of each query—here we use the number of users that issued the query—and  $f(k_{eq}, c)$  is 1 if the entity e is ranked above *c* by the search system (in our experiments we set c=100) and 0 otherwise. In order to get a number that summarizes how concentrated or biased the retrievability scores are we calculate the Gini score [24]:  $G = \frac{\sum_{i=1}^{N} (2*i-N-1)*r(\mathbf{e}_i)}{N\sum_{j=1}^{N} r(\mathbf{e}_j)}$ , where G=1 means only one entity concentrates all the retrievability, and G=0 means every

<sup>13</sup>The size of **Q** is 100k for all computations.

entity in the collection has the same retrievability score. In order to perform statistical testing for the Gini scores we follow [22].

## 5 RESULTS

In this section, we first describe the experimental results on H1training dense retrieval models on synthetic queries leads to less retrievability bias than training on real queries and clicked entitiesfollowed by the results for H2-suggesting broad queries generated by our proposed method CtrlQGen leads to less retrievability bias when compared to the set of queries from the logs.

## 5.1 H1: Modifying the Ranker with Generated **Queries as Training Data**

Evaluation with narrow intent queries. Table 2 displays R@100 and Gini scores for different retrieval models on the three datasets which contain mostly narrow intent queries. Zero-shot models do not have access to any Click relevance labels for training. As expected, a Bi-Encoder that has no access to the target domain queries and entities does not perform well, and it has worse effectiveness than BM25 (30% less R@100 on average, as seen row a vs row *b*). When using the target training data to fine-tune the dense retrieval model (Bi-Encoder<sub>Click</sub>) we observe that it outperforms zero-shot models significantly, with absolute gains of R@100 up to 158% (row h vs row b). However, both the model trained on the Click data (row h) and the pre-trained Bi-Encoder (row c) have significantly more bias than BM25, as seen by the Gini scores increases of 9.2% and 10% respectively.

When using the synthetic queries created by any of the query generation models to train the dense retrieval methods (InPars, QGen, CtrlQGen) as described in Section 3.2.1, we observe significant drops of 10% Gini on average (rows d,e,f vs row h), indicating positive evidence for our first hypothesis that a model trained on the synthetic queries lead to less retrievability bias than the model trained on the Click data. Specifically, with CtrlQGen<sup>14</sup> we show that we can get statistically significant better effectiveness and retrievability for Tracks and Books than the query generation baselines with 24% more R@100 and 3% less Gini on average over all datasets and baselines (row f vs rows d, e). We also show that we improve the retrievability over the model trained on Click data (row f vs row h) by 10% Gini. This effectively makes more than 62k (9%) entities in the Tracks dataset retrievable compared to Bi-Encoder<sub>Click</sub>, i.e. the entity goes from zero to a non-zero value.

We see also that with a combination of synthetic queries from CtrlQGen and queries from the Click dataset <sup>15</sup> (row g) we can achieve similar effectiveness to the model training on the Click dataset (no statistical difference) while having less retrievability bias for both Tracks and Podcasts datasets with statistical significance, being Pareto optimal when considering both objectives.

Evaluation with broad intent queries. In order to understand how the models perform for exploratory and complex information needs, we take a closer look at the effectiveness and retrievability of the models in a set containing only broad intent queries. Table 3

<sup>&</sup>lt;sup>8</sup>This was shown to be effective for the validation sets of Podcasts and Books. For Tracks we did not observe the same, so we used a fixed prompt with the same two examples randomly selected from the dataset.

https://bigscience.huggingface.co/blog/bloom

<sup>&</sup>lt;sup>10</sup>We explore larger GPT-3 models on the appendix and see that the larger 175B parameter one does not significantly improve over smaller models. <sup>11</sup>https://www.sbert.net/docs/pretrained\_models.html

<sup>&</sup>lt;sup>12</sup>A second stage re-ranker in this pipeline could be precision-focused if the retriever is able to find enough relevant and diverse options.

 $<sup>^{14} \</sup>rm We \ employ \ here \ CtrlQGen_{\it narrow} \ which \ sets \ (P_{\it narrow}, P_{\it broad}) \ as \ (100\%, 0\%) \ and$ WeakLabeling-IP as found to be optimal in the validation experiments (c.f. Table 4). <sup>15</sup>We set the percentage as the optimal one in the validation set: 10% synthetic queries and 90% queries and clicks from Click.

