IntenT5: Search Result Diversification using Causal Language Models

Sean MacAvaney, Craig Macdonald, Roderick Murray-Smith, Iadh Ounis
{sean.macavaney,craig.macdonald,roderick.murray-smith,iadh.ounis}@glasgow.ac.uk
University of Glasgow
Glasgow, UK

ABSTRACT

Search result diversification is a beneficial approach to overcome under-specified queries, such as those that are ambiguous or multi-faceted. Existing approaches often rely on massive query logs and interaction data to generate a variety of possible query intents, which then can be used to re-rank documents. However, relying on user interaction data is problematic because one first needs a massive user base to build a sufficient log; public query logs are insufficient on their own. Given the recent success of causal language models (such as the Text-To-Text Transformer (T5) model) at text generation tasks, we explore the capacity of these models to generate potential query intents. We find that our method (which we call IntenT5) improves search result diversity and attains (and sometimes exceeds) the diversity obtained when using query suggestions based on a proprietary query log. Our analysis shows that our approach is most effective for multi-faceted queries and is able to generalize effectively to queries that were unseen in training data.

1 INTRODUCTION

Although contextualized language models (such as BERT [19] and T5 [42]) have been shown to be highly effective at adhoc ranking [30, 36, 37], they perform best with queries that give adequate context, such as natural-language questions [16]. Despite the rise of more expressive querying techniques (such as in conversational search systems [41]), keyword-based querying remains a popular choice for users.1 However, keyword queries can often be under-specified, giving rise to multiple possible interpretations or intents [8]. Unlike prior lexical models, which do not account for word senses or usage in context, contextualized language models are prone to scoring based on a single predominant sense, which can hinder search result quality for under-specified queries. For instance, the results in Figure 1(a) are all similar and do not cover a variety of information needs.

Under-specified queries can be considered ambiguous and/or faceted [12]. For ambiguous queries, intents are distinct and often correspond to different word senses. For example, the query “penguins” may refer to either the animal or the American ice hockey team (among other senses). In Figure 1, we see that the monoT5 model [37] only identifies passages for the former sense in the top results. In fact, the first occurrence of a document about the hockey team is ranked at position 158, likely meaning that users with this

1 https://trends.google.com

Permission to make digital or hard copies of part or all 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 third-party components of this work must be honored. For all other uses, contact the owner/author(s).
We fine-tune the model on a moderately-sized collection of queries without needing a massive amount of interaction data is desirable. (ORCAS [15]), and evaluate using 6 TREC diversity benchmark algorithms, or using the “gold” intents used for diversity evaluation [18].

Thus, an effective approach for generating potential query intents for search result diversification (Section 2.2), and neural ranking (Section 2.3).

2 BACKGROUND AND RELATED WORK

In this section, we cover background and prior work related to search result diversification (Section 2.1), causal language modeling (Section 2.2), and neural ranking (Section 2.3).

2.1 Search Result Diversification

Search result diversification techniques aim to handle ambiguous queries. Early works aimed to ensure that the retrieved documents addressed distinct topics - for instance, Maximal Marginal Relevance (MMR) [4] can be used to promote documents that are relevant to the user’s query, but are dissimilar to those documents already retrieved. In doing so, the typical conventional document independence assumption inherent to the Probability Ranking Principle is relaxed. Indeed, by diversifying the topics covered in the top-ranked documents, diversification approaches aim to address the risk that there are no relevant documents retrieved for the user’s information need [48]. Other approaches such as IA-Select used category hierarchies to identify documents with different intents [1].

Given an under-specified (ambiguous or multi-faceted) query \( q \) and a candidate set of documents \( d \), the potential query intents \( \{i_1, i_2, ..., i_d\} \) can be identified as sub-queries, i.e., query formulations that more clearly identify relevant documents about a particular interpretation of the query. These intents are usually identified from interaction data, such as query logs [43]. In academic research, query suggestions from major search engines often serve as a stand-in for this process [18, 43]. The candidate documents are re-scored for each of the intents. The scores from the individual intents are then aggregated into a final re-ranking of documents, using an algorithm such as xQuAD or PM2.

Aggregation strategies typically attempt to balance relevance and novelty. xQuAD [43] iteratively selects documents that exhibit

Figure 2: Overview of our search result diversification system using IntenT5 to generate potential query intents.
high relevance to the original query and are maximally relevant to the set of intents. As documents are selected, the relevance scores of documents to intents already shown are marginalized. The balance between relevance to the original query and the intents are controlled with a parameter $\lambda$. PM2 [18] is an aggregation strategy based on a proportional representation voting scheme. This aggregation strategy ignores relevance to the original query, and iteratively selects the intent least represented so far. The impact of the selected intent and the intents that are not selected when choosing the next document is controlled with a parameter $\lambda$ (not to be confused with xQuAD’s $\lambda$).

More recently, there has been a family of work addressing learned models for diversification [20, 49, 51]; we see this as orthogonal to our work here, since we do not consider learned diversification approaches. Indeed, in this work, we study the process of query intent generation for search result diversification, rather than aggregation strategies. For further information about search result diversification, see [44].

