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Bandit algorithms in information retrieval evaluation and ranking

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Bandit algorithms in information retrieval evaluation and ranking

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Abstract. Bandit algorithms have been widely used in many application areas including information retrieval evaluation and ranking. This is largely due to their exceptional performance. The aim of this study is to examine the overall published studies in terms of trends that shape the use of bandit algorithms in the evaluation and ranking of information retrieval systems. This study also seeks to classify the bandit algorithms used in the research domain. In totality the evaluation metrics, datasets, contribution facets of primary studies as well as the bandit categories are discussed.

1. Introduction

Bandit algorithms have been widely used in many application areas since their introduction in 1952. These areas include medical treatment, product selection, anomaly detection and information retrieval (IR) tasks[2] . Key retrieval tasks such as evaluation and ranking in the last decade have been addressed using bandit algorithms[15,20]. Retrieval ranking and evaluation play pivotal roles in the functionality of any IR system, and the improvement of these tasks eventually leads to satisfied users with better livelihoods, since their information needs will have been met. Over the past 10 years, the number of publications has increased in various electronic databases on bandit algorithm usage in information retrieval evaluation and ranking. However, there is no systematic mapping study in this area. The purpose of this systematic mapping study is to fill this gap by analyzing published studies and this will help researchers understand the most used bandit algorithms in retrieval evaluation and ranking tasks, the most appropriate datasets, the evaluation metrics mostly utilized and the contribution facet distribution.

An evidence-based systematic mapping methodology[5] is adopted for this study. Based on mapping methodology, a systematic protocol is initially constructed consisting of search phrases to use in order to find relevant studies, rules to follow when including and excluding studies, selection process, what data to extract and synthesis.

This study is structured into sections as follows: Section 2 presents the description of related work, Section 3 presents the research method, Section 4 presents the result and discussion and Section 5 presents the conclusion.

2. Related Work

In the study by Moghadasi et al. [1], challenges of generating relevance judgements at high cost in retrieval experimentations and methods of performing low cost evaluations are discussed. In the survey by Sui et al. [2], dueling bandit algorithms and their theoretical proofs are discussed. In the study by Hofmann et al. [3], there is a discussion of online IR evaluation and ranking.

3. Research Method

The systematic mapping protocol for this work was developed by using the systematic mapping guidelines described by Petersen et al. [5] and some guidelines outlined by Kitchenham and Charters [4] that apply to mapping studies were also used. The protocol comprises of the following: research questions, sources of data and search strategy, the selection of studies and the extraction and synthesis of data.

Figure 1 shows how we classified the primary studies.

