Correlation and Prediction of Evaluation Metrics in Information Retrieval

Mucahid Kutlu¹, Vivek Khetan², Matthew Lease²

¹ Computer Science and Engineering Department, Qatar University, Doha, Qatar
² School of Information, University of Texas at Austin, USA
mucahidkutlu@qu.edu.qa, vivek.khetank@utexas.edu, ml@utexas.edu

Abstract. Because researchers typically do not have the time or space to present more than a few evaluation metrics in any published study, it can be difficult to assess relative effectiveness of prior methods for unreported metrics when baselining a new method or conducting a systematic meta-review. While sharing of study data would help alleviate this, recent attempts to encourage consistent sharing have been largely unsuccessful. Instead, we propose to enable relative comparisons with prior work across arbitrary metrics by predicting unreported metrics given one or more reported metrics. In addition, we further investigate prediction of high-cost evaluation measures using low-cost measures as a potential strategy for reducing evaluation cost. We begin by assessing the correlation between 23 IR metrics using 8 TREC test collections. Measuring prediction error wrt. \( R^2 \) and Kendall’s \( \tau \), we show that accurate prediction of MAP, P@10, and RBP can be achieved using only 2-3 other metrics. With regard to lowering evaluation cost, we show that RBP(p=0.95) can be predicted with high accuracy using measures with only evaluation depth of 30. Taken together, our findings provide a valuable proof-of-concept which we expect to spur follow-on work by others in proposing more sophisticated models for metric prediction.

Keywords: Information Retrieval; Evaluation; Metrics; Prediction

1 Introduction

To assess an IR system’s effectiveness for different search scenarios, researchers have proposed a wide variety of evaluation metrics, each providing a different view of system effectiveness [1]. For example, while precision@10 (P@10) and reciprocal rank (RR) are often used to evaluate the quality of the top search results, mean average precision (MAP) and rank-biased precision (RBP) [2] are often used to quality of search results at greater depth.

Popular evaluation tools such as trec_eval³ compute many more evaluation metrics than IR researchers typically have time or space to analyze and report. Even for the most knowledgeable and diligent researcher, it is challenging to

³ trec.nist.gov/trec_eval/
decide which small subset of metrics should be reported to best characterize a
given IR system’s performance. Of course, presenting only a few metrics cannot
fully characterize system performance. Information is thus lost in publication,
and some interested reader will be disappointed to find a particular desired
metric missing, especially when trying to baseline a new method for a given
metric, or when conducting a meta-review comparison of prior work.

To compute a different metric of interest, one strategy is to try to reproduce
prior work. However, this is often difficult (and sometimes impossible) in prac-
tice, as the written description of a method is often incomplete and even shared
sourcecode can be difficult or impossible for others to run, especially as compil-
ers, programming languages, and operating systems change. Another strategy
is to share system outputs, enabling others to compute any metric of interest
for those outputs. While Armstrong et al. [3] proposed and deployed a central
repository[^2] to store IR system runs, their proposal did not achieve broad buy-in
from IR researchers and was ultimately abandoned. Realistically, it seems such
broad buy-in is unlikely unless eventually mandated by research funding agen-
cies. A similar situation exists in the field of biomedical literature mining [4,5],
where lack of shared data has generated a large body of research in mining pub-
lished papers to infer additional information. With published papers being the
most standard and enduring record of research studies, the capacity to predict
an arbitrary metric of interest given only one or more other metric scores, easily
obtained from published studies, could be quite valuable in practice.

Another potential application of such prediction could be to decrease the
massive cost of evaluation by enabling prediction of high-cost measures using
low-cost measures. That is, instead of collecting many relevance judgments to
calculate a particular high-cost measure (e.g. MAP@1000), we would rather col-
llect fewer judgments, calculate any number of low-cost measures (e.g. P@10,
MAP@10, nDCG@10) and predict a high-cost measure of interest.