### 2.2 Causal Language Modeling

Causal Language Models (CLMs) predict the probability of a token $w_k$ given the prior tokens in the sequence: $P(w_k|w_{k-1}, w_{k-2}, \ldots, w_1)$. This property makes a CLM able to generate text: by providing a prompt, the model can iteratively predict a likely sequence of following tokens. However, a complete search of the space is exponential because the probability of each token depends on the preceding generated tokens. Various strategies exist for pruning this space. A popular approach for reducing the search space is a beam search, where a fixed number of high-probability sequences are explored in parallel. Alternative formulations, such as Diverse Beam Search [46] have been proposed, but we found these techniques unnecessary for short texts like queries. We refer the reader to Meister et al. [32] for more details about beam search and text generation strategies.

While CLMs previously accomplished modeling with recurrent neural networks [24, 33], this modeling has recently been accomplished through transformer networks [17]. Networks pre-trained with a causal language modeling objective, for instance T5 [42], can be an effective starting point for further task-specific training [42]. In the case of T5, specific tasks are also cast as sequence generation problems by encoding the source text and generating the model prediction (e.g., a label for classification tasks).

In this work, we explore the capacity of CLMs (T5 in particular) for generating a diverse set of possible query intents. This differs from common uses of CLMs insofar as predicting a single token (‘true’ or ‘false’ for relevance) given the text of the query and document and a prompt. Here, the probability of ‘true’ is used as the ranking score. Doc2Query models [38, 39] generate possible queries, conditioned on document text, to include in an inverted index.

Unlike prior neural ranking efforts, we focus on diversity ranking, rather than adhoc ranking. Specifically, we use a neural CLM to generate possible query intents given a query text, which differs from prior uses of CLMs in neural ranking. These query intents are then used to score and re-rank documents. To our knowledge, this is the first usage of neural ranking models for diversity ranking. For further details on neural ranking and re-ranking models, see [27, 34].

### 3 Generating Query Intents

In this section, we describe our proposed IntenT5 model for query intent generation (Section 3.1), as well as two model adaptations intended to improve the handling of ambiguous queries: distributional causal language modeling (Section 3.2) and representation swapping (Section 3.3).

#### 3.1 IntenT5

Recall that we seek to train a model that can be used to generate potential query intents. We formulate this task as a sequence-to-sequence generation problem by predicting additional terms for the user’s initial (under-specified) query.

We first fine-tune a T5 [42] model using a causal language modeling objective over a collection of queries. Note that this training approach does not require search frequency, session, or click information; it only requires a collection of query text. This makes a variety of data sources available for training, such as the ORCAS [15] query collection. This is a desirable quality because releasing query text poses fewer risks to personal privacy than more extensive interaction information.

Recall that for a sequence $w$ consisting of $k$ tokens, causal language models optimize for $P(w_k|w_{k-1}, w_{k-2}, \ldots, w_1)$. To generate intents, we use a beam search to identify highly-probable sequences. No length penalization is applied, but queries are limited to 10 generated tokens. We apply basic filtering techniques to remove generated intents that do not provide adequate additional context. In particular, we first remove terms that appear in the original query.  

---

2We found that this covers the vast majority of cases for this task, in practice.
When training, the prefix tree is used to find all subsequent tokens we see that the prefix “Penguins are” diverges into a variety of we only consider exact term matches for this filter. We also discard Typical natural language prose, such as the type of text found in documents, lends itself well to CLM because the text quickly diverges into a multitude of meanings. For instance, in Figure 3, a DCLM objective optimizes for all possible subsequent tokens (e.g., “adaptation, animal, antarctica, etc.”) rather than implicitly learning this distribution over numerous training samples.

Figure 4: Graphical distinction between Causal Language Modeling (CLM, (a)) and our proposed Distributional Causal Language Modeling (DCLM, (b)). Given a prompt (e.g., ‘penguins’), a DCLM objective optimizes for all possible senses. Normally, the surrounding words in a piece of text offer adequate context to disambiguate word senses. However, short queries inherently lack such context. For instance, in the case where a query contains only a single term, we find that transformer models simply choose a predominant sense (e.g., the animal sense for the query “penguins”). When used with the IntenT5 model, we find that this causes the generated intents to lack diversity of word senses (we demonstrate this in Section 6). We introduce an approach we call Representation Swapping (RS) to overcome this issue.

RS starts by building a set of k prototype representations for each term in a corpus. For a given term, a random sample of passages from a corpus that contain the term are selected. Then, the term’s internal representations are extracted for each passage. Note that because of the context from other terms in the passage,

3.2 Distributional Causal Language Modeling

Typical natural language prose, such as the type of text found in documents, lends itself well to CLM because the text quickly diverges into a multitude of meanings. For instance, in Figure 3, we see that the prefix “Penguins are” diverges into a variety of sequences (e.g., “a group of,” “birds, not,” “carnivores with,” etc.). If structured by prefixes, this results in long chains of tokens. Keyword queries, on the other hand, typically have a hierarchical prefix-based nature. When structured as a tree, it tends to be shallow and dense. For instance, in Figure 3, a distribution of terms is likely to follow the prefix ‘penguins’ (e.g., adaptations, animals, hockey, etc.). Similarly, a distribution of terms follows the prefix ‘penguins hockey’ (e.g., game, live, news, score, etc.).