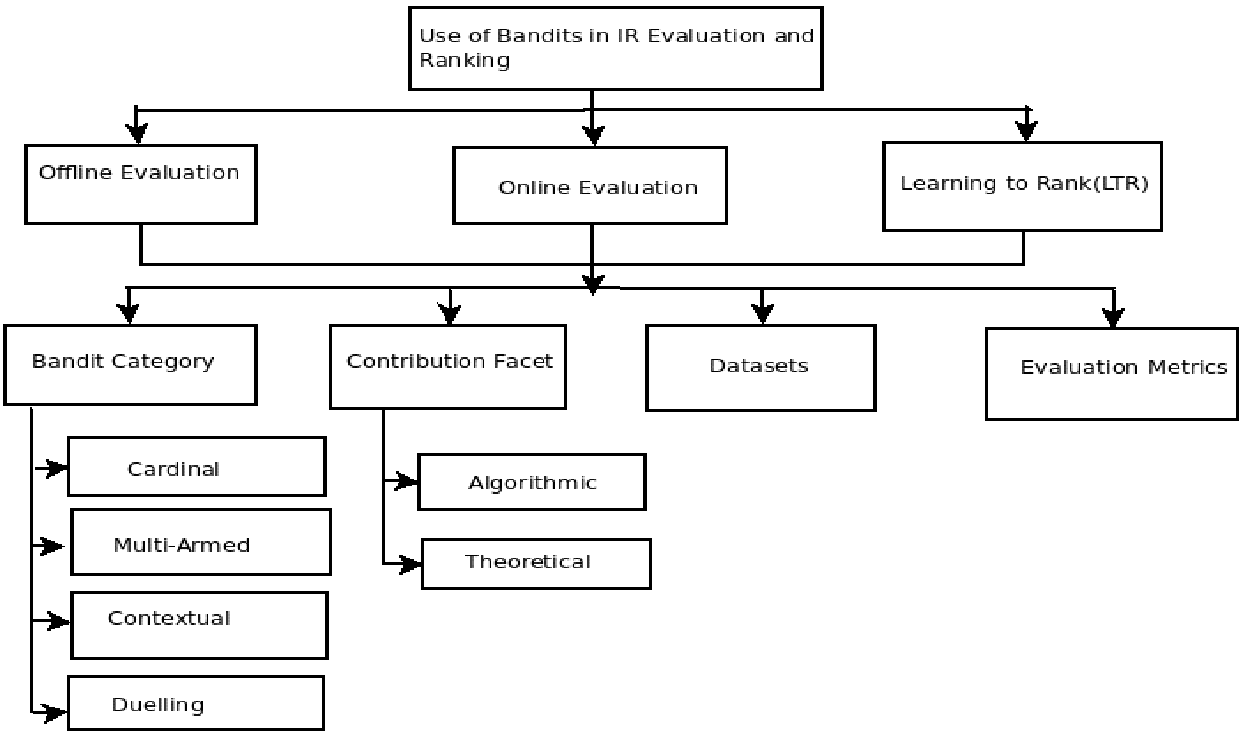

Fig 1. Classification scheme

3.1 Research Questions

The primary question for this systematic study is: “What is the state-of-the-art in use of bandit algorithms in IR evaluation and ranking”. This is divided into five research questions. Table 1 enlists the formulated research questions along with the rationale of each research question.

Table 1. Research Questions and Motivation

Research question number	Research question	Motivation
RQ1	What bandit algorithms have been used in IR evaluation and ranking?	To identify commonly used bandit algorithms in IR evaluation and ranking
RQ2	What contribution facets do the primary studies provide?	To identify the contribution facets of the primary studies.
RQ3	What data sets are widely used by research community in bandit usage in IR evaluation and ranking?	To build a list of appropriate datasets for use in research which involves usage of bandits in IR evaluation and ranking.

RQ4	What are the trends of publications of the relevant studies?	To highlight publication distribution of studies in the last 10 years.
RQ5	What are the most used evaluation metrics?	To highlight the appropriate evaluation metrics in research involving usage of bandits in IR evaluation and ranking.

3.2 Data Sources and Search Strategy
Searching followed a systematic process which comprised of: 1) the selection of terms that would be used for searching; 2) how the searching was going to be conducted; and 3) selection of databases that would be used for search. Table 2 shows the search keywords used in the search.

Table 2. Several phrases used in the search.

Number	Search Term
1	bandits information retrieval evaluation
2	bandits AND "retrieval" AND "evaluation"
3	bandit and "information retrieval evaluation"
4	bandit and "learning to rank"
5	+(bandit)+("information retrieval")

Several databases were chosen based on the likelihood of being repositories of information retrieval research articles. This was after scrutiny of some earlier reviews [1, 2]. Databases below were found to be huge repositories of information retrieval research papers. These databases are Association of Computing Machinery ,Now Publishers, Science Direct, Springer Link and IEEE Xplore.

3.3 Selection of Studies
The selection of studies was carried in phases that are summarized in Table 3 below.

Table 3. Study selection process

Phase	Criteria	Number of studies
Phase 1	Search Terms	154
Phase 2	IC2	152
Phase 3	IC1	135
Phase 4	IC3 and EC1	18

The criteria for inclusion(IC) and exclusion(EC) of studies described in Table 4 is strictly followed for all the studies that met the search criteria in the first phase.

Table 4. Inclusion and Exclusion criteria

Criteria	Description
IC1	Publications that have been peer-reviewed and published in a conference or journal are included
IC2	Publications must be in English language. Publications in languages other than English are excluded.
IC3	Publications must describe the use of bandits in IR evaluation and ranking sufficiently well that it is possible to identify the bandit algorithm.

