Beyond Probability Ranking Principle: Modeling the Dependencies among Documents

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ABSTRACT

Probability Ranking Principle (PRP) [30], which assumes that each document has a unique and independent probability to satisfy a particular information need, is one of the fundamental principles for ranking. Traditionally, heuristic ranking features and well-known learning-to-rank approaches have been designed by following the PRP principle. Recently, neural IR models, which adopt deep learning to enhance the ranking performances, also obey the PRP principle. Though it has been widely used for nearly five decades, in-depth analysis shows that PRP is not an optimal principle for ranking, due to its independent assumption that each document should be independent of the rest candidates. Counter examples include pseudo relevance feedback [24], interactive information retrieval [45], search result diversification [10] etc. To solve the problem, researchers recently proposed to model the dependencies among the documents during the designing of ranking models. A number of ranking models have been proposed and state-of-the-art ranking performances have been achieved. This tutorial aims to give a comprehensive survey on these recently developed ranking models that go beyond the PRP principle. The tutorial tries to categorize these models based on their intrinsic assumptions: assuming that the documents are independent, sequentially dependent, or globally dependent. In this way, we expect the researchers focusing on ranking in search and recommendation can have a novel angle of view on the designing of ranking models, and therefore can stimulate new ideas on developing novel ranking models.

The material of this tutorial can be found in https://github.com/pl8787/wsdm2021-beyond-prp-tutorial.

CCS CONCEPTS

• **Information systems** → **Retrieval models and ranking**; • **Computing methodologies** → **Neural networks**.

KEYWORDS

Learning to rank; Deep Learning; Probability Ranking Principle

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1 MOTIVATION AND INTRODUCTION

Ranking is at the core of many AI applications such as web search [25], recommendation [38], question answering [11], and dialogue system [19]. In general, the goal of ranking is to sort result candidates into a special sequence so that the utility of the final ranked list could be maximized. For example, in Information Retrieval, one of the most famous ranking theory is the **Probability Ranking Principle (PRP)** which assumes that the effectiveness of a ranking system to its users will be optimized if it can present documents/items in order of the decreasing probabilities of relevance. In other words, the utility of a ranked list with respect to a user can be maximized as long as we score and rank documents according to their intrinsic relevance to user's information need.

In the last decades, considerable retrieval models and ranking systems have been proposed under the vanilla form of the Probability Ranking Principle. Proposed by Robertson in 1977 [29], PRP assumes that each document has a unique probability to satisfy a particular information need. To obtain the best ranked lists under PRP, the ranking scores of documents should align with their probabilities of relevance and can be assigned independently to each other. Thus, previous work on ranking function developments mostly focus on predicting the relevance between queries and documents using a univariate scoring function that score each query-document pair separately. For instances, traditional retrieval models such as TF-IDF [23], BM25 [31], and language modeling approaches [43] build heuristic ranking functions using the exact match signals of query and document words to determine each document's relevance with respect to a query; Learning-to-rank algorithms, despite their pointwise [15], pairwise [7, 21], or listwise [5, 6, 9, 35] loss functions, combine features from different information sources to score each query-document pair and rank them accordingly; More recently, Neural IR models, e.g. representation learning models [16, 18], matching function learning models [17, 26, 27, 33], and their combination [12], bridge the semantic gap between query and document using deep learning methods and predict the relevance of each query-document pair automatically from their raw text.

Despite widely adopted, the power of PRP-based ranking models, however, have been found limited in recent studies [1, 3, 20]. First, PRP argues that each document has an intrinsic probability of relevance for each query, which essentially assume that the relevance scores of each document could or should be estimated independently. Such independent scoring paradigms prevent traditional learning-to-rank models from modeling cross-document interactions and capturing local context information. As shown by previous studies on pseudo relevance feedback [24] and query-dependent learning-to-rank [8], incorporating local context information such as query-level document feature distributions can significantly improve the effectiveness of modern ranking systems. Second, as pointed by Robertson [30], PRP works document-by-document while the results of ranking should be evaluated request-by-request. Behavior analysis on search engine users manifest that user’s interactions with information retrieval systems show strong *comparison* patterns [22, 41]. In practice, search engine users often compare multiple documents on a result page before generating a click action. Studies on query-document relevance annotations show that information from other documents in the same ranked list could affect an annotator’s decision on the current document [32, 40], which challenge the basic hypothesis that relevance should be modeled independently on each document for a single information request.