Based on this observation, we propose a new variant of Causal Language Modeling (CLM) designed for keyword queries: Distributional Causal Language Modeling (DCLM). In contrast with CLM, DCLM considers other texts in the source collection when building the learning objectives through the construction of a prefix tree. In other words, while CLM considers each sequence independently, DCLM builds a distribution of terms that follow a given prefix. Visually, the difference between the approaches are shown in Figure 4. When training, the prefix tree is used to find all subsequent tokens across the collection given a prefix and optimizes the output of the model to generate all these tokens (with equal probability). The training process for DCLM is given in Algorithm 1.

3.3 Representation Swapping

In a transformer model – which is the underlying neural architecture of T5 – tokens are represented as contextualized vector representations. These representations map tokens to a particular sense – this is exploited by several neural ranking models (like

Algorithm 1 DCLM Training Procedure

```
tree ← BuildPrefixTree(corpus)
repeat
  prefix ← (RandomSelect(tree.children))
  targets ← prefix.children
  while |prefix[−1].children| > 0 do
    Optimize P(prefix[−1].children|prefix)
    prefix = {prefix, RandomSelect(prefix[−1].children)}
  end while
until converged
```
these representations include the sense information. All of the these representations for a given term are then clustered into \( k \) clusters. A single prototype representation for each cluster is selected by finding the representation that is closest to the median value across the representations in the cluster. Using this approach, we find that the sentences from which the prototypes were selected often express different word senses. Finally, when processing a query, the IntenT5 model is executed multiple times: once with the original representation (obtained from encoding the query alone), and then \( k \) additional times for each term. In these instances, the internal representations of a given term are swapped with the prototype representation. This allows the T5 model to essentially inherit the context from the prototype sentence for the ambiguous query, and allows the model to generate text based on different senses. This approach only needs to be applied for shorter queries, since longer queries provide enough context on their own. This introduces a parameter \( l \), as the maximum query length. The final intents generated by the model are selected using a diversity aggregation algorithm like xQuAD, which ensures a good mix of possible senses in the generated intents.

4 EXPERIMENTAL SETUP

We experiment to answer the following research questions:

- **RQ1**: Can the intents generated from IntenT5 be used to diversify search results?
- **RQ2**: Do queries that appeared in the IntenT5 training data perform better than those that did not?
- **RQ3**: Does IntenT5 perform better at ambiguous or multi-faceted queries?
- **RQ4**: Does training with a distributional causal language modeling objective or performing representation swapping improve the quality of the generated intents?

4.1 IntenT5 Training and Settings

Although IntenT5 can be trained on any moderately large collection of queries, we train the model using the queries from the ORCAS [15] dataset. With 10.4M unique queries, this dataset is both moderately large\(^5\) and easily accessible to researchers without signed data usage agreements. The queries in ORCAS were harvested from the Bing logs, filtered down to only those where users clicked on a document found in the MS MARCO [3] document dataset. Queries in this collection contain an average of 3.3 terms, with the majority of queries containing either 2 or 3 terms. The IntenT5 model is fine-tuned from \( \text{t5-base} \) using default parameters (learning rate: \( 5 \times 10^{-5} \), 3 epochs, Adam optimizer).

When applying RS, we use \( k = 5 \), \( l = 1 \), xQuAD with \( \lambda = 1 \), and use agglomerative clustering, based on qualitative observations during pilot studies. We select 1,000 passages per term from the MS MARCO document corpus, so as not to potentially bias our results to our test corpora.

4.2 Evaluation

We evaluate the effectiveness of our approach on the TREC Web Track (WT) 2009–14 diversity benchmarks [8–11, 13], consisting of 300 topics and 1,090 sub-topics in total. Table 1 provides a summary of these datasets. These benchmarks span two corpora: WT09–12 use ClueWeb09-B (50M documents) and WT13–14 use ClueWeb12-B13 (52M documents). We use the keyword-based “title” queries, simulating a setting where the information need is under-specified. To the best of our knowledge, these are the largest and most extensive public benchmarks for evaluating search result diversification.

We measure system performance with three diversification-aware variants of standard evaluation measures: \( \alpha \)-nDCG@20 [7], ERR-IA@20 [5], and NRPB [12]. These are the official task evaluation metrics for WT10–14 (WT09 used \( \alpha \)-nDCG@20 and P-IA@20). \( \alpha \)-nDCG is a variant of nDCG [23] that accounts for the novelty of topics introduced. We use the default \( \alpha \) parameter (the probability of an incorrect positive judgment) of 0.5 for this measure. ERR-IA is a simple average over the Expected Reciprocal Rank of each intent, since WT09–14 weight the gold query intents uniformly. NRPB (Novelty-and-Rank-Biased Precision) is an extension of RBP [35], measuring the average utility gained as a user scans the search results. Metrics were calculated from the official task evaluation script \( \text{ndeval} \).\(^6\) Furthermore, as these test collections were created before the advent of neural ranking models, we also report the judgment rate among the top 20 results (\( \text{Judge}@20 \)) to ascertain the completeness of the relevance assessment pool in the presence of such neural models.