Table 2: Retrieval effectiveness ( $\mathbb{R}@100^{\uparrow}$  the higher the better) and retrievability bias (Gini  $\downarrow$  the lower the better) of dense retrieval models trained on different training data for predominantly narrow queries (Click test sets). Bold indicate the best model for each category with statistical significance and superscripts indicate statistically significant improvements over the respective model using students t-test at 0.95 confidence with Bonferoni correction for multiple comparisons. The values for the Books dataset on row (c) are not included as they are already a synthetic set of queries.

		R@100↑			Gini↓				
Zero-shot (no target domain Click training data)	Tracks	Podcasts	Books	Tracks	Podcasts	Books			
(a) BM25	0.182 <sup>b</sup>	0.436 <sup>b</sup>	<b>0.721</b> <sup>bd</sup>	0.752 <sup>bh</sup>	0.666 <sup>bcdefh</sup>	<b>0.</b> 779 <sup>b</sup>			
(b) Bi-Encoder	0.142	0.323	0.415	$0.818^{h}$	0.765	0.836 <sup>d</sup>			
(c) Bi-Encoder <sub>WeakLabeling-Un</sub> (Ours)	<b>0.222</b> <i>abd</i>	<b>0.465</b> <sup>b</sup>	-	0.748 <sup>abh</sup>	$0.730^{bh}$				
Fine-tuned on synthetic data (target domain Click training data to train query generators)									
(d) Bi-Encoder <sub>InPars</sub> [15] (e) Bi-Encoder <sub>QGen</sub> [40] (f) Bi-Encoder <sub>CtrlQGen</sub> (Ours)	0.202 <sup>ab</sup> 0.296 <sup>abcd</sup> <b>0.333</b> <sup>abcde</sup>	$0.474^{ab}$ <b>0.503</b> <sup>abc</sup> $0.500^{abc}$	0.492 <sup>b</sup> 0.755 <sup>abd</sup> <b>0.770<sup>abde</sup></b>	0.712 <sup>abch</sup> 0.701 <sup>abcdh</sup> <b>0.693<sup>abcdeh</sup></b>	0.677 <sup>bch</sup> <b>0.674<sup>bcdfh</sup></b> 0.676 <sup>bdch</sup>	0.842 0.766 <sup>abgh</sup> <b>0.762</b> <sup>abegh</sup>			
<b>Fine-tuned on target data or in combination with synthetic data</b> (access to target domain Click training data)									
(g)Bi-Encoder <sub>Click+CtrlQGen</sub> (Ours) (h)Bi-Encoder <sub>Click</sub>	0.361 <sup>abcdef</sup> <b>0.366</b> <sup>abcdef</sup>	0.622 <sup>abcdef</sup> <b>0.634</b> <sup>abcdef</sup>	<b>0.775</b> <sup>abde</sup> 0.769 <sup>abde</sup>	<b>0.817</b> <sup>bh</sup> 0.856	<b>0.741</b> <sup>bh</sup> 0.763 <sup>b</sup>	0.768 <sup>ab</sup> <b>0.767</b> <sup>abg</sup>			

Table 3: Retrieval effectiveness ( $\mathbb{R}@100^{\uparrow}$  the higher the better) and retrievability bias (Gini  $\downarrow$  the lower the better) of dense models trained on different training data for a subset of broad queries. Bold indicates the best model for each category with statistical significance and superscripts indicate statistically significant improvements over the respective model using Students t-test at 0.95 confidence with Bonferoni correction. When the set of queries Q' were generated with ( $P_{narrow}$ ,  $P_{broad}$ ) as (100%, 0%), we refer to it as CtrlQGen<sub>narrow</sub>, with (0%, 100%) we call it CtrlQGen<sub>broad</sub> and with (50%, 50%) as CtrlQGen<sub>both</sub>.

Method	R@	2100↑	Gini ↓		
	Tracks <sub>broad</sub>	Podcasts <sub>broad</sub>	Tracks <sub>broad</sub>	Podcasts <sub>broad</sub>	
(a) Bi-Encoder <sub>CtrlQGen<sub>broad</sub></sub>	<b>0.074</b> <sup>bcdef</sup>	0.800 <sup>ef</sup>	0.596 <sup>b</sup>	0.831 <sup>bf</sup>	
(b) Bi-Encoder <sub>Click</sub>	$0.035^{def}$	$0.756^{f}$	0.878	0.846	
(c)Bi-Encoder <sub>CtrlQGenboth</sub>	$0.033^{def}$	$0.780^{f}$	0.492 abef	$0.831^{bf}$	
(d) Bi-Encoder <sub>InPars</sub> [15]	0.010	<b>0.827</b> <sup>cef</sup>	<b>0.489</b> <sup>abcef</sup>	<b>0.816</b> <sup>abcf</sup>	
(e) Bi-Encoder <sub>OGen</sub> [40]	0.009	$0.744^{f}$	$0.540^{ab}$	$0.820^{abcf}$	
(f) Bi-Encoder <sub>CtrlQGennarrow</sub>	0.003	0.609	0.517 <sup>abe</sup>	0.835 <sup>b</sup>	

