

Tie-breaking Bias: Effect of an Uncontrolled Parameter on Information Retrieval Evaluation*

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Abstract. We consider Information Retrieval evaluation, especially at TREC with the `trec_eval` program. It appears that systems obtain scores regarding not only the relevance of retrieved documents, but also according to document names in case of ties (i.e., when they are retrieved with the same score). We consider this tie-breaking strategy as an uncontrolled parameter influencing measure scores, and argue the case for fairer tie-breaking strategies. A study of 22 TREC editions reveals significant differences between the Conventional unfair TREC's strategy and the fairer strategies we propose. This experimental result advocates using these fairer strategies when conducting evaluations.

1 Introduction

Information Retrieval (IR) is a field with a long tradition of experimentation dating back from the 1960s [1]. The IR community notably benefited from TREC evaluation campaigns and workshops. Since 1992, these have been offering researchers the opportunity to measure system effectiveness and discuss the underlying theoretical aspects [2, 3]. At TREC, evaluation results of IR systems (IRs), a.k.a. search engines, are computed by the `trec_eval` [4] program. Many subsequent IR evaluation initiatives also rely on `trec_eval`, such as tasks of NTCIR [5], CLEF [6], and ImageCLEF [7].

As a general rule when conducting a scientific experiment, one should identify all the parameters at stake and control all but one to be able to test its effect on the measured artifact. Controlling parameters is a key concern since conclusions may be biased when two or more parameters vary at the same time during the experiment. Following on from studies on IR evaluation methodology such as Voorhees's [8] and Zobel's [9] we identified an uncontrolled parameter in TREC through `trec_eval`: evaluation results not only depend on retrieved documents, but also on how they were named in case of ties (i.e., *ex aequo* documents). This is a major issue since 'lucky' ('unlucky') IRs can get better (worse) results than they would deserve in an unbiased evaluation.

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This paper is organized as follows. In Sect. 2, we present how IRSs are commonly evaluated according to the Cranfield paradigm. Then, we detail in Sect. 3 the issue we identified in TREC methodology, that we call the ‘tie-breaking bias.’ In Sect. 4, we propose alternative reordering strategies for canceling out the effect of the considered uncontrolled parameter. A comparison of the current TREC strategy with our proposal is detailed in Sect. 5. Our findings and limitations of our analyses are discussed in Sect. 6. Finally, related works are reviewed in Sect. 7 before concluding the paper and giving insights into research directions.

2 Tie-breaking Prior to Evaluating IRSs Effectiveness

This section introduces the concepts considered throughout the paper. Our brief description may be complemented by [10], which details IR evaluation at TREC and its realization with the `trec_eval` program. At TREC, at least one *track* a year is proposed. A track is comprised of 50+ *topics*; each one is identified with a *qid*. Participants in a track contribute at least one *run* file. Among the fields of this file, `trec_eval` only considers the following: *qid*, the document identifier *docno*, and the similarity *sim* of *docno* regarding *qid*, as provided by the IRS. In addition, the *query relevance judgments* file (i.e., *qrels*) results from manual assessment. The `trec_eval` program only considers the 3 following fields from it: *qid*, *docno*, and *rel*, which represents the relevance of *docno* regarding *qid*. The $rel \in [1, 127]$ value is assigned to relevant documents. Other values (e.g., $rel = 0$) represent non-relevant documents. Prior to computing effectiveness measures, `trec_eval` pre-processes the run file. Since it ignores its *rank* field, documents are reordered as follows: “internally ranks are assigned by sorting by the *sim* field with ties broken deterministically (using *docno*)” [4]. Buckley and Voorhees comment this rationale and underline the importance of tie-breaking:

“For TREC-1 . . . Each document was also assigned a *rank* by the system, but this *rank* was deliberately ignored by `trec_eval`. Instead, `trec_eval` produced its own ranking of the top two hundred documents¹ based on the RSV [*sim*] values to ensure consistent system-independent tie breaking among documents that a system considered equally likely to be relevant (the ordering of documents with tied RSV values was arbitrary yet consistent across runs). Breaking ties in an equitable fashion was an important feature at the time since many systems had large number of ties—Boolean and coordination-level retrieval models could produce hundreds of documents with the same RSV.” [10, p. 55]

Finally, `trec_eval` uses *qrels* and the reordered run to compute several effectiveness measures. In the remainder of this paper, let us consider a system s , a topic t , and a document d of the run, and the following measures: Reciprocal Rank $RR(s, t)$ of top relevant document, Precision at d cutoff $P(s, t, d)$, Average Precision $AP(s, t)$, and Mean Average Precision $MAP(s)$. Due to space limitation, we do not elaborate on these measures and refer the reader to [11, ch. 8] for a comprehensive definition.