To test the significance of differences, we use paired t-tests with \( p < 0.05 \), accounting for multiple tests where appropriate with a Bonferroni correction. In some cases, we test for significant equivalences (i.e., that the means are the same). For these tests, we use a two-sided test (\( \text{TOST} \)) with \( p < 0.05 \). Following prior work using a TOST for retrieval effectiveness [31], we set the acceptable equivalence range to \( \pm 0.01 \).

4.3 Baselines

To put the performance of our method in context, we include several adhoc and diversity baselines. As adhoc baselines, we compare with DPH [2], a lexical model (we found it to perform better than BM25 in pilot studies), Vanilla BERT [30], monoT5 [37], and a ColBERT [25] re-ranker.\(^7\) Since the neural models we use have a maximum sequence length, we apply the MaxPassage [16] scoring approach. Passages are constructed using sliding windows of 150 tokens (stride 75). For Vanilla BERT, we trained a model on MS MARCO using the original authors’ released code. For monoT5 and ColBERT, we use versions released by the original authors that were trained on the MS MARCO dataset [3]. This type of zero-shot transfer

---

\(^{5}\) It is widely known that Google processes over 3B queries daily, with roughly 15% being completely unique.

\(^{6}\) https://trec.nist.gov/data/web/10/ndeval.c

\(^{7}\) We only use ColBERT in a re-ranking setting due to the challenge in scaling its space intensive dense retrieval indices to the very large ClueWeb datasets.
from MS MARCO to other datasets has generally shown to be effective [28, 37], and reduces the risk of over-fitting to the test collection.

**Google Suggestions.** We compare with the search suggestions provided by the Google search engine through their public API. Though the precise details of the system are private, public information states that interaction data plays a big role in the generation of their search suggestions [45], meaning that this is a strong baseline for an approach based on a query log. Furthermore, this technique was used extensively in prior search result diversification work as a source of query intents [18, 43]. Note that the suggestions are sensitive to language, geographic location and current trends; we use the suggestions in English for United States (since the TREC assessors were based in the US); we will release a copy of these suggestions for reproducibility.

**Gold Intents.** We also compare with systems that use the “Gold” intents provided by the TREC task. Note that this is not a realistic system, as these intents represent the evaluation criteria and are not known a priori. Furthermore, the text of these intents are provided in natural language (similar to TREC description queries), unlike the keyword-based queries they elaborate upon. Hence, these Gold intents are often reported to represent a potential upperbound on diversification effectiveness, however, later we will show that intents generated by IntenT5 can actually outperform these Gold intents.\(^8\)

### 4.4 Model Variants and Parameter Tuning

We aggregate the intents from IntenT5, Google suggestions, and the Gold intents using xQuAD [43] and PM2 [18], representing two strong unsupervised aggregation techniques.\(^9\) For all these models, we tune the number of generated intents and the aggregation \(\lambda\) parameter using a grid search over the remaining collections (e.g., WT09 parameters are tuned in WT10–14). We search between 1–20 intents (step 1) and \(\lambda\) between 0–1 (step 0.1). Neural models re-rank the top 100 DPH results. In summary, an initial pool of 100 documents is retrieved using DPH. Intents are then chosen using IntenT5 (or using the baseline methods). The documents are then re-scored for each intent using DPH, Vanilla BERT, monoT5, or ColBERT. The scores are then aggregated using xQuAD or PM2.

## 5 RESULTS

In this section, we provide results for research questions concerning the overall effectiveness of IntenT5 (Section 5.1), the impact of queries appearing in the training data (Section 5.2), the types of under-specification (Section 5.3) and finally the impact on ambiguous queries in particular (Section 5.4). Later in Section 6, we provide a qualitative analysis of the generated queries.

### 5.1 RQ1: IntenT5 Effectiveness

We present the diversification results for WT09–14 in Table 2. We generally find that our IntenT5 approach can improve the search result diversity for both lexical and neural models, when aggregating using either PM2 or xQuAD. In fact, there is only one setting (monoT5 scoring with xQuAD aggregation) where diversity is not significantly improved when using IntenT5. The overall best-performing result uses IntenT5 (ColBERT scoring with PM2 aggregation). These results also significantly outperform the corresponding versions that use Google suggestions and the Gold intents. Similarly, when using Vanilla BERT, IntenT5 also significantly outperforms the model using Google suggestions. For DPH and monoT5, the diversity effectiveness of IntenT5 is similar to that of the Google suggestions; the differences are not statistically significant. However, through equivalence testing using a TOST we find that there is insufficient evidence that the means are equivalent across all evaluation metrics. Curiously, both BERT-based models (Vanilla BERT and ColBERT) are more receptive to the IntenT5 queries than Google suggestions or Gold intents. This suggests that some underlying language models (here, BERT), may benefit more from artificially-generated intents than others.

---

\(^8\)For instance, this may be caused by an intent identified by an IntenT5 model resulting in a more effective ranking than the corresponding Gold intent.

\(^9\)Although “learning-to-diversify” approaches, such as M^3^Div [21], can be effective, our work focuses on explicit diversification. The explicit setting is advantageous because it allows for a greater degree of model interpretability and transparency with the user.