shows that a model trained on synthetic queries from CtrlQGen gets significantly better when we include broader queries in the training (going from 0, 50 and 100% on rows f, c and a).

A model trained only on synthetic broad queries outperforms a model trained on Click data by 111% of R@100 for Tracks<sub>broad</sub> with statistical significance (row *a* vs row *b*). We also observe significant drops in the retrievability bias when we compare models trained with CtrlQGen queries with models trained with Click data, going from 0.878 to 0.596 and from 0.846 to 0.831 as seen in Table 3 (row *a* vs row *b*). Baseline models to generate queries (rows *d* and *e*) also have significantly less retrievability bias than the model trained on click data (row *b*) **showing again positive evidence for our first hypothesis** that models trained on synthetic queries lead to less retrievability bias. **Contribution of each module of CtrlQGen**. When using the set of queries generated by WeakLabeling–Un(no supervision available) to train the dense retriever, we get statistically significant improvements over the model that is not fine-tuned (row *c* vs row *b*, going from 0.142 to 0.222 R@100 and from 0.323 to 0.465 R@100 for the Tracks and Podcasts datasets as seen in Table 2. Using the remaining components of CtrlQGen we obtain significant improvements over using solely WeakLabeling–Un. A natural question is from which modules the improvements are coming. To answer this question Table 4 displays an ablation study on the components of CtrlQGen. If we remove all components of CtrlQGen we end up with the baseline QGen (first line of the table). We incrementally add each component of the model in the following rows.

Table 4: Ablation study where we add components of the proposed CtrlQGen to QGen one at a time using Click validation sets which has predominantly narrow queries. We also report the effectiveness for the broad queries only datasets. The † superscripts indicate statistically significant improvements over QGen using students t-test at 0.95 confidence.

	Predominantly narrow queries					Broad queries				
		R@100↑			Gini ↓		R@100↑		Gini ↓	
	Tracks	Podcasts	Books	Tracks Podcasts Books		Tracks <sub>broad</sub>		Podcasts <sub>broad</sub>		
QGen [40]	0.289	0.512	0.756	0.701	0.674	0.766	0.009	0.744	0.540	0.820
+ (1) Serialization	<b>0.312</b> <sup>†</sup>	0.509	<b>0.761</b> <sup>†</sup>	<b>0.694</b> <sup>†</sup>	<b>0.666</b> <sup>†</sup>	<b>0.761</b> <sup>†</sup>	0.006	0.711	<b>0.528</b> <sup>†</sup>	0.824
+ (2a,3) Intent-aware Generation WeakLabeling-IP	<b>0.305</b> <sup>†</sup>	0.505	$0.761^\dagger$	<b>0.688</b> <sup>†</sup>	0.669 <sup>†</sup>	<b>0.756</b> <sup>†</sup>	0.008	0.751	$0.528^\dagger$	0.820
+ (2a,2b,3) Intent-aware Generation WeakLabeling-IP+WeakLabeling-Un	0.289	0.508	-	0.704	0.704	-	<b>0.036</b> <sup>†</sup>	<b>0.787</b> <sup>†</sup>	<b>0.486</b> <sup>†</sup>	0.829
+ (1,2a,3) CtrlQGen WeakLabeling-IP	<b>0.300</b> <sup>†</sup>	$0.522^{\dagger}$	<b>0.763</b> <sup>†</sup>	<b>0.694</b> <sup>†</sup>	0.676	<b>0.760</b> <sup>†</sup>	0.007	0.713	$0.522^\dagger$	0.822
+ (1,2a,2b,3) CtrlQGen WeakLabeling-IP+WeakLabeling-Un	0.283	0.490	-	0.701	0.674	-	<b>0.033</b> <sup>†</sup>	<b>0.780</b> <sup>†</sup>	<b>0.480</b> <sup>†</sup>	0.833

The main findings are that (I) the serialization component, where we indicate which the metadata columns and their respective values as opposed to values only, is beneficial for both R@100 and Gini for both the narrow evaluation set of queries and broad set of queries and (II) the WeakLabeling-Un is only beneficial for the broad set of queries as WeakLabeling-IP cover narrow queries well (they are the majority of the available existing queries).