¹ Since TREC-2, the top 1,000 documents is kept [10, p. 58].

The next section presents an issue related to the way document ties are broken at TREC. We argue that this issue makes the current tie-breaking strategy an uncontrolled parameter in IR experiments.

3 On How the Tie-breaking Bias Influences IR Evaluation

Let us consider, in Fig. 1(a), a sample of a run concerning the top 3 documents retrieved by an IRS for a given topic t ($qid = 3$). Suppose that 5 documents are relevant documents for t in the collection, including **WSJ5** (in bold). Since `trec_eval` ignores ranks it reorders the run by ascending `qid`, descending `sim`, and descending `docno` for tie-breaking purpose. The resulting document list is presented in Fig. 1(b) where the relevant **WSJ5** document is assigned rank #1. Notice that reciprocal rank is $RR(s, t) = 1$, precision at **WSJ5** is $P(s, t, \mathbf{WSJ5}) = 1$ and $AP(s, t) = 1/5$. Now, without making any changes to the document contents, which still remain relevant for topic t , suppose that **WSJ5** had been named **AP8** instead. So, relevant document **AP8** is initially ranked #2 (i.e., the same position as **WSJ5**), as shown in Fig. 1(c). Then, due to the reordering process, LA12 remains ranked #1 by descending `docno`, remaining above **AP8**. Notice that reciprocal rank and average precision have been halved.

(a)	<table style="border-collapse: collapse; width: 100%;"> <thead> <tr> <th style="border: none;">qid</th> <th style="border: none;">docno</th> <th style="border: none;">sim</th> <th style="border: none;">rank</th> </tr> </thead> <tbody> <tr> <td style="border: none;">3</td> <td style="border: none;">LA12</td> <td style="border: none;">0.8</td> <td style="border: none;">1</td> </tr> <tr> <td style="border: none;">3</td> <td style="border: none;">WSJ5</td> <td style="border: none;">0.8</td> <td style="border: none;">2</td> </tr> <tr> <td style="border: none;">3</td> <td style="border: none;">FT8</td> <td style="border: none;">0.5</td> <td style="border: none;">3</td> </tr> </tbody> </table>	qid	docno	sim	rank	3	LA12	0.8	1	3	WSJ5	0.8	2	3	FT8	0.5	3	→	<table style="border-collapse: collapse; width: 100%;"> <thead> <tr> <th style="border: none;">qid</th> <th style="border: none;">docno</th> <th style="border: none;">sim</th> <th style="border: none;">$RR(s, t)$</th> <th style="border: none;">$P(s, t, d)$</th> <th style="border: none;">$AP(s, t)$</th> </tr> </thead> <tbody> <tr> <td style="border: none;">3</td> <td style="border: none;">WSJ5</td> <td style="border: none;">0.8</td> <td style="border: none;">1</td> <td style="border: none;">1</td> <td style="border: none;">1/5</td> </tr> <tr> <td style="border: none;">3</td> <td style="border: none;">LA12</td> <td style="border: none;">0.8</td> <td style="border: none;">1</td> <td style="border: none;">1/2</td> <td style="border: none;">1/5</td> </tr> <tr> <td style="border: none;">3</td> <td style="border: none;">FT8</td> <td style="border: none;">0.5</td> <td style="border: none;">1</td> <td style="border: none;">1/3</td> <td style="border: none;">1/5</td> </tr> </tbody> </table>	qid	docno	sim	$RR(s, t)$	$P(s, t, d)$	$AP(s, t)$	3	WSJ5	0.8	1	1	1/5	3	LA12	0.8	1	1/2	1/5	3	FT8	0.5	1	1/3	1/5	(b)
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Fig. 1. Effect of document naming on reordered run and measure values

This minimal example illustrates the issue addressed in the paper: IRS scores depend not only on their ability to retrieve relevant documents, but also on document names in case of ties. Relying on `docno` field for breaking ties here implies that the *Wall Street Journal* collection (**WSJ*** documents) is more relevant than the *Associated Press* collection (**AP*** documents) for whatever the topic, which is definitely wrong. This rationale introduces an uncontrolled parameter in the evaluation regarding all rank-based measures, skewing comparisons unfairly. Let us justify our statement by considering the example of *AP*:

1) Tie-breaking effect on *inter-system* comparison, where $AP(s_1, t)$ of system s_1 and $AP(s_2, t)$ of system s_2 are considered for a given topic t . This comparison is unfair since AP values can be different although both the systems returned the same result $[R_{0.8}, N_{0.8}, N_{0.5}]$ where R_x is a relevant document (N_x is a nonrelevant document) retrieved with `sim` = x . This is the case when we associate the run in Fig. 1(a) with s_1 , and the run in Fig. 1(c) with s_2 . Indeed $AP(s_1, t) = 1/1 \cdot 1/5$ whereas $AP(s_2, t) = 1/2 \cdot 1/5 = 1/10$, thus showing a 200% difference.

2) Tie-breaking effect on *inter-topic* comparison, where we consider $AP(s, t_1)$ and $AP(s, t_2)$ of a single system for two topics t_1 and t_2 . Such a comparison is made in TREC’s *robust* [12] track for characterizing easy and difficult information needs. It is unfair since TREC reordering process may have benefited system s for t_1 (by re-ranking relevant tied documents upwards in the list) while having hindered it for t_2 (by re-ranking relevant tied documents downwards in the list). As a result, the IRS designers may conduct failure analysis to figure out why their system poorly performed on some topics. Poor results, however, may only come from misfortune when relevant documents are reorganized downwards in the result list only because of their names. Imagining that every relevant document comes from the AP collection, they will be penalized since they will be re-ranked at the bottom of the tied group when reordering by decreasing `docno`.

Breaking ties as currently proposed at TREC introduces an uncontrolled parameter affecting IR evaluation results. In order to avoid this tie-breaking issue, the next section introduces our proposal: alternative reordering strategies.

4 Realistic and Optimistic Tie-breaking Strategies

The current tie-breaking strategy (`qid asc, sim desc, docno desc`) introduces an uncontrolled parameter, as it relies on the `docno` field for reordering documents with the same `sim` value. Another strategy would be to randomize tied documents; this is not suitable as evaluations would be unfair and not reproducible (non deterministic). However, evaluations must measure how well a contribution performed, not how well chance benefited an IRS. Alternatively, relying on the initial `rank`s (from `run`) implies the same issue: IRS designers may have untied their run by assigning random `rank`s, as they were not able to compute a discriminative `sim` for those documents. As a result, random-based and initial `rank`-based approaches do not solve the tie-breaking issue.

In this section, we propose two tie-breaking strategies that are not subject to the bias presented in this paper. Figure 2 shows merged runs and `qrels`, as well as the result of current TREC Conventional strategy for reordering ties and the two strategies that we propose:

1. *Realistic reordering* stipulates that tied nonrelevant documents should come above relevant documents in the ranked list because the IRS was not able to differentiate between them. The reordering expression meeting this requirement is “`qid asc, sim desc, rel asc, docno desc`.”

$$\text{Example: } [R_x, N_x, R_x] \xrightarrow[\text{qid asc, sim desc, rel asc, docno desc}]{\text{Realistic reordering}} [N_x, R_x, R_x].$$

2. *Optimistic reordering* stipulates that tied relevant documents should come above nonrelevant documents in the ranked list because the IRS may present them together, within clusters for instance. The reordering expression meeting this requirement is “`qid asc, sim desc, rel desc, docno desc`.”

$$\text{Example: } [R_x, N_x, R_x] \xrightarrow[\text{qid asc, sim desc, rel desc, docno desc}]{\text{Optimistic reordering}} [R_x, R_x, N_x].$$

Regarding the selected reordering strategy (Realistic, Conventional or Optimistic) the value of a measure can differ. Notice that Optimistic reordering is fair but game-able, which is bad: a run comprised of ties only would be evaluated just like if it ranked all relevant documents at the top. As a result, we recommend the use of Realistic strategy for conducting fair evaluations. In the remainder of the paper, ‘ M_S ’ denotes measure M with reordering strategy $S \in \{R, C, O\}$. Notice the total order $M_R \leq M_C \leq M_O$ between measure values.

qid	docno	sim	rank	rel
8	CT5	0.9	1	1
8	AP5	0.7	2	0
8	WSJ9	0.7	3	0
8	AP8	0.7	4	1
8	FT12	0.6	5	0

