Learning to Rank in Theory and Practice

From Gradient Boosting to Neural Networks and Unbiased Learning

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ABSTRACT

This tutorial aims to weave together diverse strands of modern Learning to Rank (LtR) research, and present them in a unified full-day tutorial. First, we will introduce the fundamentals of LtR, and an overview of its various sub-fields. Then, we will discuss some recent advances in gradient boosting methods such as LambdaMART by focusing on their efficiency/effectiveness trade-offs and optimizations. Subsequently, we will then present TF-Ranking, a new open source TensorFlow package for neural LtR models, and how it can be used for modeling sparse textual features. Finally, we will conclude the tutorial by covering unbiased LtR – a new research field aiming at learning from biased implicit user feedback.

The tutorial will consist of three two-hour sessions, each focusing on one of the topics described above. It will provide a mix of theoretical and hands-on sessions, and should benefit both academics interested in learning more about the current state-of-the-art in LtR, as well as practitioners who want to use LtR techniques in their applications.

CCS CONCEPTS

• **Information systems → Learning to rank**.

KEYWORDS

Learning to rank; Efficiency/effectiveness trade-offs; Deep learning; Unbiased learning

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1 OVERVIEW

This full-day tutorial is organized in three sessions lasting two hours each. Together these sessions provide a wide overview of recent advances in the field of Learning to Rank (LtR).

Session I: Efficiency/Effectiveness Trade-offs

We propose an analysis of the efficiency/effectiveness trade-offs in Learning to Rank. In the last years, LtR, had a significant influence in the Information Retrieval field, with large research efforts coming both from the academia and the industry. Indeed, efficiency requirements must be fulfilled in order to make an effective research product deployable within an industrial environment. The evaluation of a model can be too expensive due to its size, the features used and several other factors.

This session discusses the recent solutions that allow to build an effective ranking model that satisfies temporal budget constrains at evaluation time. We first introduce LtR solutions for a multi-stage ranking pipeline with a focus on decision tree ensembles. Then we present several complementary strategies for optimizing the efficiency of a *ranking forest* including: feature analysis [19], tree pruning [9], effectiveness optimization at training time [16], approximate computation [3] and efficient traversal [5].

This session will be presented by Claudio Lucchese from the Ca' Foscari University of Venice and Franco Maria Nardini from the National Research Council of Italy.

Session II: Neural Learning to Rank using TensorFlow

A number of open source packages harnessing the power of deep learning have emerged in recent years and are under active development, including TensorFlow [1], PyTorch [13], Caffe [7], and MXNet [4]. Supervised learning is one of the main use cases of deep learning packages. For example, one task in the ImageNet competitions [15] is to predict image categories, which can be formulated as a multi-class classification problem. However, compared with the comprehensive support for classification or regression in open-source deep learning packages, there is a paucity of support for ranking problems.

To address this gap, we developed TensorFlow Ranking[1]: an open-source library for training large-scale LtR models using deep

[1] https://github.com/tensorflow/ranking

learning in TensorFlow [12]. The library is flexible and highly configurable: it provides an easy-to-use API to support different scoring mechanisms, loss functions, example weights, and evaluation metrics. In this hands-on tutorial, we aim to cover how TensorFlow Ranking can be effectively employed in a variety of learning-to-rank scenarios.

First, we will present a brief overview of neural LtR, TensorFlow and Estimator frameworks. Then, we will introduce Tensorflow Ranking components and APIs, and demonstrate how it can handle advanced losses, scoring functions and sparse textual features. Finally, we will provide hands-on codelabs using two existing LtR datasets: MSLR-Web30k [14] and MS MARCO [10].

This session will be presented by Rama Kumar Pasumarthi, Sebastian Bruch, Michael Bendersky and Xuanhui Wang from Google Research.

Session III: Unbiased Learning to Rank

User interactions provide great potential for LtR: they give valuable implicit feedback and are easy to obtain in large amounts. However, user interactions contain biases such as position bias: documents displayed at higher ranks receive more attention. Naively learning from interactions while ignoring such biases can lead to detrimental performance. Consequently, the field of Unbiased LtR aims to learn the true user preferences from their interactions, thus avoiding the effect of biases. In this part we will cover and contrast the two main approaches to Unbiased LtR: *Counterfactual* LtR and *Online* LtR.

Counterfactual LtR [8, 17] uses an explicit model position bias, and through an inverse propensity weighing approach optimizes LtR metrics without bias. In addition to the learning method, we will discuss how models of position bias can be inferred [2, 18] and other practical considerations.

Online LtR [20] methods directly interact with users, and perform randomizations allowing them to deal with several biases. We will discuss the important *Dueling Bandit* approach [20], as well as the recent *Pairwise* approach [11].

Finally, we compare and contrast both approaches: on a theoretical level and by looking at empirical comparisons [6]. We discuss the situations for which each approach was designed, and the places were they are applicable. This helps LtR practitioners to choose between the two approaches.

This third session will be presented by Harrie Oosterhuis, Rolf Jagerman, and Maarten de Rijke from the University of Amsterdam.

2 SUPPORTING MATERIALS

You can find more materials related to this tutorial on our website http://ltr-tutorial-sigir19.isti.cnr.it/.

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