## 5.2 H2: Modifying the Set of Queries by Suggesting Generated Queries

In order to test our second hypothesis that suggesting broad queries with CtrlQGen leads to less retrievability bias compared to the queries found in the logs, we rely on a simulation where a percentage of suggested queries are accepted and added into the set of queries as described in Section 3.2.2. For each entity in the top-5 ranked list for the log queries we create 3 query suggestions.

Figure 4 displays the results of this simulation. We see that if the Bi-Encoder is trained on a set of broad queries, the retrievability of the system drops significantly as higher percentages of suggested broad queries by CtrlQGen are accepted, with decreases of Gini up to 11% and 7% for Tracks and Podcasts *showing positive evidence for our second hypothesis*. If we consider that all queries are accepted by the users a total of 78k (11%) entities for the Tracks dataset would become retrievable, i.e. retrievability different than zero, compared to using CtrlQGen<sub>both</sub> with the log queries. We also see that only modifying the set of queries is not enough, as a Bi-Encoder trained on the Click data does not achieve the same effect, showing that it is also necessary to employ a model that was trained for both narrow and broad queries.

## 6 CONCLUSION

We propose here CtrlQGen, a new approach to generate synthetic queries for entities that allows to control for the query intent and

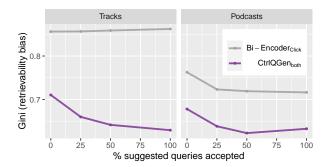


Figure 4: Suggesting broad queries with CtrlQGen reduces the retrievability of a model trained on synthetic data.

that can work in the absence of annotated data through the use of a weak-labeling function that leverages content metadata. We study the impact that the generated queries have on decreasing the retrievability bias and effectiveness, i.e. on helping the search engine surface more entities while avoiding negative effects on the relevance of results. Our experimental results in three different domains show that training dense retrieval models on synthetic queries from CtrlQGen leads to significant decreases in the retrievability bias of the system with comparable effectiveness. We also demonstrate how to reduce the retrievability bias by suggesting queries generated by CtrlQGen.

As future work, we believe important directions to be: (I) taking into account the interplay between recommendation and search in the measure of the accessibility of an entity, (II) improving the representation of entities for which most metadata information is not available and (III) study methods to reduce the retrievability of a system for re-ranking scenarios (IV) study the impact of increased content retrievability on content discovery.