↙

qid	docno	sim	rel
8	CT5	0.9	1
8	WSJ9	0.7	0
8	AP5	0.7	0
8	AP8	0.7	1
8	FT12	0.6	0

(b) Realistic reordering

↓

qid	docno	sim	rel
8	CT5	0.9	1
8	WSJ9	0.7	0
8	AP8	0.7	1
8	AP5	0.7	0
8	FT12	0.6	0

(c) Conventional reordering

↘

qid	docno	sim	rel
8	CT5	0.9	1
8	AP8	0.7	1
8	WSJ9	0.7	0
8	AP5	0.7	0
8	FT12	0.6	0

(d) Optimistic reordering

Fig. 2. Realistic, Conventional, and Optimistic reordering strategies for a run

We demonstrated in this section how an uncontrolled parameter (i.e., document naming) affects IRSs scores. In order to foster fairer evaluation, we proposed alternative Realistic and Optimistic reordering strategies. In the next section, we conduct an analysis of past TREC datasets to measure the effect of the chosen reordering strategy on evaluation results.

5 Effect of the Tie-breaking Bias on IR Evaluation

We studied the effect of the tie-breaking bias on the results of 4 TREC tracks: *ad hoc* (1993–1999), *routing* (1993–1997), *filtering* (limited to its *routing* subtask, 1998–2002, as other subtasks feature binary *sim* values, making them inappropriate for our study), and *web* (2000–2004). The corresponding 22 editions comprise 1,360 *runs* altogether, whose average length is 50,196 lines. This represents 3 Gb of raw data retrieved from `trec.nist.org` and analyzed as follows. In Sect. 5.1, we evaluate to what extent runs are concerned with the uncontrolled parameter issue by assessing the proportion of document ties within runs. Then, in Sect. 5.2, we report the differences between scores obtained with the proposed fair reordering strategies *vs* the Conventional strategy promoted at TREC.

5.1 Proportion of Document Ties as Observed in 22 Trec Editions

In the remainder of the paper, we call a *result-list* the sample of a run concerning a specific topic *qid* submitted in a given *year*, and denote it $\text{runid}_{\text{qid}}^{\text{year}}$. Since

differences in scores arise when a result-list contains tied documents, this section assesses how often such a phenomenon happened in the considered TREC dataset. Table 1 shows statistics related to each track: the considered editions (Year) and number of submitted runs (detailed for each year, and overall). Two other indicators are provided, regarding \star the percentage of ties in result-lists, and \star the average number of tied documents when grouped by equal similarity (sim). Statistics related to minimum (Min), average (Avg), maximum (Max) and standard deviation (SD) are also reported. For instance, the result-list featured in Fig. 2 contains $\star^{3/5} = 60\%$ of tied documents, and \star presents an average of $(1+3+1)/3 = 1.7$ tied documents per sim.

Table 1. Proportion of document ties as observed in the runs of 4 TREC tracks

Track	Year	# of runs	\star Tied docs in a result-list (%)				\star Avg # of tied docs per sim			
			Min	Avg	Max	SD	Min	Avg	Max	SD
<i>ad hoc</i>	1993	36	0.0	30.3	100.0	36.0	2.2	4.4	28.0	4.2
	1994	40	0.0	28.4	100.0	35.9	1.9	9.5	37.3	11.2
	1995	39	0.0	29.2	99.9	32.8	1.0	2.8	26.2	4.2
	1996	82	0.0	24.1	100.0	32.3	2.0	4.1	35.1	4.7
	1997	79	0.0	24.7	100.0	34.7	1.8	4.5	25.8	5.1
	1998	103	0.0	19.0	100.0	27.4	1.0	2.5	33.8	4.4
	1999	129	0.0	15.6	100.0	24.6	1.5	3.7	22.9	4.4
	Avg over 508 runs \rightarrow		0.0	24.5	100.0	32.0	1.6	4.5	29.9	5.5
<i>filtering</i>	1998	47	0.0	26.8	100.0	40.8	41.0	42.0	51.8	2.2
	1999	55	0.0	7.5	100.0	23.8	2.1	2.1	2.7	0.1
	2000	53	0.0	21.1	100.0	38.1	15.3	22.3	37.1	10.0
	2001	18	0.0	25.6	100.0	30.3	19.8	33.3	69.6	17.0
	2002	17	0.0	34.6	100.0	37.2	2.5	23.3	97.9	33.2
		Avg over 190 runs \rightarrow		0.0	23.1	100.0	34.0	16.1	24.6	51.8
<i>routing</i>	1993	32	0.0	32.9	100.0	39.9	1.1	4.1	38.2	6.0
	1994	34	0.0	31.0	100.0	37.6	2.3	5.5	30.9	5.9
	1995	27	0.0	24.9	99.2	27.4	1.0	1.5	14.7	1.4
	1996	26	0.0	21.3	100.0	24.5	1.4	7.2	40.0	10.7
	1997	34	0.0	27.4	100.0	33.7	6.7	13.0	54.3	10.9
		Avg over 153 runs \rightarrow		0.0	27.5	99.8	32.6	2.5	6.3	35.6
<i>web</i>	2000	104	0.0	29.3	100.0	34.3	2.9	9.3	79.6	16.6
	2001	96	0.0	32.0	100.0	31.9	25.8	27.8	63.8	5.7
	2002	71	0.0	25.8	100.0	33.5	1.0	3.6	44.7	6.3
	2003	164	0.0	18.8	100.0	27.8	1.4	2.3	12.0	1.8
	2004	74	0.0	24.9	100.0	34.4	1.5	4.3	39.6	6.2
		Avg over 509 runs \rightarrow		0.0	26.2	100.0	32.4	6.5	9.5	47.9
Total avg over 1,360 runs \rightarrow			0.0	25.2	100.0	32.7	6.2	10.6	40.3	7.8