To address this challenge, we first investigate the correlation between a wide
range of evaluation metrics. Using runs submitted to 8 TREC tracks, we compute
23 evaluation measures for every track, system, and topic in order to assemble
a large database of paired metric scores. We then calculate Pearson correlation
between each evaluation measure pairs. In our extensive experiments, we find
out that many metrics are strongly correlated (i.e., \( \rho > 0.9 \)) such as:

- **average precision** (AP), **R-Precision** (R-Prec), and bpref
- RBP(p=0.5) and RR
- RBP(p=0.95), RBP(p=0.8), P@10 and P@20
- nDCG@20 and RBP(0.8).

Following this, we report use of linear regression to predict one metric given 1-3
other metrics. We explore prediction of 12 measures and evaluate our prediction
model on 3 test collections. Results show we can accurately predict:

- MAP given nDCG and R-Prec

[^2]: [www.evaluatIR.org](http://www.evaluatIR.org)
– $P@10$ given $RBP(p=0.5)$ and $RBP(p=0.8)$
– $RBP(p=0.5)$ given $RR$ and $RBP(0.8)$
– $RBP(p=0.8)$ given $P@10$, $RBP(p=0.5)$ and $RBP(p=0.95)$

Therefore, if a system’s performance is reported with these measures, we can still reliably predict its performance on the respective measure.

Finally, we investigate prediction of high-cost measures using low-cost measures. We show we can accurately predict $RBP(p=0.95)$ at evaluation depth of 1000 and 100 given measures computed at depth 30, which shows the promise of this strategy for lowering evaluation cost.

Contributions of our work include:

– We analyze correlation between 23 metrics, using more recent collections than prior work. This includes expected reciprocal rank (ERR) and RBP using graded relevance judgments, whereas relevant prior work used only binary relevance judgments for these metrics.
– We show that accurate prediction of metrics can be achieved using only 2-3 other metrics. Further improvements can be expected using more sophisticated prediction models and larger training data.
– We show that our prediction model can also be used to decrease the cost of evaluation by predicting high-cost measures using low-cost measures.

Section 2 discusses the prior work. Section 3 describes the data used in our experiments. Section 4 and 5 present correlation and prediction of evaluation metrics, respectively. Finally, we conclude in Section 6.

2 Related Work

In order to better understand similarity between evaluation metrics, several studies have investigated correlation between them.

Tague-Sutcliffe and Blustein [6] investigate correlation between 7 measures on TREC-3 data and show that R-Prec and AP are strongly correlated. This high correlation between R-Prec and MAP is also confirmed by Buckley and Voorhees [7] using Kendall’s $\tau$ on TREC-7. Baccini et al. [8] measure correlations between 130 measures calculated by trec_eval using data from the TREC-(2-8) ad hoc task and group them into 7 clusters based on correlation. Sakai [9] compares 14 graded-level and 10 binary level metrics using three different data sets from NTCIR. In another work [10], Sakai studies correlation between $P(+)\text{-measure}$, $O\text{-measure}$, normalized weighted reciprocal rank and RR, and concludes that they are highly correlated each other except RR. Egghe [11] investigates the correlation between precision, recall, fallout and miss. Ishioka [12] explores relation between F-measure, break-even point, and 11-point averaged precision. Thom et al. [13] also studies correlation between 5 evaluation measures using TREC Terabyte Track 2006. None of these works cover ERR and RBP; we investigate correlation of 23 measures including ERR and RBP.

Jones et al. [14] examine disagreement between 14 evaluation metrics including ERR and RBP using TREC-(4-8) ad hoc tasks, and TREC Robust 2005 and
2006 tracks. However, they use only binary relevance judgments in their analysis, which makes ERR identical to RR, whereas we consider graded relevance judgments. In addition, the most recent test collections used in this related prior work is TREC Robust Track 2006 and Terabyte Track 2006. In contrast, we consider more recent TREC test collections (i.e. Web Tracks 2010-2014).

