

Corpora Performance Prediction

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Abstract

Retrieval corpora are usually created to answer specific types of information needs. For example, medical search engines collect medical documents to support medical queries. Existing query performance prediction (QPP) methods aim to predict how effectively individual queries will be served by a search system. Instead, we focus on the ability of corpora to serve different types of queries. We propose the task of corpora performance prediction (CPP) to automatically predict, without relevance judgments, for what kinds of queries given retrieval corpora will be effective. Given a set of corpora, queries, and QPP methods, we obtain corpus “signatures” by measuring the performance of each query on each corpus with all predictors. Analyzing those corpus signatures, we aim to answer questions such as what search tasks are supported on each corpus? We realize our CPP concept using 250k queries from the Archive Query Log on five corpora (MS MARCO passage, a subsample of MS MARCO, Touché, NFCorpus, and Cranfield) with all predictors from the QPPTK framework. Our experiments show that the QPP methods yield helpful corpus performance predictions that characterize our corpora.

Keywords

Query Performance Prediction, Retrievability, Query Logs

1. Introduction and Background

While query performance prediction (QPP) addresses the fine-grained effectiveness of individual queries—supporting tasks like query suggestion [1] and routing [2]—we propose corpus performance prediction (CPP) to answer holistic questions about entire corpora. Traditional QPP methods, whether pre- or post-retrieval, estimate query-specific retrieval quality for query-level downstream tasks such as suggestion [1] and re-writing [3] but overlook broader corpus utility. In contrast, CPP aggregates QPP predictions over a fixed reference set of diverse queries, enabling systematic comparisons of corpora and the answering of holistic questions about each corpora. By analyzing how corpora perform across query classes (e.g., medical, programming), CPP identifies functional strengths (e.g., NFCorpus for evidence-based medicine) and coverage gaps, guiding applications like domain-specific search engine design. We operationalize CPP using the Archive Query Log (AQL) [4], which provides 64M queries mapped to 550 search providers (as taxonomic classes). A fixed subset of 250K queries, applied uniformly across corpora, isolates corpus-specific capabilities by standardizing evaluation. Aggregating QPP predictors (via QPPTK) over this query set generates corpus “fingerprints,” allowing the comparison of effectiveness for distinct query types and domains. For instance, corpora expected to excel in narrow classes (e.g., Touché for argumentative queries) may suit specialized systems, while those with uniform performance (e.g., MS MARCO) serve general search.

Where QPP makes pair-wise comparisons between topics, we instead aggregate predictors over a fixed set of queries that do not originate from the test collection corresponding to the corpus. Such a process is favorable as, with a large sample size, the estimation of a population mean is reduced. This allows for an unsupervised approach to meaningfully compare corpora and the retrievability of text in different domains. In probing corpora of varying size and class specificity, we explore a new way to compare corpora in terms of query effectiveness as opposed to other textual similarities. Both as a diagnostic tool and potentially as an intervention in a broader search system, CPP may provide

a suitable heuristic to complement QPP. With such goals in mind, we apply several common QPP heuristics on a large scale. We run experiments on five corpora using QPPTK [5] against PyTerrier [6] indices.

This approach bypasses reliance on test-collection-specific queries, instead leveraging population-level QPP aggregation to reduce variance and enable unsupervised corpus comparison. Our findings demonstrate that CPP discriminates corpora by their functional strengths: MS MARCO, collected from web-scale query logs, yields broad query support, while NFCorpus and Cranfield are predicted to be ineffective across general domains. Correlation analyses reveal content-driven similarities (e.g., Touché and a sub-sample of MS MARCO share structural traits). In contrast, weak correlations (e.g., MS MARCO vs. NFCorpus) underscore divergent use cases and help us understand the capabilities of performance predictors over *query classes* as opposed to individual topics. Stability analyses confirm that aggregating QPP predictions over larger query samples reduces variance, enabling robust corpus comparisons—though multilingual queries remain challenging due to monolingual corpora and QPP limitations. These insights provide initial evidence for CPP as a scalable, unsupervised framework for diagnosing corpus utility, guiding tasks like hybrid corpus selection and gap identification. By linking corpus design to real-world query distributions, CPP complements QPP, bridging granular query analysis with macro-level corpus understanding.