WWW '23, May 1-5, 2023, Austin, TX, USA

## REFERENCES

- Maryam Aziz, Alice Wang, Aasish Pappu, Hugues Bouchard, Yu Zhao, Benjamin Carterette, and Mounia Lalmas. 2021. Leveraging Semantic Information to Facilitate the Discovery of Underserved Podcasts. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management. 3707–3716.
- [2] Leif Azzopardi and Maarten De Rijke. 2006. Automatic construction of knownitem finding test beds. In Proceedings of the 29th annual international ACM SIGIR conference on Research and Development in Information Retrieval. 603–604.
- [3] Leif Azzopardi, Maarten De Rijke, and Krisztian Balog. 2007. Building simulated queries for known-item topics: an analysis using six european languages. In Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval. 455–462.
- [4] Leif Azzopardi and Vishwa Vinay. 2008. Accessibility in information retrieval. In European Conference on Information Retrieval. Springer, 482–489.
- [5] Leif Azzopardi and Vishwa Vinay. 2008. Retrievability: An evaluation measure for higher order information access tasks. In Proceedings of the 17th ACM conference on Information and knowledge management. 561–570.
- [6] Peter Bailey, Alistair Moffat, Falk Scholer, and Paul Thomas. 2017. Retrieval consistency in the presence of query variations. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval. 395–404.
- [7] David Bainbridge, Sally Jo Cunningham, and J Stephen Downie. 2003. How people describe their music information needs: A grounded theory analysis of music queries. (2003).
- [8] Shariq Bashir and Andreas Rauber. 2010. Improving retrievability of patents in prior-art search. In European Conference on Information Retrieval. Springer, 457–470.
- [9] Shariq Bashir and Andreas Rauber. 2017. Retrieval Models Versus Retrievability. In Current Challenges in Patent Information Retrieval. Springer, 185–212.
- [10] Elias Bassani and Gabriella Pasi. 2021. Semantic Query Labeling Through Synthetic Query Generation. In Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval (Virtual Event, Canada) (SIGIR '21). Association for Computing Machinery, New York, NY, USA, 2278–2282. https://doi.org/10.1145/3404835.3463071
- [11] Nicholas J. Belkin, Paul Kantor, Edward A. Fox, and Joseph A Shaw. 1995. Combining the evidence of multiple query representations for information retrieval. *Information Processing & Management* 31, 3 (1995), 431–448.
- [12] Rodger Benham, Joel Mackenzie, Alistair Moffat, and J Shane Culpepper. 2019. Boosting search performance using query variations. ACM Transactions on Information Systems (TOIS) 37, 4 (2019), 1–25.
- [13] Toine Bogers and Marijn Koolen. 2018. "I'm looking for something like...": Combining Narratives and Example Items for Narrative-driven Book Recommendation. In Knowledge-aware and Conversational Recommender Systems Workshop. CEUR Workshop Proceedings.
- [14] Toine Bogers and Vivien Petras. 2017. Supporting book search: A comprehensive comparison of tags vs. controlled vocabulary metadata. *Data and Information Management* 1, 1 (2017), 17–34.
- [15] Luiz Bonifacio, Hugo Abonizio, Marzieh Fadaee, and Rodrigo Nogueira. 2022. InPars: Unsupervised Dataset Generation for Information Retrieval. In Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval. 2387–2392.
- [16] Huanhuan Cao, Daxin Jiang, Jian Pei, Qi He, Zhen Liao, Enhong Chen, and Hang Li. 2008. Context-aware query suggestion by mining click-through and session data. In Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining. 875–883.
- [17] Messaoud Chaa, Omar Nouali, and Patrice Bellot. 2018. Combining tags and reviews to improve social book search performance. In *International Conference* of the Cross-Language Evaluation Forum for European Languages. Springer, 64–75.
- [18] Anirban Chakraborty, Debasis Ganguly, and Owen Conlan. 2020. Retrievability based document selection for relevance feedback with automatically generated query variants. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management. 125–134.
- [19] Sukmin Cho, Soyeong Jeong, Wonsuk Yang, and Jong C Park. 2022. Query Generation with External Knowledge for Dense Retrieval. In Proceedings of Deep Learning Inside Out (DeeLIO 2022): The 3rd Workshop on Knowledge Extraction and Integration for Deep Learning Architectures. 22–32.
- [20] Zhuyun Dai, Vincent Y Zhao, Ji Ma, Yi Luan, Jianmo Ni, Jing Lu, Anton Bakalov, Kelvin Guu, Keith B Hall, and Ming-Wei Chang. 2022. Promptagator: Few-shot Dense Retrieval From 8 Examples. arXiv preprint arXiv:2209.11755 (2022).
- [21] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018).
- [22] Luis Fernando Gamboa, Andrés García-Suaza, and Jesús Otero. 2010. Statistical inference for testing Gini coefficients: An application for Colombia. *Ensayos* sobre Politica Economica 28, 62 (2010), 226–241.