A primary contribution of our work is investigating prediction of evaluation measures. While Aslam et al. [15] also proposes predicting evaluation measures, they require a corresponding retrieved ranked list as well as another evaluation metric. They conclude that they can infer accurately user-oriented measures (e.g. P@10) from system-oriented measures (e.g. AP, R-Prec). In contrast, we predict evaluation measure of a system given only other evaluation measures without requiring the corresponding ranked lists.

3 Experimental Data

In order to investigate correlation and prediction of evaluation measures, we used the submitted runs and relevance judgments of Web Tracks (WT) of TREC-2000, 2010-2014 and Robust Track (RT) of TREC-2004. We consider only ad hoc retrieval. Table 1 lists the test collections used in our study.

| Test Collection | Document Collection          | # Systems | Topics |
|-----------------|------------------------------|-----------|--------|
| WT2000          | WT10g                        | 105       | 451-500|
| WT2001          | WT10g                        | 97        | 501-550|
| RT2004          | TREC disks 4&5, minus the Congressional Record | 110 | 301-450, 601-700 |
| WT2010          | ClueWeb'09                    | 55        | 51-99  |
| WT2011          | ClueWeb'09                    | 62        | 101-150|
| WT2012          | ClueWeb'09                    | 48        | 151-200|
| WT2013          | ClueWeb'12                    | 59        | 201-250|
| WT2014          | ClueWeb'12                    | 30        | 251-300|

Using the system runs submitted to these selected TREC tracks and their respective relevance judgments, we calculated 9 different evaluation metrics, including AP, bpref [24], ERR [25], nDCG, P@K, RBP [2], recall (R), RR [26], and R-Prec. We used various cut-off thresholds for the metrics. The cut-off threshold for a particular metric is shown by ”@” sign followed by the threshold value (e.g. P@10, R@100). Unless stated, we set the cut-off threshold to 1000, which is trec_eval’s default. The cut-off threshold for ERR is set to 20 because it has been used as one of the official measures in WT2014. RBP uses a parameter, called p, representing the probability of a user desiring to see the next retrieved page. In our calculations, we test 0.5, 0.8 and 0.95 for the p parameter, which
are also the p values explored by Moffat and Zobel [2]. Using these metrics, we generated two datasets:

- **Topic-Wise (TW) Dataset:** We calculated each metric mentioned above for each system for each separate topic. We used 10, 20, 100 and 1000 cut-off thresholds for AP, nDCG, P@K and R@K. In total, we calculated 23 evaluation measures.

- **System-Wise (SW) Dataset:** We calculated each metric mentioned above for each system, averaging over all topics in the corresponding test collection. For AP score, in addition to MAP, we also calculated GMAP (i.e. geometric mean of AP).

In order to calculate RBP and ERR, we used the RBP implementation provided by its authors and the ERR implementation provided by TREC. For the rest of the performance measures, we used trec_eval 9.0. As in any large dataset, various runs had missing data that resulted in only a subset of evaluation measures being computed. In such cases, we filtered out any such suspicious null or zero values. We also detected runs that have identical ranked lists in WT2013 and WT2014 test collections and filtered out identical submissions.

### 4 Correlation of Measures

We studied the correlation of measures using the TW dataset instead of the SW dataset to avoid losing any information by averaging scores across topics. In particular, we calculated Pearson correlation between measures across different topics using system runs in all test collections mentioned in Table 1. The correlation results are shown in Figure 1.