Overall, IRSs participating in early TREC *ad hoc* editions contributed more result-lists with tied documents than later on. This is in line with Buckley and Voorhees’s observation [10, p. 55] quoted in Sect. 2.

Averaging over each track, 25.2% of a result-list is comprised of tied documents. This proportion is highly variable, as highlighted by an average 32.7% standard deviation (strikingly similar for each track). Moreover, each year featured result-lists with no ties at all (i.e., $\text{Min}^\star = 0.0$). It also happened that some result-lists consisted of tied documents only (1,338 result-lists over the

4 tracks). The latter case may be illustrated at TREC *ad hoc* by `ibmge2`¹⁹⁹⁶₂₉₁ as an example of non-discrimination: all retrieved documents share the same $\text{sim} = -126.000000$ score. Those result-lists are most likely to obtain completely different results according to the applied tie-breaking strategy.

Regarding a run, when we consider the retrieved documents grouped by sim , we notice a great variability. Some result-lists have no ties ($\text{Min}^\star = 1.0$, which corresponds to $\text{Min}^\star = 0.0$) while others have on average up to 97.9 documents with the same sim value. The average group size of 10.6 documents implies that a document ranked at position $r + 10$ with Realistic strategy can be re-ranked r th with another strategy if lucky enough. Generalizing this observation, the larger the tied document group is, the larger the unfair position gain or loss will be.

This section showed that result-lists are likely to contain several tied documents. Thus, the uncontrolled parameter that we identified may affect IR evaluation. This hypothesis is tested in the next section.

5.2 Result Differences Regarding the Adopted Reordering Strategy

We emphasize comparisons between M_R and M_C (i.e., Realistic *vs* Conventional) to show how luck increased the M_R score deserved in a fair and unbiased setting. Notice however that larger differences will be observed when comparing M_R and M_O as the tested measures are totally ordered: $M_R \leq M_C \leq M_O$, cf. Sect. 4. For each measure, we first present systems that most benefited from the uncontrolled parameter by showing the top 3 differences between unfair M_C and fair M_R . Then, we generalize these findings by reporting statistical significance of $M_C - M_R$ for each track as a whole (i.e., considering every contributed runs). Significance p -values result from Student’s paired (difference is observed between paired M_C and M_R values) one-tailed (because $M_C \geq M_R$) t -test. Sanderson and Zobel [13] showed that it is more reliable than other tests, such as Wilcoxon’s signed rank test. The difference between tested samples is statistically significant when $p < \alpha$, with $\alpha = 0.05$. The smaller p -value, the more significant the difference is [14]. Finally, correlation between samples is reported according to Pearson’s r product-moment correlation coefficient for interval scales, and Kendall’s τ rank correlation coefficient for ordinal scales.

Effect on Reciprocal Rank. The effect of the chosen reordering strategy on the rank of the first relevant document is shown in Tab. 2. We report reciprocal ranks RR_x truncated to four digits but computations were done using exact values. Rank positions $1/RR_x$ are also presented because they seem helpful for the reader. Table 2 is ordered by descending $\delta_{RC} = 1/RR_R - 1/RR_C$ to focus on most ‘lucky’ systems. Statistical tests reported in Tab. 5 show a significant difference between RR_C and RR_R . With a Conventional strategy, the first relevant document is significantly ranked higher in the result-list than with a Realistic Strategy although the IRS remains the same. Despite this difference, a strong correlation ($\geq 99\%$) exists between the measure values resulting from both strategies except for the *filtering* track, as characterized by a weaker correlation (89%). Overall, RR_C and RR_R values are correlated, showing a slight but significant difference.