- [23] Jean Garcia-Gathright, Brian St. Thomas, Christine Hosey, Zahra Nazari, and Fernando Diaz. 2018. Understanding and evaluating user satisfaction with music discovery. In The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval. 55–64.
- [24] Joseph L Gastwirth. 1972. The estimation of the Lorenz curve and Gini index. The review of economics and statistics (1972), 306–316.
- [25] Derek Greene and Pádraig Cunningham. 2013. Discovering latent patterns from the analysis of user-curated movie lists. arXiv preprint arXiv:1308.5125 (2013).
- [26] Fred X Han, Di Niu, Kunfeng Lai, Weidong Guo, Yancheng He, and Yu Xu. 2019. Inferring search queries from web documents via a graph-augmented sequence to attention network. In *The World Wide Web Conference*. 2792–2798.
- [27] Christine Hosey, Lara Vujović, Brian St. Thomas, Jean Garcia-Gathright, and Jennifer Thom. 2019. Just give me what I want: How people use and evaluate music search. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 1–12.
- [28] Rosie Jones, Ben Carterette, Ann Clifton, Maria Eskevich, Gareth JF Jones, Jussi Karlgren, Aasish Pappu, Sravana Reddy, and Yongze Yu. 2021. TREC 2020 podcasts track overview. arXiv preprint arXiv:2103.15953 (2021).
- [29] Jaehun Kim, Julián Urbano, Cynthia Liem, and Alan Hanjalic. 2020. One deep music representation to rule them all? A comparative analysis of different representation learning strategies. *Neural Computing and Applications* 32, 4 (2020), 1067–1093.
- [30] Marijn Koolen, Toine Bogers, Maria Gäde, Mark Hall, Iris Hendrickx, Hugo Huurdeman, Jaap Kamps, Mette Skov, Suzan Verberne, and David Walsh. 2016. Overview of the CLEF 2016 social book search lab. In *International conference of the cross-language evaluation forum for European languages*. Springer, 351–370.
- [31] Ravi Kumar, Silvio Lattanzi, and Prabhakar Raghavan. 2011. An algorithmic treatment of strong queries. In Proceedings of the fourth ACM international conference on Web search and data mining. 775–784.
- [32] Audrey Laplante. 2008. Everyday life music information-seeking behaviour of young adults: an exploratory study. (2008).
- [33] Ang Li, Jennifer Thom, Praveen Chandar, Christine Hosey, Brian St Thomas, and Jean Garcia-Gathright. 2019. Search mindsets: Understanding focused and nonfocused information seeking in music search. In *The World Wide Web Conference*. 2971–2977.
- [34] Ruohan Li, Jianxiang Li, Bhaskar Mitra, Fernando Diaz, and Asia J Biega. 2022. Exposing Query Identification for Search Transparency. In Proceedings of the ACM Web Conference 2022. 3662–3672.
- [35] Davis Liang, Peng Xu, Siamak Shakeri, Cicero Nogueira dos Santos, Ramesh Nallapati, Zhiheng Huang, and Bing Xiang. 2020. Embedding-based zero-shot retrieval through query generation. arXiv preprint arXiv:2009.10270 (2020).
- [36] Yen-Chieh Lien, Rongting Zhang, F Maxwell Harper, Vanessa Murdock, and Chia-Jung Lee. 2022. Leveraging Customer Reviews for E-commerce Query Generation. In European Conference on Information Retrieval. Springer, 190–198.
- [37] Jimmy Lin, Rodrigo Nogueira, and Andrew Yates. 2021. Pretrained transformers for text ranking: Bert and beyond. Synthesis Lectures on Human Language Technologies 14, 4 (2021), 1–325.
- [38] Binsheng Liu, Xiaolu Lu, and J Shane Culpepper. 2021. Strong natural language query generation. *Information Retrieval Journal* 24, 4 (2021), 322–346.
- [39] Yidan Liu, Min Xie, and Laks VS Lakshmanan. 2014. Recommending user generated item lists. In Proceedings of the 8th ACM Conference on Recommender systems. 185–192.
- [40] Ji Ma, Ivan Korotkov, Yinfei Yang, Keith Hall, and Ryan McDonald. 2020. Zeroshot neural passage retrieval via domain-targeted synthetic question generation. arXiv preprint arXiv:2004.14503 (2020).
- [41] Craig Macdonald and Nicola Tonellotto. 2020. Declarative Experimentation inInformation Retrieval using PyTerrier. In Proceedings of ICTIR 2020.
- [42] Rishabh Mehrotra. 2021. Algorithmic Balancing of Familiarity, Similarity, & Discovery in Music Recommendations. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management. 3996–4005.
- [43] Qiaozhu Mei, Dengyong Zhou, and Kenneth Church. 2008. Query suggestion using hitting time. In Proceedings of the 17th ACM conference on Information and knowledge management. 469–478.
- [44] Rodrigo Nogueira, Jimmy Lin, and AI Epistemic. 2019. From doc2query to docTTTTTquery. Online preprint 6 (2019).
- [45] Rodrigo Nogueira, Wei Yang, Jimmy Lin, and Kyunghyun Cho. 2019. Document expansion by query prediction. arXiv preprint arXiv:1904.08375 (2019).
- [46] Gustavo Penha, Arthur Câmara, and Claudia Hauff. 2022. Evaluating the robustness of retrieval pipelines with query variation generators. In European Conference on Information Retrieval. Springer, 397–412.
- [47] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. arXiv preprint arXiv:1910.10683 (2019).
- [48] Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics. https://arxiv.org/abs/1908.10084