---

Table 2: Results over the combined TREC WebTrack 2009–14 diversity benchmark datasets. \(\alpha\)-nDCG, ERR-IA, and Judged are computed with a rank cutoff of 20. The highest value in each section is listed in bold. PM and xQ indicate the PM2 and xQuAD aggregators, respectively. Statistically significant differences between each value and the corresponding non-diversified baseline are indicated by \(^*\) (paired t-test, Bonferroni correction, \(p < 0.05\)).

| System   | Agg. | \(\alpha\)-nDCG | ERR-IA | NRBP | Judged |
|----------|------|-----------------|--------|------|--------|
| DPH      |      | 0.3969          | 0.3078 | 0.2609 | 62%    |
| + IntenT5 PM |    | 0.4213 *       | 0.3400 * | 0.3053 | 56%    |
| + Google Sug. PM | | 0.4232 *      | 0.3360 * | 0.3000 | 58%    |
| + Gold PM |      | 0.4566 *       | 0.3629 * | 0.3254 | 53%    |
| + IntenT5 xQ |    | 0.4049          | 0.3213 | 0.2845 | 58%    |
| + Google Sug. xQ | | 0.4203 *      | 0.3326 | 0.2963 | 59%    |
| + Gold xQ |      | 0.4545 *       | 0.3616 * | 0.3230 | 56%    |
| Vanilla BERT |  | 0.3790          | 0.2824 | 0.2399 | 54%    |
| + IntenT5 PM |    | 0.4364 *       | 0.3475 * | 0.3104 | 60%    |
| + Google Sug. PM | | 0.4110 *      | 0.3119 | 0.2689 | 57%    |
| + Gold PM |      | 0.4214 *       | 0.3214 * | 0.2803 | 50%    |
| + IntenT5 xQ |    | 0.4328 *       | 0.3448 * | 0.3085 | 59%    |
| + Google Sug. xQ | | 0.4120 *      | 0.3140 * | 0.2722 | 59%    |
| + Gold xQ |      | 0.4228 *       | 0.3236 * | 0.2813 | 55%    |
| monoT5   |      | 0.4271          | 0.3342 | 0.2943 | 58%    |
| + IntenT5 PM |    | 0.4510          | 0.3589 | 0.3213 | 58%    |
| + Google Sug. PM | | 0.4506          | 0.3567 | 0.3181 | 58%    |
| + Gold PM |      | 0.4722 *       | 0.3777 * | 0.3409 | 58%    |
| + IntenT5 xQ |    | 0.4444          | 0.3549 | 0.3183 | 58%    |
| + Google Sug. xQ | | 0.4492 *      | 0.3625 * | 0.3276 | 58%    |
| + Gold xQ |      | 0.4574 *       | 0.3696 * | 0.3353 | 58%    |
| ColBERT  |      | 0.4271          | 0.3334 | 0.2953 | 57%    |
| + IntenT5 PM |    | 0.4711 *       | 0.3914 * | 0.3616 | 58%    |
| + Google Sug. PM | | 0.4561          | 0.3654 | 0.3316 | 57%    |
| + Gold PM |      | 0.4548          | 0.3520 | 0.3106 | 51%    |
| + IntenT5 xQ |    | 0.4707 *       | 0.3890 * | 0.3584 | 63%    |
| + Google Sug. xQ | | 0.4552 *      | 0.3638 * | 0.3287 | 61%    |
| + Gold xQ |      | 0.4560          | 0.3608 | 0.3226 | 56%    |
Table 3: Diversification performance stratified by the frequency of the query text in ORCAS. Ranges were selected to best approximate 3 even buckets. Statistically significant differences between the unmodified system are indicated by * (paired t-test, Bonferroni correction, \( p < 0.05 \)).

| System    | Agg. | \( \alpha \)-nDCG@20 |
|-----------|------|----------------------|
|           | 0–1  | 2–37                | 38+          |
| DPH       | 0.4930 | 0.3876            | 0.3048       |
| + IntenT5 | PM 0.5217 * 0.4283 | 0.3901          |
| + Google Sug. | PM 0.5026 * 0.4435 | 0.3204          |
| + Gold    | PM 0.5311 * 0.4648 * 0.3704 |
| + IntenT5 | xQ 0.4970 * 0.4177 | 0.2960          |
| + Google Sug. | xQ 0.5004 * 0.4379 | 0.3192          |
| + Gold    | xQ 0.5259 * 0.4708 * 0.3640 |
| Vanilla BERT | 0.4467 | 0.3756            | 0.3112       |
| + IntenT5 | PM * 0.5043 * 0.4403 | 0.3615          |
| + Google Sug. | PM 0.4634 | 0.4186            | 0.3487          |
| + Gold    | PM * 0.4831 * 0.4290 | 0.3492          |
| + IntenT5 | xQ * 0.5041 * 0.4308 | 0.3598          |
| + Google Sug. | xQ 0.4853 | 0.4027            | 0.3439          |
| + Gold    | xQ * 0.4770 * 0.4362 | 0.3531          |
| monoT5    | 0.5080 | 0.4331            | 0.3364       |
| + IntenT5 | PM 0.5262 | 0.4707            | 0.3530          |
| + Google Sug. | PM 0.5305 | 0.4598            | 0.3577          |
| + Gold    | PM * 0.5421 * 0.4712 * 0.3997 |
| + IntenT5 | xQ 0.5180 | 0.4648            | 0.3474          |
| + Google Sug. | xQ 0.5217 | 0.4509            | 0.3714          |
| + Gold    | xQ 0.5270 | 0.4657            | 0.3762          |
| ColBERT   | 0.4938 | 0.4241            | 0.3600       |
| + IntenT5 | PM * 0.5484 * 0.4934 | 0.3685          |
| + Google Sug. | PM 0.5067 | 0.4625            | 0.3968          |
| + Gold    | PM 0.5254 | 0.4726            | 0.3635          |
| + IntenT5 | xQ * 0.5440 * 0.4868 | 0.3783          |
| + Google Sug. | xQ 0.5141 | 0.4631            | 0.3857          |
| + Gold    | xQ 0.5121 | 0.4874            | 0.3669          |