EC1	Books, Thesis, workshop, lectures, forum, and patents are excluded

Table 5. Selected studies

Number	Reference List	Category
1	[7][8][9][10][11][12][15][16][17][18][19][21]	Online IR Evaluation
2	[13][22][6][21][20]	Learning to Rank
3	[14]	Offline IR Evaluation

Table 3 summarizes the entire selection process and Table 5 lists the selected studies. The first selection phase where keywords were used resulted in 154 primary studies that were retrieved. The fourth and final phase resulted in 18 primary studies that remained and these were finally reviewed.

3.4 Study Data Extraction and Data Synthesis

Information collected from the selected primary studies includes aim of study, research questions, click models, interleaving or multileaving methods, research methods, main contribution of study, year of publication, data sets, evaluation metrics and bandits algorithm used. click models are used to simulate user behaviour in both online evaluation and learning to rank while interleaving and multileaving methods are used to interleave search results during evaluation. Data collection is conducted by first author while verifications were conducted by other authors. Following the rigorous data extraction is data synthesis whose details are in the next section.

4 Results and Discussion

4.1 What bandit algorithms have been used in IR evaluation and ranking?

Figure 2 and 3 below shows that 73% of primary studies on dueling bandits are in online IR evaluation while, 27% are for online learning to rank. All the studies on cardinal bandits relate to online IR evaluation. 17% of published multi-armed bandit algorithms relate to online IR evaluation while 83% of them relate to offline IR evaluation. For offline IR evaluation, multi-armed bandits have only been used as solution for selecting relevant documents to be judged in pooling-based evaluation [14]. In future, there is need to explore the tradeoff between exploration and exploitation by e.g reshaping posterior distributions. Hierarchical bandits may need to be explored which may lead to improvement of allocation methods.

4.2 What contribution facets do the primary studies provide?

Figure 4 below shows that primary studies on offline IR evaluation only had algorithmic contributions. All primary studies on online evaluation had algorithmic contributions. However 17% of them lacked theoretical contributions. All primary studies on learning to rank had algorithmic contributions though 40% of them lacked theoretical contributions.

4.3 What data sets are widely used by research community in bandit usage in IR evaluation and ranking?

Figure 5 below shows that 83% of primary studies on online IR evaluation used the MSLR-WEB10K dataset, while 66% of them used the YLR Set 1 and YLR Set 2 datasets. All primary studies on online learning to rank used used NP2003,NP2004,HP2003,HP2004,OHSUMED, TD2003,TD2004,MQ2007 and MQ2008 datasets. All primary studies on offline IR evaluation used the TREC5,TREC6,TREC7 and TREC8.

4.4 What is the trend of publications of the relevant studies?

There have been several publications from the year 2008 to 2017. In this study, a total of 17 relevant primary studies was retrieved from publication venues. Each year from 2008 to 2012, the rate of publications was 5.8%, in the period 2013 to 2016, there was an increase in rate of publications to 23%, though a noticeable drop was observed in 2017.

4.5 What are the most used evaluation metrics?

Evaluation metrics are a way of measuring the effectiveness of IR systems. These metrics include regret, precision, normalized discounted cumulative gain(NDCG) and mean average precision(MAP). All the primary studies that relate to online IR evaluation utilized the regret measure while precision was utilized for offline IR evaluation. 60% of learning to rank primary studies utilized NDCG, 40% utilized cumulative NDCG and 20% utilized precision, MAP and cumulative MAP respectively.