- [49] Stephen E Robertson and Steve Walker. 1994. Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval. In SIGIR'94. Springer, 232–241.
- [50] Dwaipayan Roy, Zeljko Carevic, and Philipp Mayr. 2022. Studying retrievability of publications and datasets in an integrated retrieval system. arXiv preprint arXiv:2205.00937 (2022).
- [51] Bruno Sguerra, Marion Baranes, Romain Hennequin, and Manuel Moussallam. 2022. Navigational, Informational or Punk-Rock? An Exploration of Search Intent in the Musical Domain. In Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization. 202–211.
- [52] Xinyao Shen, Jiangjie Chen, Jiaze Chen, Chun Zeng, and Yanghua Xiao. 2022. Diversified query generation guided by knowledge graph. In Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining. 897–907.
- [53] Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. 2020. Mpnet: Masked and permuted pre-training for language understanding. Advances in Neural Information Processing Systems 33 (2020), 16857–16867.
- [54] Giorgos Stamatelatos, George Drosatos, Sotirios Gyftopoulos, Helen Briola, and Pavlos S Efraimidis. 2021. Point-of-interest lists and their potential in recommendation systems. *Information Technology & Tourism* 23, 2 (2021), 209–239.
- [55] Ning Su, Jiyin He, Yiqun Liu, Min Zhang, and Shaoping Ma. 2018. User intent, behaviour, and perceived satisfaction in product search. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining. 547–555.
- [56] Nandan Thakur, Nils Reimers, Andreas Rücklé, Abhishek Srivastava, and Iryna Gurevych. 2021. BEIR: A heterogenous benchmark for zero-shot evaluation of information retrieval models. arXiv preprint arXiv:2104.08663 (2021).
- [57] Federico Tomasi, Rishabh Mehrotra, Aasish Pappu, Judith Bütepage, Brian Brost, Hugo Galvão, and Mounia Lalmas. 2020. Query Understanding for Surfacing Under-served Music Content. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management. 2765–2772.
- [58] Irfan Ullah and Shah Khusro. 2020. Social book search: the impact of the social web on book retrieval and recommendation. *Multimedia Tools and Applications* 79, 11 (2020), 8011–8060.
- [59] Irfan Ullah, Shah Khusro, and Ibrar Ahmad. 2021. Improving social book search using structure semantics, bibliographic descriptions and social metadata. *Multimedia Tools and Applications* 80, 4 (2021), 5131–5172.
- [60] Mengting Wan and Julian J. McAuley. 2018. Item recommendation on monotonic behavior chains. In Proceedings of the 12th ACM Conference on Recommender Systems, RecSys 2018, Vancouver, BC, Canada, October 2-7, 2018, Sole Pera, Michael D. Ekstrand, Xavier Amatriain, and John O'Donovan (Eds.). ACM, 86–94. https://doi.org/10.1145/3240323.3240369
- [61] Kexin Wang, Nandan Thakur, Nils Reimers, and Iryna Gurevych. 2021. Gpl: Generative pseudo labeling for unsupervised domain adaptation of dense retrieval. arXiv preprint arXiv:2112.07577 (2021).
- [62] Colin Wilkie and Leif Azzopardi. 2013. Relating retrievability, performance and length. In Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval. 937–940.
- [63] Colin Wilkie and Leif Azzopardi. 2014. A retrievability analysis: Exploring the relationship between retrieval bias and retrieval performance. In Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management. 81–90.
- [64] Shengyao Zhuang, Houxing Ren, Linjun Shou, Jian Pei, Ming Gong, Guido Zuccon, and Daxin Jiang. 2022. Bridging the Gap Between Indexing and Retrieval for Differentiable Search Index with Query Generation. arXiv preprint arXiv:2206.10128 (2022).
- [65] Guido Zuccon, Joao Palotti, and Allan Hanbury. 2016. Query variations and their effect on comparing information retrieval systems. In Proceedings of the 25th ACM International on Conference on Information and Knowledge Management. 691–700.

## A UNSUPERVISED WEAK LABELING FUNCTIONS

In this appendix, we define the functions used in WeakLabeling-Un.

## A.1 Random Terms Selection

Samples words from the entity *e*, given possible *P* length percentages for the query with probability *Pr*.

```
def sample_words(e, P, Pr):
words = tokenize(e)
p_words_to_sample = np.random.choice(P, 1, p=Pr)
n = int(len(words) * p_words_to_sample)
words = np.random.choice(words, n, replace=False)
return words
```

## A.2 Query Variation Ordering

Generates a query variation by shuffling two random words from the query.

```
def qv_ordering(q):
words = tokenize(q)
idxs = [i for i in range(0, len(words))]
p1, p2 = np.random.choice(idxs, 2, replace=False)
words[p1], words[p2] = words[p2], words[p1]
return " ".join(words)
```