Table 2. Top 3 differences between Conventional $1/RR_C$ and Realistic $1/RR_R$ ranks

Track	Result-list	RR_R	RR_C	RR_O	$1/RR_R$	$1/RR_C$	$1/RR_O$	δ_{RC}
<i>ad hoc</i>	padre2 ¹⁹⁹⁴ ₁₉₅	0.0011	0.0667	0.0769	946	15	13	931
	anu5aut1 ¹⁹⁹⁶ ₂₉₇	0.0010	0.0149	1.0000	992	67	1	925
	anu5aut2 ¹⁹⁹⁶ ₂₉₇	0.0010	0.0149	1.0000	992	67	1	925
<i>filtering</i>	antrpohsu00 ²⁰⁰⁰ ₃₂	0.0000	0.5000	1.0000	988	2	1	986
	antrpnohsu00 ²⁰⁰⁰ ₆₂	0.0000	0.0909	1.0000	988	11	1	977
	antrpohsu00 ²⁰⁰⁰ ₆₂	0.0000	0.0909	1.0000	988	11	1	977
<i>routing</i>	cir6roul ¹⁹⁹⁷ ₁₁₈	0.0010	0.1429	1.0000	970	7	1	963
	cir6roul ¹⁹⁹⁷ ₁₆₁	0.0010	0.0250	0.1429	998	40	7	958
	virtue3 ¹⁹⁹⁷ ₂₂₈	0.0011	0.2000	0.5000	949	5	2	944
<i>web</i>	irtLnut ²⁰⁰¹ ₅₁₆	0.0010	1.0000	1.0000	993	1	1	992
	ictweb10nfl ²⁰⁰¹ ₅₂₅	0.0010	0.1667	1.0000	992	6	1	986
	ictweb10nf ²⁰⁰¹ ₅₂₅	0.0010	0.1667	1.0000	992	6	1	986

Effect on Average Precision. The three most affected systems regarding AP are shown in Tab. 3, for each track and reordering strategy. Gain between paired strategies is also presented. We focus on $gain_{CR}$, between AP_C and AP_R , which represents the unfair gain obtained by IRSs which benefited from the uncontrolled parameter influencing TREC Conventional reordering. For instance, $gain_{CR}$ reaches 406% for $cir6roul^{1997}_{194}$, which deserves $AP_R = 0.0262$ with a fair strategy. It obtained, however, $AP_C = 0.1325$ with the Conventional strategy.

Statistical tests reported in Tab. 5 show a significant difference between AP_C and AP_R for whatever the track. Nevertheless, this difference is small in percentage, which is in line with the observed strong correlation.

Table 3. Top 3 gains between AP_C and AP_R for each 4 tracks

Track	Result-list	AP_R	AP_C	AP_O	$gain_{OR}$ (%)	$gain_{CR}$ (%)	$gain_{CO}$ (%)
<i>ad hoc</i>	ibmgd2 ¹⁹⁹⁶ ₂₉₁	0.0000	0.0001	0.0074	49,867	318	11,858
	issahl ¹⁹⁹⁵ ₂₄₆	0.0001	0.0003	0.0018	2,718	311	585
	harris1 ¹⁹⁹⁷ ₃₂₇	0.0139	0.0556	0.0556	300	300	0
<i>filtering</i>	IAHKaf12 ¹⁹⁹⁸ ₁₃	0.0005	0.0116	0.0116	2,200	2,200	0
	IAHKaf32 ¹⁹⁹⁸ ₁₃	0.0005	0.0116	0.0116	2,200	2,200	0
	IAHKaf12 ¹⁹⁹⁸ ₃₉	0.0029	0.0625	0.2500	8,400	2,025	300
<i>routing</i>	cir6roul ¹⁹⁹⁷ ₁₆₁	0.0000	0.0008	0.0060	11,995	1,435	688
	cir6roul ¹⁹⁹⁷ ₁₉₄	0.0262	0.1325	0.2626	902	406	98
	erliR1 ¹⁹⁹⁶ ₇₇	0.0311	0.1358	0.5714	1,736	336	321
<i>web</i>	ICTWebTD12A ²⁰⁰³ ₁₅	0.0064	0.2541	0.2544	3,861	3,856	0
	irtLnut ²⁰⁰¹ ₅₁₆	0.0012	0.0355	0.2667	22,070	2,853	651
	iswt ²⁰⁰⁰ ₄₉₀	0.0000	0.0004	0.0007	4,248	2,173	91