There are several observations we can make from these results. First, R-Prec has high correlation with bpref, MAP and nDCG@100, confirming prior work’s findings that MAP and R-Prec are highly correlated [6, 7, 15]. Second, RR is strongly correlated with RBP(p=0.5) and its correlation with RBP measures decreases as the p parameter of RBP increases. This is because as p increases, RBP becomes more of a deep-rank metric while RR metric ignores the documents ranked after the first relevant document. Third, nDCG@20, which is used as one of the official metrics of WT2014, is highly correlated with RBP(p=0.8). This finding indirectly verifies that nDCG@20 is an appropriate measure for web search tasks, connecting with Park and Zhang’s [27] suggestion that p=0.78 is an appropriate value of RBP for modeling behaviour of web users. Fourth, nDCG is highly correlated with MAP and R-Prec and its correlation with R@K consistently increases as K increases. Fifth, most correlated with RBP(p=0.8) and RBP(p=0.95) are P@10 (ρ = 0.97) and P@20 (ρ = 0.98), respectively. Sixth, Sakai and Kando [28] report that RBP(p=0.5) basically ignores relevant documents ranked lower than 10. Our results are consistent with this finding such

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5 http://people.eng.unimelb.edu.au/ammoffat/rbp_eval-0.2.tar.gz
6 https://github.com/trec-web/trec-web-2014
that the maximum Pearson correlation between RBP($p=0.5$) and nDCG@$K$ is obtained when $K=10$, and this correlation decreases as $K$ increases. Finally, among all measures, P@$1000$ is the least correlated one with others, suggesting that it captures an effectiveness measure of IR systems that no other metric does.

5 Prediction of Metrics

In this section, we describe our prediction model and experimental setup, and report results of experiments we conducted to investigate prediction of evaluation measures.
5.1 Prediction Model & Experimental Setup

One key goal of our work is to predict a system’s missing evaluation measure using reported ones. Thus, we build a linear regression model using only evaluation measures of systems as features. We use the SW dataset in our experiments for prediction because studies generally report their average performance over a set of topics, instead of reporting their performance for each topic. We use data extracted from WT2000, WT2001, RT2004, WT2010 and WT2011 as the training dataset. WT2012, WT2013 and WT2014 are used to evaluate our prediction model. In order to evaluate the prediction accuracy, we report $R^2$ and Kendall’s $\tau$ correlation.

5.2 Prediction Using Varying Number of Measures

In this section, we explore the best predictors for 12 evaluation measures including R-Prec, bpref, RR, ERR@20, MAP, GMAP, nDCG, P@10, R@100, RBP(0.5), RBP(0.8) and RBP(0.95). Researchers can report different combinations of evaluation measures, yielding a huge number of cases we might consider. In order to reduce our search space, we investigate which $N$ evaluation measure(s) are the best predictors for a particular measure and vary $N$ from 1 to 3. Specifically, in prediction of a particular measure, we try all combinations of size $N$ using the remaining 11 evaluation measures on WT2012 and pick the one that yields the best Kendall’s $\tau$ correlation. Then, the selected combination of measures are used for predicting the respective measure on WT2013 and WT2014. The experimental results are shown in Table 2. Kendall’s $\tau$ scores higher than 0.9 (a traditionally-accepted threshold for an acceptable correlation [29]) are bolded.

bpref. We achieve the highest $\tau$ correlation and interestingly the worst $R^2$ using only nDCG on WT2014. This shows that while predicted measures are not accurate, rankings of systems based on predicted scores can be highly correlated with the actual ranking. We observe the same pattern of results in prediction of RR on WT2012 and WT2014, R-prec on WT2013 and WT2014, R@100 on WT2013, and nDCG in all three test collections.

GMAP & ERR. GMAP and ERR seem to be the most challenging measures to predict because we could never reach 0.9 $\tau$ correlation in any of the prediction cases of these two measures. Initially, $R^2$ scores we achieve for ERR consistently increase in all three test collections as we use more evaluation measures for prediction, suggesting that we can achieve higher prediction accuracy using more independent variables.

MAP. We can predict MAP with very high prediction accuracy and achieve higher than 0.9 $\tau$ correlation in all three test collections using R-Prec and nDCG as predictors. As we use RR as the third predictor, $R^2$ increases in all cases and $\tau$ correlation slightly increases on average (0.924 vs. 0.922).

nDCG. Interestingly, we achieve the highest $\tau$ correlations using only bpref; $\tau$ decreases as more evaluation measures are used as independent variables. Even
though we reach high \( \tau \) correlations for some cases (e.g. 0.915 \( \tau \) on WT2014 using only \( \text{bpref} \)), nDCG seems to be one of the hardest measures to predict.