(Count) (105) (96) (99)

These results provide a clear answer to RQ1: the intents generated from IntenT5 can be used to significantly improve the diversity of search results. Further, they can also, surprisingly, outperform Google suggestions and Gold intents.

5.2 RQ2: Effect of Queries in Training Data

It is possible that the IntenT5 model simply memorizes the data that is present in the training dataset, rather than utilizing the language characteristics learned in the pre-training process to generalize to new queries. To investigate this, we stratify the dataset into three roughly equal-sized buckets representing the frequency that the query appears in ORCAS. We use simple case-insensitive string matching, and count matches if they appear anywhere in the text (not just at the start of the text). We find that roughly one third of the WebTrack diversity queries either do not appear at all in ORCAS, or only appear once. For these queries, IntenT5 is forced to generalize. The next bucket (2–37 occurrences in ORCAS) contains roughly the next third of the WebTrack queries, and 38 or more queries forms the final bucket. We present the results of this experiment in Table 3. Here, we find that our IntenT5 model excels at cases where it either needs to generalize (first bucket) or where memorization is manageable (second bucket); in 11 of the 16 cases, IntenT5 scores higher than the Google suggestions. Further, IntenT5 boasts the overall highest effectiveness in both buckets: 0.5484 and 0.4934, respectively (for ColBERT + IntenT5 + PM2). In the final case, where there are numerous occurrences in the training data, IntenT5 never significantly outperforms the baseline system. Unsurprisingly, Google suggestions score higher than IntenT5 for these queries (6 out of 8 cases). Since frequent queries in ORCAS are likely frequent in general, Google suggestions can exploit frequency information from their vast interaction logs (which are absent from ORCAS).

To gain more insights into the effects of training data frequency, we qualitatively evaluate examples of generated intents. For instance, the query "gmat prep classes" (which only occurs once in ORCAS, as a verbatim match), generates intents such as "requirements", "registration", and "training". Although these are not perfect matches with the Gold intents (companies that offer these courses, practice exams, tips, similar tests, and two navigational intents), they are clearly preferable to the Google suggestions, which focus on specific locations (e.g., "near me", "online", "chicago", etc.), and demonstrate the ability for the IntenT5 model to generalize. For the query "used car parts", which occurs in ORCAS 13 times, IntenT5 generates some of the queries found in ORCAS (e.g., "near me") but not others (e.g., "catalog"). For the query "toilets", which occurs 556 times in ORCAS, IntenT5 again generates some queries present in the training data (e.g., "reviews") and others that are not (e.g., "installation cost").

These results answer RQ2: IntenT5 effectively generalizes beyond what was seen in the training data. However, it can struggle with cases that occur frequently. This suggests that an ensemble approach may be beneficial, where intents for infrequent queries are generated from IntenT5, and intents for frequent queries are mined from interaction data (if available). We leave this to future work.

5.3 RQ3: Types of Under-specification

Recall that under-specified queries can be considered multi-faceted or ambiguous. To answer RQ3, we investigate the performance of IntenT5 on different types of queries, as indicated by the TREC labels. Note that WT13–14 also include a total of 49 queries that are fully specified ("single", e.g., "reviews of les miserables"). Table 4 provides these results. We find that IntenT5 excels at handling faceted queries, often yielding significant gains. When it comes to ambiguous queries, however, IntenT5 rarely significantly improves upon the baseline. Note that all intent strategies, including when using the Gold intents, struggle with ambiguous queries. However, we acknowledge that the ambiguous query set is rather small (only 62 queries). This could motivate the creation of a larger ambiguous web search ranking evaluation dataset in the future to allow further study of this interesting and challenging problem. Finally, we notice that IntenT5 can also improve the performance of the fully-specified queries, most notably for Vanilla BERT and ColBERT where the non-diversified models otherwise significantly underperform DPH.
Table 4: Diversification performance by query type. Significant differences between the unmodified system are indicated by * (paired t-test, Bonferroni correction, \( p < 0.05 \)).