2. Methodology and Experimental Setup

Our experiments are intended as a preliminary setup to collect feedback during the workshop.

2.1. Corpus Performance Prediction

The main idea behind corpus performance prediction (CPP) is to use a large, fixed set of queries and a query performance predictor to probe a corpus. Formally, given a set of queries \mathbb{Q} , each belonging to a class $q \in \mathbb{Q}_{c_i}$, a query performance predictor f , and a document corpus \mathbb{C} , the objective is to aggregate the query performance predictions over each class of queries: $CPP(c_i) = \frac{1}{|\mathbb{Q}_{c_i}|} \sum_{q \in \mathbb{Q}_{c_i}} f(q, \mathbb{C})$. The corpus performance values of each class of queries can then be used to analyze differences between corpora such as domain or query taxonomies; we use domains in this work. For this, we plot the distribution of QPP values over each class. We use 12 QPPs from QPPTK in their dockerized version [7] from TIRA/TIREx [8, 9]: *(max/avg)-IDF* [10], *SCQ*, *(max/avg)SCQ* [10], *var*, *(max/avg)-var* [10], *weighted information gain (WIG)* [11], *normalized query commitment (NQC)* [12], *score magnitude and variance (SMV)* [13], and *clarity* [14].

2.2. Data

We start our preliminary experiments with a sample of 20,000 queries from the Archive Query Log (AQL) [4] to probe information retrieval corpora (Table 1 shows examples from our sample). The corpora we investigate include the (1) MS MARCO passage collection, (2) a subsample of the MS MARCO passage collection with all documents retrieved within the top-100 results by any run submitted to the 2019/2020 Deep Learning tracks [15, 16] (this reduces the corpus size to ca. 60 000 documents while still allowing for reliable evaluation [17]; our assumption is that QPPs should identify that most non-Deep Learning queries should not work for this subsample), (3) the Touché subset of BEIR [18, 19] as an argument retrieval collection; (4) NFCorpus [20], a medical IR collection; and (5) the original Cranfield collection [21] which we include as it contains only 1 400 documents so that we expect to see that most domains can not be served from this tiny collection. The diversity of these five corpora should make meaningful differences apparent through probing.

Query Sampling A unique feature of the Archive Query Log (AQL) is that it consists of the actual search engine result pages (SERPs) of real search engines (or generally any search provider). Using the

Table 1

Examples of queries from a selection of ten random providers from the AQL.

| Provider | Query |
|----------|---|
| 360 | 郭飞雄 让保罗贝尔蒙多 微信上线抗疫状态 英语培训 何为摄影 |
| amazon | humankind heritage edition playstation Levi's Women's Jeans るろうに black Adam ropa leselupe usb |
| baidu | cycle怎么读的 "Benoit Gilson" "tortsfamous.com" feb时空裂缝 16mm无缝钢管 |
| bing | Raebareli, Uttar Pradesh wikipedia Willy de Paula Faria community renewal services chicago Ubuntu Foundation Marco Valério Messala Corvino |
| github | topic:minnan org:kfcd topic:fortran org:boostorg sado topic:jenkins org:lavabit topic:filesystem fork:true |
| google | "Entoprocta" "Darwin Deez" "Constellations" "Csereüvegek" site:hu.wikipedia.org "Samarqand Restaurant" -wikipedia "Armas e equipamentos da Guerra Russo-Ucraniana" -wikipedia |
| naver | 바나다 알루미늄 블루투스 삼각대 셀카봉, WS-SQB641(화이트) 후기 hijrah 힐로 스테인레스 싱크롤 선반 20롤 대형, 블랙 후기 sumer 위성인터넷 |
| yahoo | ISSN "0340-1707" payless All Size Waste Dumpsters Calgary wichita craigslist what causes vertigo in older adults belvedere palace vienna |
| yandex | абвгдейка телепередача 1975 Юрий Хой - Первая любовь полярные ночи милые обманщицы сериал yeralash tv periodic |
| youtube | deshawn #Поле_Tapo DOC JAMIESON bonde das minas 15-7830 |