**P@10.** Using RBP(0.5) and RBP(0.8), which are both highly correlated measures with P@10, we are able to achieve very high \( \tau \) correlation and \( R^2 \) in all three test collections (0.912 \( \tau \) and 0.983 \( R^2 \) on average). We reach nearly perfect prediction accuracy (\( R^2 = 0.994 \)) on WT2012.

**RBP(0.5).** In all three prediction cases, RR is selected as one of the independent variables, as expected because of being the most correlated measure with RBP(0.5) (See Figure 1). While using only RR is not sufficient to reach 0.9 \( \tau \) correlation, when we use also RBP(0.8) (the second most correlated measure) we reach very high prediction accuracy in all three test collections (0.919 \( \tau \) and 0.924 \( R^2 \) on average).

**RBP(0.8).** P@10 is the most correlated measure with RBP(0.8) and is selected as one of the independent variables in all cases, as expected. Using P@10 and RBP(0.5), we are able to achieve more than 0.9 \( \tau \) correlation and more than 0.98 \( R^2 \) in all test collections. Using P@10, RBP(0.5) and RBP(0.95), we achieve the highest \( R^2 \) (0.998) and \( \tau \) (0.973) among all 108 cases (i.e., 3 test collections x 12 measures x 3 different independent variable sets).

**RBP(0.95).** Compared to RBP(0.5) and RBP(0.8), we achieve noticeably lower prediction performance, especially on WT2013 and WT2014. On WT2012, which is used as the development set in our experimental setup, we reach high prediction accuracy when we use 2-3 independent variables.

**R-Prec, RR and R@100.** In predicting these three measures, while we reach high prediction accuracy in many cases, there is no independent variable group yielding high prediction performance on all three test collections.

Overall, we achieve high prediction accuracy for MAP, P@10, RBP(0.5) and RBP(0.8) on all test collections. RR and RBP(0.8) are the most frequently selected independent variables (10 and 9 times, respectively). Generally, using a single measure is not sufficient to reach 0.9 \( \tau \) correlation. However, we are able to achieve very high prediction accuracy using only 2 measures for many scenarios.