Table 4. Top 3 gains between MAP_C and MAP_R for each 4 tracks

Track	Result-list	MAP_R	MAP_C	MAP_O	gain $_{OR}$ (%)	gain $_{CR}$ (%)	gain $_{CO}$ (%)
<i>ad hoc</i>	padre1 ¹⁹⁹⁴	0.1060	0.1448	0.2967	180	37	105
	UB99SW ¹⁹⁹⁹	0.0454	0.0550	0.0650	43	21	18
	harris1 ¹⁹⁹⁷	0.0680	0.0821	0.0895	32	21	9
<i>filtering</i>	IAHKaf12 ¹⁹⁹⁸	0.0045	0.0396	0.0558	1,140	779	41
	IAHKaf32 ¹⁹⁹⁸	0.0045	0.0396	0.0558	1,140	779	41
	TNOAF103 ¹⁹⁹⁸	0.0144	0.0371	0.0899	524	158	142
<i>routing</i>	cir6rou1 ¹⁹⁹⁷	0.0545	0.0792	0.2306	323	45	191
	erliR1 ¹⁹⁹⁶	0.1060	0.1412	0.2507	137	33	78
	topic1 ¹⁹⁹⁴	0.2062	0.2243	0.2543	23	9	13
<i>web</i>	ictweb10nf ²⁰⁰¹	0.0210	0.0464	0.4726	2,150	121	919
	ictweb10nfl ²⁰⁰¹	0.0210	0.0463	0.4660	2,119	120	907
	irtLnut ²⁰⁰¹	0.0102	0.0221	0.2343	2,202	117	960

Effect on Mean Average Precision. The three most affected systems regarding MAP are shown in Tab. 4, for each track and reordering strategy. Values for gain $_{CR}$ are smaller than for AP because several AP values are considered for computing their average (i.e., MAP). Since some result-lists are not skewed by the uncontrolled parameter, the influence of skewed AP values on MAP is limited, as counterbalanced by these non-skewed AP . Despite this smoothing effect due to using the arithmetic mean, we observed unjustified gains yet. For instance, padre1¹⁹⁹⁴ earned an extra 37% MAP by only benefiting from the uncontrolled parameter. Thus, without any tangible contribution it was granted $MAP_C = 0.1448$, although it only deserves $MAP_R = 0.1060$ in a unbiased setting. Provided that it had been even luckier, it could have unduly obtained up to $MAP_O = 0.2967$.

Although correlated (Tab. 5), MAP_C and MAP_R values are significantly different. Regarding ranks, however, Kendall’s τ shows that IRS ranks computed from MAP do not differ significantly for whatever the track or the reordering strategy. This is due to the fact that difference in MAP is not large enough to change IRS ranks. Moreover, we studied the effect of the tie-breaking strategy (MAP_R vs MAP_C) on the statistical significance of differences between paired systems, for each edition. There are up 9% wrong conclusions: t -test would have concluded to significant differences ($p < 0.05$) with Conventional strategy, but to the contrary with Realistic strategy, and vice versa. As another observation, we found that the rank of 23% of the systems is different when computed on MAP_R or MAP_C . When removing the 25% worst systems, there is still 17% of affected systems. This contradicts the assumption that most ties would have been provided by bad systems. Moreover, we noticed that, for instance, *ad hoc* uwmt6a0¹⁹⁹⁷ was ranked 1st, although containing 57% of ties.

We showed in this section that RR_R , AP_R and MAP_R are statistically different from Conventional counterparts, meaning that there is a noticeable difference between the proposed Realistic fair reordering strategy and TREC’s strategy. We discuss the implications of these findings in the next section.