presence or absence of search results on each search engine result page as an indicator of “retrievability”,¹ we first partition the queries of the AQL into retrievable and non-retrievable queries. From the 15 most popular search providers of the AQL,² we then randomly sample up to 10,000 retrievable and up to 10,000 non-retrievable queries per provider. The 15 search providers are then used as classes for corpus

¹We assume that if a SERP returns no results, the query is not retrievable.

²As per Alexa rank, reflecting global popularity of websites, we use its latest ranking before its discontinuation in 2022.

Table 2Kendall’s τ correlation between the NQC values of different corpora, across all search providers.

| | Touche | MS MARCO | Subsample | NF Corpus | Cranfield |
|-----------|--------|----------|-----------|-----------|-----------|
| Touche | - | 0.3225 | 0.4627 | 0.2313 | 0.0977 |
| MS MARCO | - | - | 0.2578 | 0.0845 | 0.0021 |
| Subsample | - | - | - | 0.2925 | 0.1361 |
| NF Corpus | - | - | - | - | 0.3574 |
| Cranfield | - | - | - | - | - |

performance prediction. These classes include eight general web search engines (360, Baidu, Bing, Google, Naver, Sogou, Yahoo, Yandex), three online shops (AliExpress, Amazon, eBay), two media portals (IMDb, YouTube), a code collaboration platform (GitHub), and a microblogging website (Weibo).

Measures We use Kendall’s τ to compute agreement between predictors, considering both the query-level and class-level agreement. Given that a class can only be represented by a finite number of queries, how does the sample size affect domain comparisons? Thus, we take sub-samples of classes to compute, under permutation, the probability that two classes invert in order. This can be seen as the stability of comparing domains and corpora. For a given fraction t being the portion of each class, we take N samples and compute query performance prediction by applying a predictor f on that sample. Within each dataset, we rank classes $\mathbb{Q} \in \mathcal{Q}$, where \mathcal{Q} is the set of all classes, and observe if their comparison has swapped and store these values in a preference matrix $B \in \mathbb{Z}^{|\mathcal{Q}| \times |\mathcal{Q}|}$, i.e., for two classes $\mathbb{Q}_{c_1}, \mathbb{Q}_{c_2}$ if $f(\mathbb{Q}_{c_1}) > f(\mathbb{Q}_{c_2})^3$, $B_{c_1, c_2} = 1$. After all comparisons are made, the probability of a comparison inverting is thus $\frac{\min(B_{c_1, c_2}, B_{c_2, c_1})}{N}$. When the probability of two classes swapping under different permutations is high, and their average QPP scores are far apart, this suggests comparison instability. To compute similarity of two corpora with respect to a reference query set, we define a representation of a corpus \mathbb{C} for a predictor f and reference query set \mathbb{Q} as a vector $v \in \mathbb{R}^{|\mathbb{Q}|}$ where each $v_i = f(q, \mathbb{C})$, $q \in \mathbb{Q}$. We compute corpus similarity as cosine similarity between QPP representations, i.e., $\text{sim}(u, v) = \frac{u \cdot v}{|u||v|}$.

3. Analysis

We describe the results of our experiments on the five corpora with the 12 QPP methods.

3.1. Comparing Corpora by Class Performance

Figure 1 illustrates three different QPP methods used to probe the five corpora. The avg-idf highlights which corpora are best at supporting which queries. In general, Cranfield and NFCorpus obtain very low avg-idf values; while MS MARCO, perhaps the most diverse of the five corpora, obtains the highest avg-idf values. The SCQ figure highlights these differences even more, while the NQC figure highlights the lower extremes of corpora that are unable to support certain queries (i.e., multilingual).