## A.3 Query Variation Misspelling

Generates a query variation by adding a misspelling error with *P* probabilities of removing and addition.

```
def qv_misspelling(q, P):
t = np.random.choice(["rem", "mdf"], 1, p=P)
idxs=[i for i in range(len(query))]
l=string.ascii_letters
if t == "rem":
    idx_rem = np.random.choice(idxs, 1)[0]
    qv = q[0:idx_rem] + q[idx_rem+1:]
elif t == "mdf":
    idx_mdf = np.random.choice(idxs, 1)[0]
    char_add = np.random.choice(len(1), 1)[0]
    qv = q[0:idx_mdf] + 1[char_add] + q[idx_mdf+1:]
return av
```

## A.4 Query Variation Prefix

Generates a query variation by removing *P* percentages of the suffix of the query with probabilities *Pr*.

```
def qv_prefix_query(q, P, Pr):
rem = np.random.choice(P, 1, p=Pr)
return q[:int((1-rem)*len(q))]
```

## A.5 Query from Free-Text Column by Summarization

Generates a query by summarizing the value of a free-text column (*broad-fields-ft*). For our experiments we rely on the pre-trianed summarizer model *snrspeaks/t5-one-line-summary*<sup>16</sup>.

## B BIAS MITIGATION FOR THE CLICK DATASET

In this appendix, we investigate if it is possible to mitigate the biases of the Click data with a simpler approach.

When fine-tuning the Bi-Encoder with Click data in our experiments we do not employ the same combination of queries and entities twice, even if that pair is highly popular in the logs. This is already a way of reducing the bias in the Click dataset. However, there are still many query variations that lead to the same entities, i.e. queries with different forms but with the same underlying information need, which are not removed when we get distinct queries for training. In order to mitigate this bias from the Click data by removing multiple queries that lead to the same entity, we

<sup>&</sup>lt;sup>16</sup>https://huggingface.co/snrspeaks/t5-one-line-summary

randomly select only one of the queries for each entity to train the Bi-Encoder model on.

The result of this experiment is that such a bias mitigation strategy indeed improves the retrievability of the system: the Gini scores go from 0.856 to 0.803 for Tracks and from 0.763 to 0.713 for Podcasts. However the mitigated Click data approach still leads to 30% and 5% more retrievability bias than CtrlQGen, for Tracks and Podcasts respectively.

### C SCALING INPARS WITH GPT-3

In this appendix, we test if increasing the model size of the InPars model using GPT-3 as the language model has a significant effect on the Bi-Encoder trained with such synthetic queries.

We see from 5 that this is not the case for both datasets, and the highest R@100 is reached when using the 1.2B GPT-3 model (*babbage-001*). Similar results were found in the InPars paper [15].

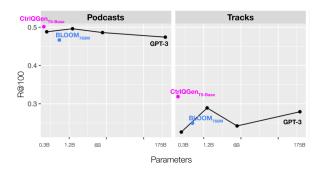


Figure 5: Scaling InPars baseline using GPT-3.

## D OVERLAP OF GENERATED QUERIES

In this appendix, we check if the queries generated by CtrlQGen have a significant overlap with either the log queries (is CtrlQGen just copying existing queries?) or with the input entity (is CtrlQGen just copying words from the input entity?).

## D.1 With log queries from Click

Out of the 10k narrow queries generated by CtrlQGen to test the first hypothesis (results from Tables 2), there are only 6% and 12% exact matches with set of queries from the logs (Click) for the Tracks and Podcasts datasets respectively. For the second hypothesis, out of the 376k broad queries generated, there are only 2% and 1% are exact matches with the set of queries from the logs. This shows the diversity of the generated queries from the log.

## D.2 With the input entity

Out of the 10k narrow queries generated by CtrlQGen to test the first hypothesis, 25% and 48% are not a subset of the serialized entity for Tracks and Podcasts datasets respectively. For the second hypothesis, out of the 376k broad queries generated, a total of 70% of queries are not subsets of the serialized entity for both datasets. This shows that while for narrow queries substrings of the entity are the majority of the cases when generating broad queries this

is not the case. Also, this indicates that for both cases the model is not always selecting parts of the input as the query.

## **E DATASET DETAILS**

For the Books dataset, we take into account the top two most-voted reviews and use the first 50 tokens. For the Tracks dataset, we use the first lyric line and the most frequent lyric line and employ a maximum of 25 descriptors. For the Podcasts dataset, we use the first 50 tokens of the description and of the transcript. For the Books and Tracks datasets we use a maximum of 25 playlists.