### 5.3 Prediction of High-Cost Measures with Low-Cost Measures

Our prediction results encouraged us to investigate whether we could also predict high-cost measures using low-cost measures. We focus on P@1000, P@100, MAP@1000, MAP@100, nDCG@1000, nDCG@100, RBP@1000, and RBP@100 as the high-cost measures. As the low-cost measures, we calculate precision, bref, ERR, infAP[30], MAP, nDCG and RBP scores of systems when evaluation depth (\( D \)) is varied from 10 to 50. We specifically use bref and infAP since they are designed for evaluating systems with incomplete relevance judgments. We set the \( p \) parameter of RBP to 0.95. For a particular evaluation depth, we calculate the powerset of the 7 measures mentioned above (excluding the empty set). Subsequently, in a similar approach in Section 5.2, we find which elements of the powerset are the best predictors of the high-cost measures on WT2012. The set of low-cost measures that yields the maximum \( \tau \) score for a particular high-cost measure is also used for predicting the respective measure on WT2013.
| Predicted Metric | Independent Variables | WT2012 | WT2013 | WT2014 |
|------------------|----------------------|--------|--------|--------|
|                  |                      | $\tau$ | $R^2$  | $\tau$ | $R^2$  |
| bpref            | nDCG                 | 0.805  | 0.603  | 0.883  | 0.079  | 0.915  | 1.174  |
|                  | nDCG R-Prec          | 0.872  | 0.202  | 0.850  | 0.094  | 0.824  | 0.989  |
|                  | RR                   | 0.764  | 0.874  | 0.734  | 0.319  | 0.704  | 1.004  |
|                  | RR RBP(0.8)          | 0.796  | 1.809  | 0.777  | 0.392  | 0.714  | 0.886  |
|                  | RR RBP(0.8) R@100    | 0.796  | 1.728  | 0.741  | 0.478  | 0.704  | 0.473  |
| ERR              |                      |        |        |        |        |        |        |
|                  | RR                   | 0.729  | 1.216  | 0.704  | 2.982  | 0.739  | 1.034  |
|                  | RR RBP(0.8)          | 0.817  | 0.877  | 0.777  | 0.600  | 0.767  | 0.818  |
|                  | RR RBP(0.8) R@100    | 0.817  | 0.882  | 0.748  | 0.514  | 0.794  | 0.854  |
| GMAP             | bpref                | 0.805  | 2.101  | 0.885  | 0.217  | 0.915  | 2.008  |
|                  | nDCG RBP(0.5)        | 0.817  | 0.877  | 0.777  | 0.600  | 0.767  | 0.818  |
|                  | nDCG RBP(0.95) RR    | 0.924  | 0.916  | 0.901  | 0.779  | 0.947  | 0.922  |
| MAP              | R-Prec               | 0.885  | 0.754  | 0.824  | 0.677  | 0.952  | 0.819  |
|                  | R-Prec nDCG          | 0.904  | 0.894  | 0.905  | 0.760  | 0.958  | 0.897  |
|                  | R-Prec nDCG RR       | 0.924  | 0.916  | 0.901  | 0.779  | 0.947  | 0.922  |
| nDCG             | bpref                | 0.885  | 2.101  | 0.885  | 0.217  | 0.915  | 2.008  |
|                  | bpref GMAP RBP(0.95) | 0.794  | 0.113  | 0.801  | 0.556  | 0.850  | 0.632  |
| P@10             | RBP(0.8)             | 0.884  | 0.942  | 0.832  | 0.895  | 0.866  | 0.893  |
|                  | RBP(0.8) RBP(0.5)    | 0.941  | 0.994  | 0.882  | 0.966  | 0.914  | 0.898  |
|                  | RBP(0.8) RBP(0.5) RR | 0.946  | 0.994  | 0.885  | 0.968  | 0.914  | 0.987  |
| RBP(0.5)         | RR                   | 0.782  | 0.901  | 0.806  | 0.921  | 0.810  | 0.878  |
|                  | RR RBP(0.8)          | 0.938  | 0.935  | 0.894  | 0.934  | 0.926  | 0.903  |
|                  | RR RBP(0.8) nDCG     | 0.936  | 0.916  | 0.882  | 0.917  | 0.942  | 0.885  |
| RBP(0.8)         | P@10                 | 0.884  | 0.932  | 0.832  | 0.885  | 0.866  | 0.894  |
|                  | P@10 RBP(0.5)        | 0.963  | 0.997  | 0.919  | 0.986  | 0.947  | 0.992  |
|                  | P@10 RBP(0.5) RBP(0.95) | 0.973  | 0.998  | 0.916  | 0.990  | 0.968  | 0.997  |
| RBP(0.95)        | R-Prec               | 0.824  | 0.346  | 0.651  | 0.786  | 0.607  | 2.401  |
|                  | bpref P@10           | 0.911  | 0.952  | 0.718  | 0.873  | 0.728  | 0.591  |
|                  | bpref P@10 RBP(0.8)  | 0.911  | 0.967  | 0.720  | 0.868  | 0.744  | 0.639  |
| R@100            | R-Prec               | 0.899  | 0.708  | 0.871  | 0.624  | 0.935  | 0.019  |
|                  | R@100 RBP(0.95)      | 0.909  | 0.952  | 0.820  | 0.882  | 0.820  | 0.759  |
|                  | R@100 RBP(0.95) GMAP | 0.924  | 0.970  | 0.833  | 0.914  | 0.841  | 0.825  |
| RR               | R-Prec               | 0.782  | 0.904  | 0.806  | 0.927  | 0.810  | 0.878  |
|                  | R-Prec RBP(0.8)      | 0.869  | 0.918  | 0.809  | 0.919  | 0.820  | 0.942  |
|                  | R-Prec RBP(0.8) ERR  | 0.876  | 0.437  | 0.818  | 0.924  | 0.915  | 0.824  |
|                  | R@100 R-Prec         | 0.889  | 0.423  | 0.871  | 0.232  | 0.935  | 1.075  |
|                  | R@100 R-Prec GMAP    | 0.899  | 0.437  | 0.871  | 0.258  | 0.940  | 1.077  |
|                  | R@100 R-Prec ERR     | 0.881  | -0.104 | 0.823  | 0.355  | 0.935  | 1.187  |