Looking at NQC in more detail, Table 2 provides correlations between the different corpora. Interestingly, the most strongly correlated corpora under NQC are Touché and the MS MARCO Subsample, while the next most strongly correlated are Cranfield and NFCorpus. The likely reason for this correlation is the similarity of their documents; the Cranfield collection is composed of research abstracts. Similarly, the NFCorpus is composed of medical abstracts; ultimately, the language used and topics covered will be similar under statistical representations, most likely leading to this correlation. The weakest correlation is between MS MARCO and Cranfield, most likely due to the very small size of Cranfield and differing content. Table 3 further breaks these results down into the correlations within each search provider to observe the relative contribution of each provider to the overall corpus performance. The strong correlations between Touché and the MS MARCO Subsample on Chinese corpora like 360, Sogou, and Weibo are most likely the reason for the strong correlation. This result highlights the similarities between these two corpora. Comparing MS MARCO Passage to Cranfield, the weakest correlations are

³Where $f(\mathbb{Q}_{c_i})$ denotes the mean of the element-wise application of f over $q \in \mathbb{Q}_{c_i}$.

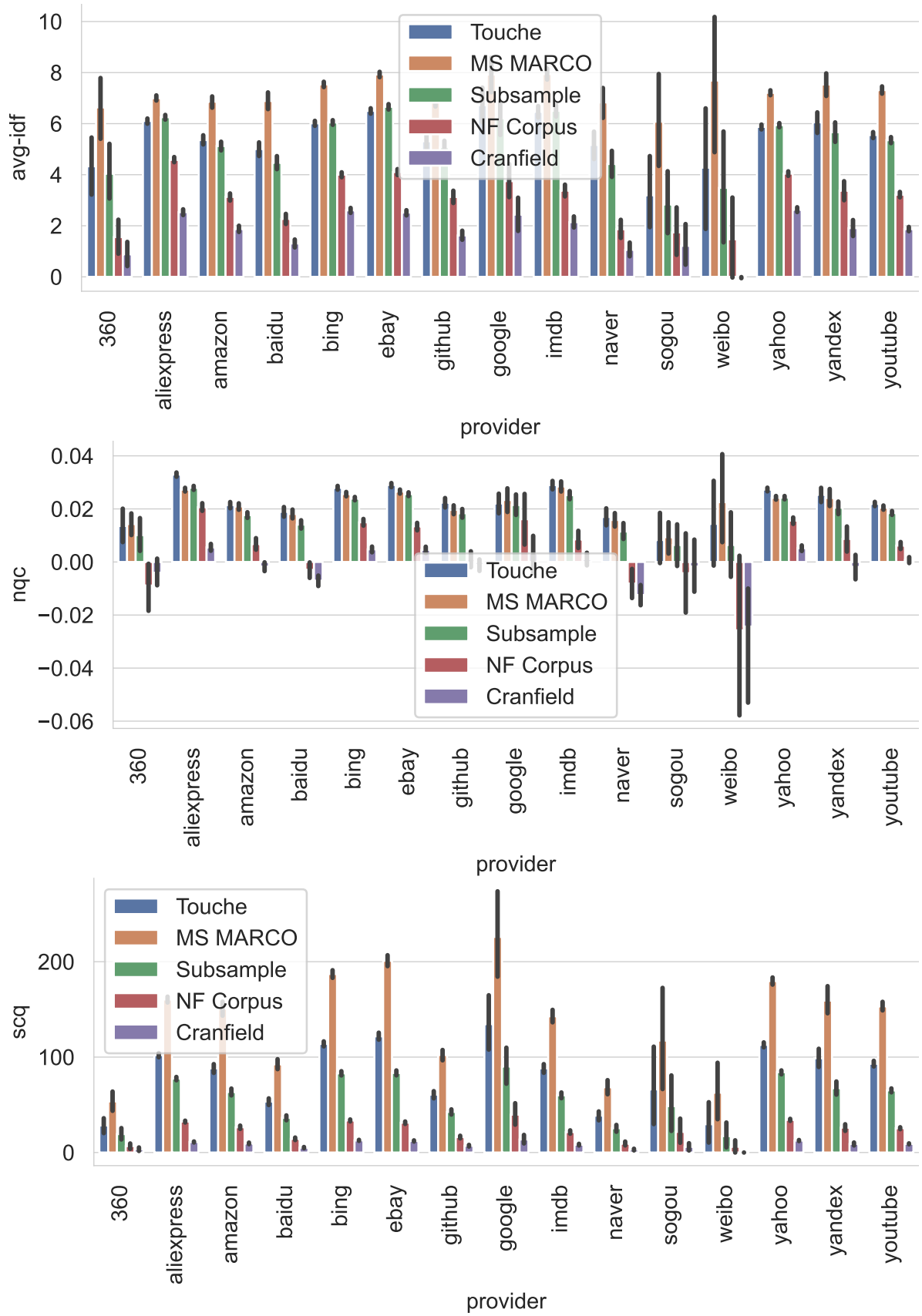


Figure 1: Distribution of AvgIDF (top), NQC (middle), and SCQ (bottom) over the three corpora. Each bar corresponds to the average value across all queries, with errors bars indicating 95% confidence interval.

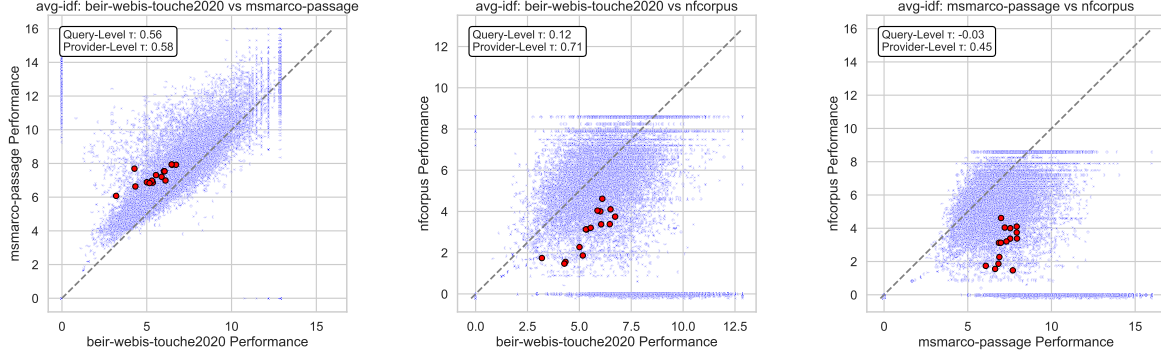