| System | Agg.       | Faceted | Ambiguous | Single |
|--------|------------|---------|-----------|--------|
| DPH    | 0.3804     | 0.2525  | 0.6399    |        |
| monoT5 | 0.4093     | 0.2576  | 0.6711    |        |
| + DCLM | 0.4130     | 0.2629  | 0.6621    |        |
| + Gold | 0.4626     | 0.2908  | 0.6399    |        |
| IntenT5| 0.3922     | 0.2433  | 0.6550    |        |
| + Google Sug. | 0.4070 | 0.2724  | 0.6553    |        |
| + Gold | 0.4565     | 0.2997  | 0.6399    |        |
| Vanilla BERT | 0.3809 | 0.2501  | 0.5323    |        |
| IntenT5 | 0.4244     | 0.3087  | 0.6415    |        |
| + Google Sug. | 0.4149 | 0.2993  | 0.5353    |        |
| + Gold | 0.4392     | 0.2831  | 0.5253    |        |
| IntenT5 | 0.4214     | 0.2997  | 0.6421    |        |
| + Google Sug. | 0.4086 | 0.2970  | 0.5681    |        |
| + Gold | 0.4409     | 0.2850  | 0.5253    |        |
| monoT5 | 0.4184     | 0.3012  | 0.6172    |        |
| + IntenT5 | 0.4445     | 0.3165  | 0.6249    |        |
| + Google Sug. | 0.4405 | 0.3342  | 0.6340    |        |
| + Gold | 0.4802     | 0.3307  | 0.6177    |        |
| IntenT5 | 0.4363     | 0.3214  | 0.6285    |        |
| + Google Sug. | 0.4385 | 0.3327  | 0.6353    |        |
| + Gold | 0.4607     | 0.3182  | 0.6177    |        |
| ColBERT | 0.4237     | 0.3267  | 0.5655    |        |
| IntenT5 | 0.4629     | 0.3246  | 0.6848    |        |
| + Google Sug. | 0.4558 | 0.3198  | 0.6268    |        |
| + Gold | 0.4740     | 0.3068  | 0.5655    |        |
| IntenT5 | 0.4596     | 0.3355  | 0.6816    |        |
| + Google Sug. | 0.4536 | 0.3355  | 0.6102    |        |
| + Gold | 0.4775     | 0.3016  | 0.5655    |        |

Curiously, we do not observe similar behavior for monoT5, suggesting that this behavior may depend on the underlying language model (BERT vs. T5).

These results answer RQ3: IntenT5 improves the diversity of multi-faceted queries and even improves ColBERT’s performance for fully-specified queries. However, like alternative approaches, it struggles to generate effective intents for ambiguous queries.

5.4 RQ4: Handling Ambiguous Queries

Given that ambiguous queries appear to be difficult to handle, we investigate two proposed approaches for overcoming this problem: Distributional Causal Language Modeling (DCLM, introduced in Section 3.2) and Representation Swapping (RS, introduced in Section 3.3). Since monoT5 and ColBERT most effectively use IntenT5 on ambiguous queries, we focus our investigation on these models.

Table 5 presents the effectiveness of these approaches, stratified by query type. In general, we observe only marginal differences by using combinations of these approaches. The most effective combination for ambiguous queries (monoT5 + IntenT5 + DCLM + RS) is not significantly more effective than the monoT5 + IntenT5 + xQuAD.

Digging deeper into the queries generated for each approach, we find that there are indeed cases where the generated intents using DCLM and RS are substantially more diverse than the base IntenT5 model. The top intents generated for the query *penguins* by IntenT5 are *meaning*, *history*, *habitat*, *information*, and *definition*; in fact, all of the top 20 intents either relate to the animal (rather than the hockey team) or are very general. Meanwhile, DCLM overcomes many of the general intents, but the queries skew heavily toward the hockey team: *schedule*, *website*, *wikipedia*, *highlights*, and *merchandise*. This problem is addressed when applying both DCLM and RS, which generates: *wikipedia*, *tickets*, *population*, *schedule*, and *website*; it covers both senses. Despite the clear benefits for some queries, the approach can cause drift on other queries, and sometimes does not pick up on important intents. For instance, the intents generated for the query *iron* with IntenT5 + DCLM + RS focus heavily on the nutrient sense, and do not identify the element or appliance sense.

To answer RQ4, although approaches like DCLM and RS can improve the diversity in isolated cases, there is insufficient evidence that these approaches can improve ranking diversity overall. We also find no significant differences in effectiveness between the DCLM and RS approaches.

6 ANALYSIS

One advantage of performing search result diversification explicitly is that the generated intents are expressed in natural language and can be interpreted. In Table 6, we present the top 5 intents generated by our models, as well as the top query suggestions from Google. For the running example of *penguins*, we see that Google

| System   | Agg.       | Faceted | Ambiguous | Single |
|----------|------------|---------|-----------|--------|
| monoT5 + IntenT5 | 0.4445     | 0.3165  | 0.6429    |        |
| + DCLM   | 0.4424     | 0.3219  | 0.6628    |        |
| + RS     | 0.4481     | 0.3279  | 0.6297    |        |
| + DCLM + RS | 0.4457     | 0.3213  | 0.6173    |        |
| monoT5 + IntenT5 | 0.4363     | 0.3214  | 0.6285    |        |
| + DCLM   | 0.4333     | 0.3421  | 0.6469    |        |
| + RS     | 0.4341     | 0.3348  | 0.6040    |        |
| + DCLM + RS | 0.4324     | 0.3129  | 0.6249    |        |
| ColBERT + IntenT5 | 0.4629     | 0.3246  | 0.6848    |        |
| + DCLM   | 0.4339     | 0.3255  | 0.6584    |        |
| + RS     | 0.4185     | 0.3185  | 0.6556    |        |
| + DCLM + RS | 0.4420     | 0.3174  | 0.6556    |        |
| ColBERT + IntenT5 | 0.4596     | 0.3355  | 0.6816    |        |
| + DCLM   | 0.4469     | 0.3260  | 0.6795    |        |
| + RS     | 0.4564     | 0.3263  | 0.6816    |        |
| + DCLM + RS | 0.4478     | 0.3250  | 0.6795    |        |
Table 6: Top intents generated using our IntenT5 model and Google search suggestions.