Table 2: System-wise Prediction Using Varying Number of Metrics. Kendall’s $\tau$ scores higher than 0.9 are bolded.
and WT2014. We repeat this process for each evaluation depth value (i.e. 10, 20, ..., 50) separately in order to see impact of the cost on the prediction. The results are shown in Figure 2.

*Fig. 2: Prediction of High-Cost Measures Using Low-Cost Measures*

For depth 1000 (Figure 2a), we achieve higher than 0.9 Kendall’s $\tau$ correlation and higher than 0.98 $R^2$ for RBP in all cases when evaluation depth of low-cost measures is 30 or more. While we are able to reach 0.9 $\tau$ correlation for MAP on WT2012, prediction of P@1000 and nDCG@1000 measures performs poorly and never reaches a high $\tau$ correlation. As expected, the performance of prediction increases when evaluation depth of high-cost measures are decreased to 100 (Figure 2a vs. Figure 2b).

Overall, RBP seems the most predictable measure using the low-cost measures while precision is the least predictable one. This is because MAP, nDCG and RBP give more weight to documents at higher ranks, which are also evaluated by the low-cost measures. On the other hand, in calculation of precision, we consider only the number of relevant documents and ignore the ranks.

6 Conclusion

In this work, we investigated correlation and prediction of evaluation measures using data from 8 TREC test collections covering ad hoc search task for web documents and news articles.
We first calculated the correlation between 23 evaluation measures. We found that the following measure groups are strongly correlated each other: 1) MAP & R-Prec & nDCG, 2) RR & RBP(0.5), 3) nDCG@20 & RBP(0.8), 4) P@10 & P@20 & RBP(0.8) & RBP(0.95). Subsequently, we built a linear regression model to predict a system’s evaluation measure using its other measures and investigated prediction of 12 measures. We found out that we can predict MAP, P@10, RBP(0.5) and RBP(0.8) accurately. Finally, we investigated prediction of high-cost measures using low-cost measures and showed that we can predict RBP(0.95) with high accuracy using measures with evaluation depth of 30.

In the future, we plan to deepen our investigation using more data from different tasks and exploring other evaluation metrics and prediction models.