Figure 2: Query (Blue) and Provider (Red) level correlation comparing different datasets in terms of avg-IDF. Provider performance is the aggregate of the effectiveness of all constituent queries.

on web search providers like Bing, Google, Yahoo, and Yandex, while the strongest correlations are on Sogou, Weibo, and Baidu. The relatively stronger correlations on these search providers may be due to them being outliers. We leave this investigation for future work.

3.2. Comparing Corpora at a Query Level

Observe in Figure 2 the comparison of QPP values across different datasets on our reference query log. It is interesting to notice that individual topics exhibit low agreement, much like query-level comparisons in Cranfield evaluation. This can partially be attributed to lexical mismatch as topics have not been designed for a particular collection. Nevertheless, aggregating topics improves the discrimination of classes with higher agreement, similar to systems in standard evaluation. In particular, compared to NFCorpus, the agreement between Touché and MS MARCO is low at a query level but improves largely at a class level. We consider that a helpful measure of corpus similarity may be how similar they are by their ability to serve a diverse reference set of queries. Thus, as outlined in Section 2.2, we measure cosine similarity between QPP representations with similarity by avg-IDF presented in Table 4. Interestingly, as seen in terms of correlation at a group level (Table 3), at a corpus level, MS MARCO is often more similar to other corpora than a subsample of itself, this may be due to QPP measures ultimately measuring the effect of a corpus in serving an information need. Thus, smaller corpora or constrained corpora exhibit similar effects.