| IntenT5                  | IntenT5 + DCLM + RS | Google Suggestions |
|--------------------------|---------------------|--------------------|
| **penguins**             |                     |                    |
| meaning wikipedia        | of madagascar       |                    |
| history tickets          | schedule            |                    |
| habitat population score |                     |                    |
| information schedule     | hockey              |                    |
| definition website game  |                     |                    |
| **mitchell college**     |                     |                    |
| football tuition baseball|                     |                    |
| meaning football covid vaccine|               |                    |
| address athletics        | athletics           |                    |
| basketball admissions    | basketball          |                    |
| website bookstore of business|                       |                    |
| **wendleton college**    | address tuition (none)|                     |
| football athletics       |                     |                    |
| website bookstore        |                     |                    |
| tuition faculty          |                     |                    |
| application address      |                     |                    |
| **electoral college**    | meaning wikipedia map|                   |
| definition meaning definition |                 |                    |
| florida definition map 2020|                 |                    |
| history articles         | definition government|                   |
| michigan election college votes|                 |                    |
| **solar panels**         | meaning installation for sale|            |
| explained installed for home|                 |                    |
| calculator installation cost cost|              |                    |
| installation on sale for rv|                |                    |
| home depot for home for house|              |                    |
| **condos in florida**    | for sale rentals on the beach|            |
| meaning beachfront for rent|                 |                    |
| near me for sale on the beach for sale|          |                    |
| reviews near me keys     |                     |                    |
| by owner reservations keys for sale|          |                    |
| **condos in new york**   | meaning for sale for rent|               |
| near me to rent zillow   |                     |                    |
| chicago address manhattan|                     |                    |
| florida weather state    |                     |                    |
| for sale nyc ny          |                     |                    |

identifies two senses (an animated film and the hockey team) while our model can identify the animal and the hockey team. For the query *mitchell college*, our model identifies several salient facets, as do the Google search suggestions. Note that this is not due to memorization; the only queries with the text *mitchell college* in the training collection are *william mitchell college of law* and *william mitchell college of law ranking*. This quality is appealing because it shows that the model is capable of generalizing beyond its training data. On the other hand, our model can be prone to constructing information, such as for the (fictitious) *wendleton college*. We see that these generalizations are not baked entirely into the prompt of college, however, given that the prefix *electoral college* (a process of the United States government) does not generate similar queries. These results provide qualitative evidence for our observations in Section 5.2; IntenT5 is able to effectively generalize beyond what is seen in the training data. However, we acknowledge that this quality may be undesirable in some circumstances. For the query *solar panels*, we see that our model can generate multi-word intents (which can be beneficial to neural models [16]), but can sometimes get stuck on common prefixes (e.g., “install”). We also find that our model can struggle with providing valuable recommendations based on a specified location. Although IntenT5 with DCLM and RS can predict salient intents like *beachfront* and *nyc* for the queries *condos in florida* and *condos in new york*, respectively, the base IntenT5 model relies primarily on generic intents, or even suggests alternative locations. Meanwhile, the Google suggestions are able to consistently provide location-specific intents. Overall, this analysis shows that IntenT5 generates intents that exhibit awareness of the query at hand, and that the DCLM and RS approaches can change the output of the model substantially. The intents are often comparable with those provided by a commercial search engine from interaction data.

7 CONCLUSIONS

We presented IntenT5, a new approach for generating potential query intents for explicit search result diversification. Across the TREC WebTrack 2009–2014 datasets (300 test queries in total), we found that this approach can significantly outperform other sources of query intents when used with unsupervised search result diversification algorithms and neural re-rankers, such as Vanilla BERT and ColBERT. Specifically, we observed up to a 15% relative improvement above query suggestions provided by Google (as measured by NRBK, when re-ranking with Vanilla BERT and aggregating with PM2). The proposed approach significantly improves the performance on multi-faceted queries and can even overcome shortcomings on fully-specified queries. We found that IntenT5 has difficulty handling ambiguous queries, and proposed two approaches for overcoming these ambiguities. Although we observed that these approaches can qualitatively improve the generated intents, we found insufficient evidence that these modifications are beneficial in aggregate. This motivates the creation of a larger and more extensive dataset of ambiguous queries for a future study. Importantly, we observed that our approach can generalize to queries that were not present in the training data. As the first work to investigate the use of contextualized language models in the context of search result diversification, we have laid the groundwork for investigating ongoing challenges, such as handling query terms with multiple senses.

ACKNOWLEDGMENTS

This work has been supported by EPSRC grant EP/R018634/1: Closed-Loop Data Science for Complex, Computationally- & Data-Intensive Analytics.

REFERENCES

[1] Rakesh Agrawal, Sreenivas Gollapudi, Alan Halverson, and Samuel Ieong. 2009. Diversifying search results. In WSDM.