References

1. Aslam, J.A., Yilmaz, E., Pavlu, V.: The maximum entropy method for analyzing retrieval measures. In: Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval, ACM (2005) 27–34
2. Moffat, A., Zobel, J.: Rank-biased precision for measurement of retrieval effectiveness. ACM Transactions on Information Systems (TOIS) 27(1) (2008) 2
3. Armstrong, T.G., Moffat, A., Webber, W., Zobel, J.: Improvements that don’t add up: ad-hoc retrieval results since 1998. In: Proceedings of the 18th ACM conference on Information and knowledge management, ACM (2009) 601–610
4. Hirschman, L., Park, J.C., Tsujii, J., Wong, L., Wu, C.H.: Accomplishments and challenges in literature data mining for biology. Bioinformatics 18(12) (2002) 1553–1561
5. de Bruijn, L., Martin, J.: Literature mining in molecular biology. In: Proceedings of the EFMI Workshop on Natural Language Processing in Biomedical Applications. (2002) 1–5
6. Tague-Sutcliffe, J., Blustein, J.: Overview of trec 2001. In: Proceedings of the third text retrieval conference (TREC-3). (1995) 385–398
7. Buckley, C., Voorhees, E.M.: Retrieval system evaluation. TREC: Experiment and evaluation in information retrieval (2005) 53–75
8. Baccini, A., Déjean, S., Lafage, L., Mothe, J.: How many performance measures to evaluate information retrieval systems? Knowledge and Information Systems 30(3) (2012) 693
9. Sakai, T.: On the reliability of information retrieval metrics based on graded relevance. Information processing & management 43(2) (2007) 531–548
10. Sakai, T.: On the properties of evaluation metrics for finding one highly relevant document. Information and Media Technologies 2(4) (2007) 1163–1180
11. Egghe, L.: The measures precision, recall, fallout and miss as a function of the number of retrieved documents and their mutual interrelations. Information Processing & Management 44(2) (2008) 856 – 876 Evaluating Exploratory Search SystemsDigital Libraries in the Context of Users Broader Activities.
12. Ishioka, T.: Evaluation of criteria for information retrieval. In: Web Intelligence, 2003. WI 2003. Proceedings. IEEE/WIC International Conference on, IEEE (2003) 425–431
13. Thom, J., Scholer, F.: A comparison of evaluation measures given how users perform on search tasks. In: ADCS2007 Australasian Document Computing Symposium, RMIT University, School of Computer Science and Information Technology (2007)
14. Jones, T., Thomas, P., Scholer, F., Sanderson, M.: Features of disagreement between retrieval effectiveness measures. In: Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, ACM (2015) 847–850
15. Aslam, J.A., Yilmaz, E., Pavlu, V.: A geometric interpretation of r-precision and its correlation with average precision. In: Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval, ACM (2005) 573–574
16. Hawking, D.: Overview of the trec-9 web track. In: TREC. (2000)
17. Voorhees, E.M., Harman, D.: Overview of trec 2001. In: TREC. (2001)
18. Voorhees, E.M.: Overview of the trec 2004 robust track. In: TREC. Volume 4. (2004)
19. Clarke, C., Craswell, N., Soboroff, I., Cormack, G.: Overview of the trec 2010 web track. In: TREC. (2010)
20. Clarke, C., Craswell, N.: Overview of the trec 2011 web track. In: TREC. (2011)
21. Clarke, C., Craswell, N., Voorhees, E.M.: Overview of the trec 2012 web track. In: TREC. (2012)
22. Collins-Thompson, K., Bennett, P., Clarke, C., Voorhees, E.M.: Trec 2013 web track overview. In: TREC. (2013)
23. Collins-Thompson, K., Macdonald, C., Bennett, P., Voorhees, E.M.: Trec 2014 web track overview. In: TREC. (2014)
24. Buckley, C., Voorhees, E.M.: Retrieval evaluation with incomplete information. In: Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval, ACM (2004) 25–32
25. Chapelle, O., Metlzer, D., Zhang, Y., Grinspan, P.: Expected reciprocal rank for graded relevance. In: Proceedings of the 18th ACM international conference on Information and knowledge management, ACM (2009) 621–630
26. Voorhees, E.M., Tice, D.M.: The trec-8 question answering track evaluation. In: TREC. Volume 1999. (1999) 82
27. Park, L., Zhang, Y.: On the distribution of user persistence for rank-biased precision. In: Proceedings of the 12th Australasian document computing symposium. (2007) 17–24
28. Sakai, Tetsuya and Kando, N.: On information retrieval metrics designed for evaluation with incomplete relevance assessments. Information Retrieval 11(5) (Oct 2008) 447–470
29. Voorhees, E.M.: Variations in relevance judgments and the measurement of retrieval effectiveness. Information processing & management 36(5) (2000) 697–716
30. Yilmaz, E., Aslam, J.A.: Estimating average precision with incomplete and imperfect judgments. In: Proceedings of the 15th ACM international conference on Information and knowledge management, ACM (2006) 102–111