Due to the nature of IDF calculation, using out-of-class topics can lead to 0 values when a word is out-of-vocabulary; hence, several topics are grouped together. Also, due to the implementation of idf in QPPtk, several values are squashed due to a logarithm transformation; these observations are intrinsic to pre-retrieval QPP methods as opposed to our particular approach.

3.3. The Robustness of class Comparisons

In Figure 3, we use sampling to simulate variable-size classes of queries, assessing the discriminative power of smaller query logs as outlined in Section 2.2. We can then compare class rankings to select a corpus or, more generally, compare corpora. Contrasting a large permutation ($t = 0.9$) with a small one ($t = 0.5$), stability improves with greater sampling, as one would expect following the hypotheses of Lesk and Salton [22] and empirical evidence of Voorhees [23] in the variations and stability of topics. Where we observe some correlation attributable to a lack of documents that can serve a query, there is no trend in the effect of class size comparisons, as shown by the Δ in class size ($|Q_{c_1}| - |Q_{c_2}|$) in comparisons. That is to say, we can often make strong comparisons between a small and large class, a helpful property depending on the provenance of one’s query log. We observe that depending on the measure, the required sample size for stable comparison of query classes would appear to vary; however, unlike Cranfield collections, QPP can be performed without human intervention, and thus, that concern is reduced in this setting.

From the inspection of unstable class comparisons, multilingual classes tend to be more unstable, which is not unexpected given largely monolingual English corpora and QPP methods ultimately validated on English corpora. Future work could consider how neural approaches [24] may be more

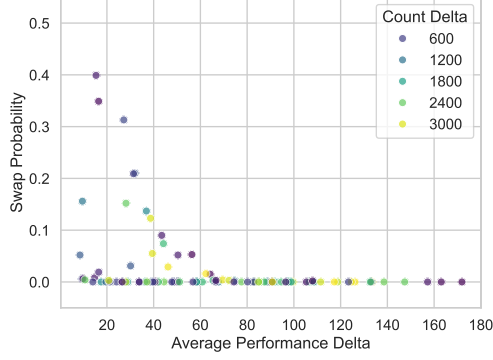
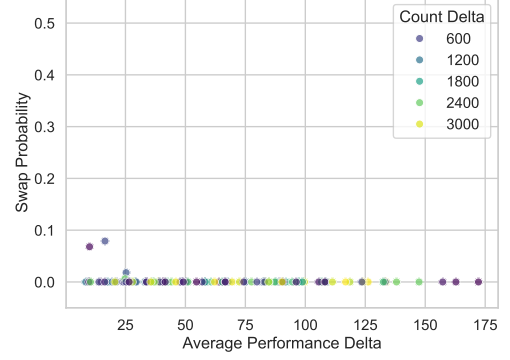
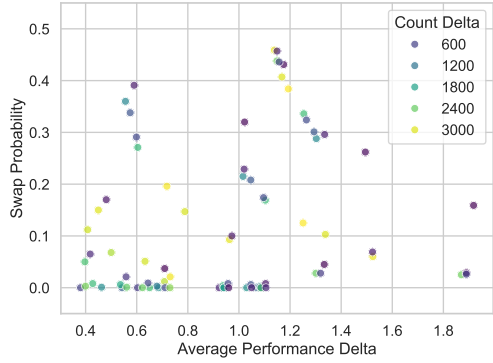
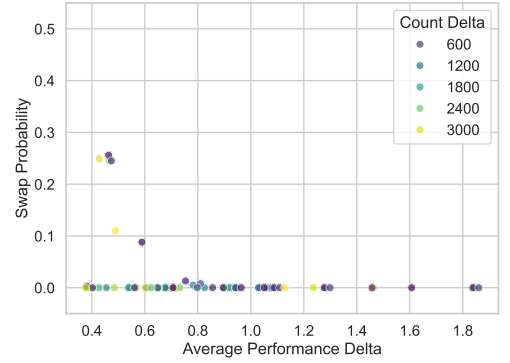
Table 3Kendall's τ correlation between the NQC values of different corpora, grouped by search providers.