Aware of those problems, a new group of ranking models [1, 3, 14, 28, 34, 37, 39, 42] constructed beyond PRP has emerged and attracted more and more attention in recent literature. Instead of scoring each query-document pair independently, they model the dependencies among documents in order to incorporate cross-document and request-level context for the evaluation and prediction of ranking scores. Generally speaking, existing work on ranking beyond PRP can be categorized into two groups: (1) the models with sequential dependency assumptions on document ranking, such as MMR and their variations [10, 36], and (2) the models with global dependency assumptions, such as query-dependent learning-to-rank [8] and multivariate learning-to-rank functions [1]. As information retrieval tasks and applications are growing much more complex today, those models constructed without the document independence assumption inherited from PRP have been shown to be promising and have great potential for online ranking systems [3, 4]

With growing popularity and potential impact of ranking algorithms beyond PRP, this tutorial aims to increase the general understanding and awareness of these techniques in our community. The people involved in this proposal have followed the studies of ranking models for a long period, and are actively working on research projects in this area. We will first introduce the well-known underlying principles used in existing ranking models as well as their characteristics in ranking practices. We will illustrate the limitations of PRP principle with real examples and formally discuss recent advances on ranking models that designed to model the dependencies among documents beyond the assumption of PRP. Overall, this tutorial aims to attract more people to look at the problem and design ranking models that better suit the need of modern AI applications. It will provide important guidance for the design of ranking systems and inspire future studies on related research topics.

Table 1: The schedule of the tutorial (starting from 8:00 am).

First Half (8:00 am - 9:30 am)
1. Introduction (20 minutes)
1.1 The Ranking Problem
1.2 Organization of the tutorial
2. Probability Ranking Principle (PRP) (20 minutes)
2.1 History of Ranking
2.2 Definition of PRP principle
Part I: Traditional Approaches for Ranking
3. Feature based Ranking Methods (20 minutes)
3.1 Heuristic Ranking Functions
3.2 Learning to Rank Approaches
4. Neural IR Models (30 minutes)
4.1 Methods of Representation Learning
4.2 Methods of Matching Function Learning
4.3 Methods of Combining
Second Half (10:00 am - 11:30 am)
Part II: Modeling the Dependencies among Documents
5. Limitations of PRP Principle (20 minutes)
6. Ranking with Sequential Dependency (30 minutes)
6.1 Heuristic Sequential Ranking Models
6.2 Reinforced Sequential Ranking Models
7. Ranking with Global Dependency (30 minutes)
7.1 List Inputted Global Ranking Models
7.2 Set Inputted Global Ranking Models
8. Conclusion and open discussions (10 minutes)

2 OBJECTIVES

In this tutorial, we want to introduce the recent advances of ranking models that go beyond probability ranking principle to a broader audience. For better understanding, we first introduce the fundamental probability ranking principle and the ranking models follow this principle as the background knowledge. After that, we discuss the limitations of PRP principle, and provide a brief survey of recent advanced ranking models that break the PRP principle. The ultimate goal of this tutorial is to tell the audience that PRP is not the optimal, that many ranking task do not satisfied this assumption. Besides, the mentioned ranking models that break PRP may provide a new trend of learning-to-rank techniques and inspire future studies on the related topics.

3 OUTLINE AND SCHEDULE

The outline of the proposed tutorial is as follows. After briefly introducing the ranking problem and describing the important probability ranking principle, it will make audience better understand the design principle of recent ranking models. In Part I, we will recapitulate traditional ranking models, including feature based ranking models and neural IR models. In Part II, we will discuss the limitations of current PRP principle using heuristic examples and need of advanced ranking tasks. To extend independent ranking models, a new branch of ranking models are proposed to model the dependencies among documents. It can be categorized into sequential dependency and global dependency for ranking. Lastly, we will summarize the tutorial and discuss the future directions.