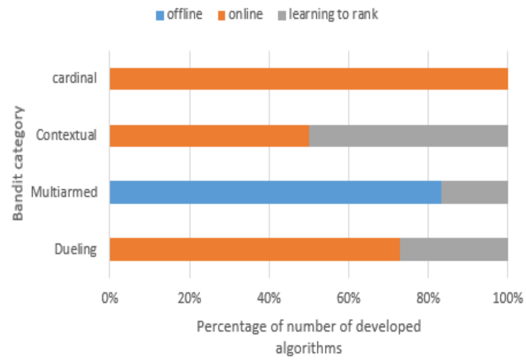

Fig 2. Percentages of bandit algorithms used per bandit category

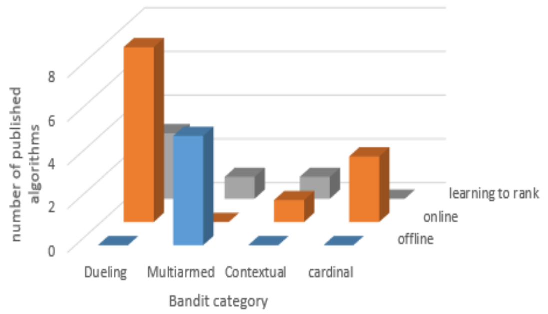

Fig 3. Number of bandit algorithms used in IR evaluation and learning to rank

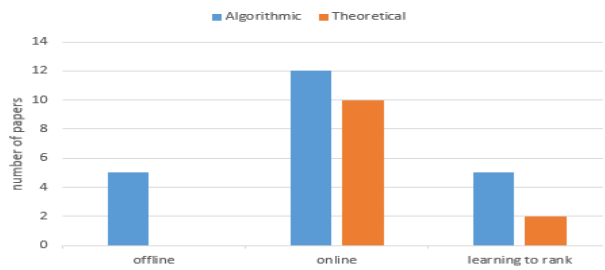

Fig 4. Algorithmic and Theoretical contributions in primary studies

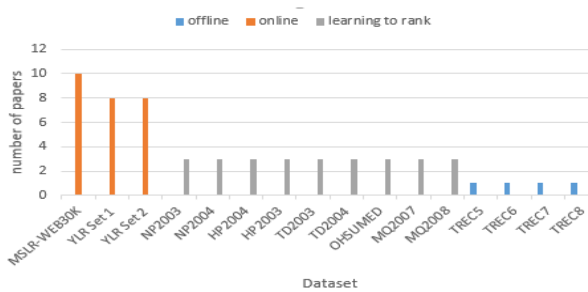

Fig 5. Data sets used in primary studies

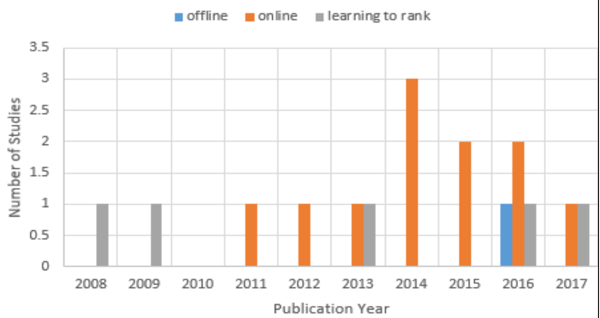

Fig 6. Number of published studies per year.

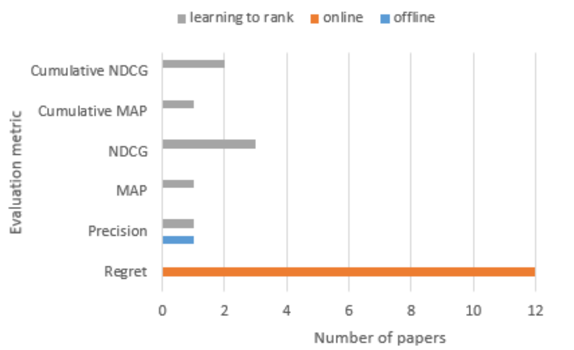

Fig 7. Evaluation metrics used in primary studies

Table 6. Datasets utilized in primary studies

Data Set	Reference	Task	Number of studies
MSLR-WEB30K, YLR Set 1, YLR Set 2	[25]	Online evaluation	10
NP2004, NP2003, HP2003, HP2004, TD2003, OHSUMED, MQ2007, MQ2008	[23]	Learning to rank	3
TREC5,TREC6,TREC7,TREC8	[24]	Offline evaluation	1

5 Conclusion

The use of bandits in information retrieval evaluation and ranking has already yielded several benefits. For instance, the use of bandits in selection of relevant documents in pooling-based evaluation has been greatly improved over the state of art. This paper has presented a mapping study that gives a summary of existing research in the use of bandits in IR evaluation and ranking for last 10 years. A classification comprising of evaluation metrics, data sets, contribution facet and bandit algorithm categories for online IR evaluation, offline IR evaluation and online learning to rank was presented. Further results and discussions were presented in the paper.

This study opens several interesting lines of research. This systematic mapping study has shown that not all primary studies have theoretical contributions. Therefore, theoretical analysis for algorithms of the affected studies is required in order to understand their strengths and drawbacks.

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