| provider | | Touche | MS MARCO | Subsample | NF Corpus | Cranfield |
|------------|-----------|--------|----------|-----------|-----------|-----------|
| 360 | Touche | - | 0.3416 | 0.6867 | 0.4459 | 0.2210 |
| | MS MARCO | - | - | 0.2955 | 0.2265 | 0.0447 |
| | Subsample | - | - | - | 0.4661 | 0.2788 |
| | NF Corpus | - | - | - | - | 0.3989 |
| | Cranfield | - | - | - | - | - |
| aliexpress | Touche | - | 0.1249 | 0.3326 | 0.1270 | 0.0353 |
| | MS MARCO | - | - | 0.0853 | -0.0343 | -0.0470 |
| | Subsample | - | - | - | 0.1856 | 0.0660 |
| | NF Corpus | - | - | - | - | 0.2147 |
| | Cranfield | - | - | - | - | - |
| amazon | Touche | - | 0.4172 | 0.5539 | 0.3483 | 0.1679 |
| | MS MARCO | - | - | 0.3710 | 0.2361 | 0.1193 |
| | Subsample | - | - | - | 0.4318 | 0.2209 |
| | NF Corpus | - | - | - | - | 0.3921 |
| | Cranfield | - | - | - | - | - |
| baidu | Touche | - | 0.5011 | 0.5932 | 0.3641 | 0.1886 |
| | MS MARCO | - | - | 0.4314 | 0.2172 | 0.1293 |
| | Subsample | - | - | - | 0.4275 | 0.2552 |
| | NF Corpus | - | - | - | - | 0.3733 |
| | Cranfield | - | - | - | - | - |
| bing | Touche | - | 0.2949 | 0.4324 | 0.1710 | 0.0400 |
| | MS MARCO | - | - | 0.2462 | 0.0367 | -0.0545 |
| | Subsample | - | - | - | 0.2180 | 0.0481 |
| | NF Corpus | - | - | - | - | 0.3458 |
| | Cranfield | - | - | - | - | - |
| ebay | Touche | - | 0.2337 | 0.3303 | 0.0980 | 0.0212 |
| | MS MARCO | - | - | 0.1581 | -0.0223 | -0.0834 |
| | Subsample | - | - | - | 0.2194 | 0.1132 |
| | NF Corpus | - | - | - | - | 0.3643 |
| | Cranfield | - | - | - | - | - |
| github | Touche | - | 0.3648 | 0.5179 | 0.3200 | 0.2413 |
| | MS MARCO | - | - | 0.3026 | 0.1500 | 0.1012 |
| | Subsample | - | - | - | 0.3579 | 0.2692 |
| | NF Corpus | - | - | - | - | 0.3954 |
| | Cranfield | - | - | - | - | - |
| google | Touche | - | 0.3434 | 0.4828 | 0.2420 | 0.0166 |
| | MS MARCO | - | - | 0.1964 | 0.1030 | -0.0534 |
| | Subsample | - | - | - | 0.2067 | -0.0662 |
| | NF Corpus | - | - | - | - | 0.3658 |
| | Cranfield | - | - | - | - | - |
| imdb | Touche | - | 0.2904 | 0.3728 | 0.1521 | 0.0949 |
| | MS MARCO | - | - | 0.1740 | -0.0242 | -0.0889 |
| | Subsample | - | - | - | 0.1729 | 0.0684 |
| | NF Corpus | - | - | - | - | 0.3722 |
| | Cranfield | - | - | - | - | - |
| naver | Touche | - | 0.4503 | 0.5588 | 0.3320 | 0.1040 |
| | MS MARCO | - | - | 0.3480 | 0.1421 | 0.0151 |
| | Subsample | - | - | - | 0.4015 | 0.2047 |
| | NF Corpus | - | - | - | - | 0.3584 |
| | Cranfield | - | - | - | - | - |
| sogou | Touche | - | 0.5029 | 0.8293 | 0.5411 | 0.5317 |
| | MS MARCO | - | - | 0.4383 | 0.2718 | 0.3775 |
| | Subsample | - | - | - | 0.5929 | 0.6189 |
| | NF Corpus | - | - | - | - | 0.3616 |
| | Cranfield | - | - | - | - | - |
| weibo | Touche | - | 0.4410 | 0.7306 | 0.2433 | 0.2533 |
| | MS MARCO | - | - | 0.2442 | 0.1684 | 0.1899 |
| | Subsample | - | - | - | 0.3785 | 0.2247 |
| | NF Corpus | - | - | - | - | 0.4432 |
| | Cranfield | - | - | - | - | - |
| yahoo | Touche | - | 0.2730 | 0.4360 | 0.1912 | 0.0315 |
| | MS MARCO | - | - | 0.2093 | 0.0360 | -0.0689 |
| | Subsample | - | - | - | 0.2316 | 0.0531 |
| | NF Corpus | - | - | - | - | 0.3060 |
| | Cranfield | - | - | - | - | - |
| yandex | Touche | - | 0.3584 | 0.4690 | 0.1750 | 0.0184 |
| | MS MARCO | - | - | 0.2375 | 0.0483 | -0.0255 |
| | Subsample | - | - | - | 0.2566 | 0.0718 |
| | NF Corpus | - | - | - | - | 0.3856 |
| | Cranfield | - | - | - | - | - |
| youtube | Touche | - | 0.4196 | 0.5532 | 0.2953 | 0.1646 |
| | MS MARCO | - | - | 0.3350 | 0.1454 | 0.0713 |
| | Subsample | - | - | - | 0.3584 | 0.2041 |
| | NF Corpus | - | - | - | - | 0.3988 |
| | Cranfield | - | - | - | - | - |