4 TARGET AUDIENCE

This tutorial focuses on introducing the new type of ranking models which go beyond probability ranking principle. They have a great importance and significant potential in a variety of information retrieval tasks, such as diversity ranking, interactive IR or personal search, and recommendation tasks. Therefore, it will be relevant and interesting to the audience of WSDM 2021 who work on search or recommendation problems. It is optional but recommended for the audience to have some basic knowledge of deep learning model and learning to rank. For example, it would be good to know the basic concepts of neural networks (e.g., fully-connected networks, transformer structures, recurrent structures, convolution structures, etc.) and ranking loss functions (e.g., pointwise, pairwise, and listwise loss functions, etc.) before attending this tutorial. Some knowledge of the machine learning techniques, reinforcement learning techniques would also help the audience better understand the content and impacts of this tutorial.

5 SUPPLEMENTAL MATERIALS

The tutorial materials to be supplied to the attendees include

Slides: tutorial slides will be made publicly available on the lecturers' personal homepages.

Bibliography: a list of references will cover all the work discussed in the tutorial and provide a good resource for further study.

Several wonderful tutorials were given at related conferences: Jun Xu, Xiangnan He and Hang Li for Deep Learning for Matching in Search and Recommendation, at SIGIR 2018, WWW 2018, WSDM 2019; Bhaskar Mitra and Nick Craswell, Neural Text Embeddings for Information Retrieval, at WSDM 2017; Kyomin Jungj, Byoung-Tak Zhan, and Prasenjit Mitra, Deep Learning for the Web, at WWW 2015; Tom Kenter et al., Neural Networks for Information Retrieval (NN4IR), at SIGIR 2017; Hang Li and Zhengdong Lu, Deep Learning for Information Retrieval, at SIGIR 2016; Ganesh Venkataraman et al., Deep Learning for Personalized Search and Recommender Systems, at KDD 2017; Alexandros Karatzoglou et al., Deep Learning for Recommender Systems, at Recsys 2017. This tutorial is significantly different from the previous tutorials in the sense that it focuses on the semantic matching problem in search and recommendation.

6 PRESENTERS' BIOGRAPHY

• Dr. **Liang Pang** is an Assistant Professor at Institute of Computing Technology, Chinese Academy of Sciences. Liang Pang's research interests focus on designing deep models for text matching and learning-to-rank in information retrieval. He has published about 30 papers at top international journals and conferences, including SIGIR, CIKM, ACL, AAAI, IJCAI etc. His work on information retrieval has received the Best Paper Runner-up of ACM CIKM 2017. He is very active in the research communities and has served or is serving top international conferences as PC member, including SIGIR, WWW, NIPS, AAAI, IJCAI, CIKM etc.

• Dr. **Qingyao Ai** is an Assistant Professor at School of Computing, University of Utah. His research mainly focuses on developing intelligent retrieval systems with machine learning techniques. He actively works on applying deep learning techniques on IR problems including ad-hoc retrieval, product search/recommendation and learning to rank. He has published more than 40 papers on top international journals or conferences such as SIGIR, CIKM, WWW, TOIS, etc. He has organized multiple tutorials/workshops [2, 13, 44, 46] and served as the senior/ordinary PC member of top-tier IR conferences including SIGIR, CIKM, WSDM, WWW, AAAI, etc.

• Dr. **Jun Xu** is a Professor at Gaoling School of Artificial Intelligence, Renmin University of China. Jun Xu's research interests focus on applying machine learning to information retrieval and recommendation. He has published more than 50 papers and 2 monographs at top international journals and conferences, including TKDE, TOIS, JMLR, SIGIR, CIKM, ACL, EMNLP etc. His work on information retrieval has received the Test of Time Award Honorable mention of ACM SIGIR 2019, Best Paper Runner-up of ACM CIKM 2017, and Best Paper Award of AIRS 2010. He has served or is serving top international conferences as Senior PC members, including SIGIR, ACML, CIKM, AAAI, and top international journal of JASIST as an editorial board member, and ACM TIST as an associate editor. He has given tutorials at top conferences like SIGIR, WSDM, TheWebConf (WWW) on the topic of deep learning for semantic matching in search and recommendation.

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