Table 5. Correlation and significance of $M_C - M_R$ ($p < 0.001$ are marked with ‘*’)

Track	RR_C vs RR_R		AP_C vs AP_R		MAP_C vs MAP_R	
	δ_{RC} (%)	corr. r	δ_{RC} (%)	corr. r	δ_{RC} (%)	corr. r
<i>ad hoc</i>	0.60*	0.99	0.37*	1.00	0.37*	1.00
<i>filtering</i>	9.39*	0.89	3.14*	0.99	3.12*	0.99
<i>routing</i>	1.14*	0.99	0.57*	1.00	0.58*	1.00
<i>web</i>	0.55*	1.00	0.40*	1.00	0.45*	1.00

6 Discussion: Tie-breaking and ‘Stuffing’ Phenomenon

In Sect. 5.2 we showed that IRS scores are influenced by luck. This is an issue when evaluating several IRSs. Comparing them according to evaluation measures may be unfair, as some may just have been luckier than others. In order to foster fairer evaluations, it may be worth supplying `trec_eval` with an additional parameter allowing reordering strategy selection: Realistic, Conventional and Optimistic. In the end, other evaluation initiatives based on `trec_eval` (e.g., NTCIR and CLEF) would also benefit from this contribution.

In addition to the tie-breaking bias, we identified a ‘stuffing’ phenomenon practiced by several IRSs. At TREC, a result-list is at most comprised of 1,000 documents. We noticed that 10.5% of the studied IRSs retrieve less than 1,000 documents for a topic and ‘stuff’ their result-lists with documents associated with $\text{sim} = 0$. This is conceptually intriguing: why would a system return an irrelevant document? One rational answer may be: among these stuffed documents some may be relevant and thus contribute to the score, even slightly. And yet, with TREC’s current reordering strategy, relevant $\text{sim} = 0$ documents may be top ranked in the ‘stuffed’ part of the result-list. As a result, they unduly contribute more than if they had been ranked further down the list by the Realistic strategy that we propose. Consequently, it seems mandatory to discourage this ‘stuffing trick’ aiming to artificially increase measure values. This represents another case for the Realistic reordering strategy that we propose.

7 Related Works

The issue of evaluating runs comprising ties with the common, tie-oblivious, measures (e.g., precision, recall, $F1$, AP , RR , $NDCG$) was reported in [15, 16]. A way to address this issue is the design of tie-aware measures. Raghavan et al. [15] proposed Precall as an extension of precision at varying levels of recall, taking into account groups of tied documents. McSherry and Najork [16] extended the six aforementioned popular measures by averaging over all permutations of tied documents in the result-list. Both of these approaches allow the deterministic comparison of IRS results.

As an alternative solution, we did not design new measures, but tackled the tie-breaking problem by means of reordering strategies applied to the runs instead. The current reordering strategy, that we called Conventional, has been im-

plemented in TREC since its inception. Besides being deterministic, the Realistic and Optimistic strategies that we propose allow the measurement of how much improvement (loss) in effectiveness can be reached when correctly (wrongly) ordering tied documents. A difference between these two bounds can be interpreted as a lack of the system in handling ties properly.

8 Conclusion and Future Work

This paper considered IR evaluation using the `trec_eval` program, which is used in major evaluation campaigns (e.g., TREC, NTCIR, CLEF) for computing IRS scores (i.e., measure values such as *MAP*). We underlined that scores depend on two parameters: *i*) the relevance of retrieved documents, and *ii*) document names when documents are tied (i.e., retrieved with a same *sim* value). We argue that the latter represents an uncontrolled parameter influencing computed scores. Indeed, luck may benefit a system when relevant documents are re-ranked higher than non relevant ones, only because of their names.

Counteracting this unfair tie-breaking strategy, we proposed two alternative strategies, namely Realistic and Optimistic reordering. A thorough study of 22 editions of TREC *ad hoc*, *routing*, *filtering*, and *web* tracks showed a statistically significant difference between the Realistic strategy that we propose *vs* TREC's current Conventional strategy for *RR*, *AP*, and *MAP*. However, measure values are not skewed enough to significantly change IRS ranks computed over *MAP*. This means that the ranking of systems is not affected. We suggest the integration of the two proposed strategies into `trec_eval`, allowing the experimenter to choose the proper behavior, enabling and fostering fairer evaluations. In addition, this would enable the identification of claimed 'improvements' that only result from chance.

Future work concern three main aspects. First, we plan to test whether the tie-breaking bias affected CLEF and NTCIR, just as it does for TREC. The DIRECT [17] service will be of great help in this respect. Second, as biased evaluation results may have skewed 'learning to rank' approaches [18], it would be worth checking them against fairer evaluation conducted with the proposed Realistic strategy. Third, the study of the 'stuffing' phenomenon discussed in Sect. 6 will quantify the proportion of scores obtained by exploiting side effects related to good knowledge of the evaluation protocol—instead of by improving IRS effectiveness.

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