Table 4

Cosine Similarity of Corpora measured by QPP representations over the reference query log applying avg-IDF.

| Dataset | MSMARCO | MSMARCO _{sub} | Touche | NFCorpus | Cranfield |
|------------------------|---------|------------------------|--------|----------|-----------|
| MSMARCO | – | – | – | – | – |
| MSMARCO _{sub} | 0.866 | – | – | – | – |
| Touche | 0.904 | 0.921 | – | – | – |
| NFCorpus | 0.700 | 0.804 | 0.746 | – | – |
| Cranfield | 0.545 | 0.624 | 0.572 | 0.692 | – |

(a) SCQ ($t = 0.5$)(b) SCQ ($t = 0.9$)(c) avg-IDF ($t = 0.5$)(d) avg-IDF ($t = 0.9$)**Figure 3:** The stability of provider comparisons across MSMARCO Passage using different QPP methods. t indicates the fraction of the total queries sampled.

robust in such comparisons in QPP as they may overcome gaps in vocabulary in standard statistical methods.

4. Conclusion

We have proposed corpus performance prediction (CPP) as a framework that uses QPP measures on a large scale to make unsupervised comparisons of retrieval corpora. We validated CPP with several common English corpora of varying and diverse sizes and the Archive Query Log from which we extracted queries grouped by domain. We show that through larger samples, much like Cranfield evaluation, we can improve the stability of domain comparisons, which could assist both in diagnostics and corpora selection. As future work, we intend to scale our experiments to more corpora and to more AQL domains and queries. Other directions could be to incorporate more accurate performance predictors, e.g., with large language model relevance assessors, as they can likely produce much more accurate predictions but then only for a small representative set of queries.

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