Tutorial: Modern Theoretical Tools for Understanding and Designing Next-generation Information Retrieval System

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ABSTRACT
In the relatively short history of machine learning, the subtle balance between engineering and theoretical progress has been proved critical at various stages. The most recent wave of AI has brought to the IR community powerful techniques, particularly for pattern recognition. While many benefits from the burst of ideas as numerous tasks become algorithmically feasible, the balance is tilting toward the application side. The existing theoretical tools in IR can no longer explain, guide, and justify the newly-established methodologies. With no choices, we have to bet our design on black-box mechanisms that we only empirically understand.

The consequences can be suffering: in stark contrast to how the IR industry has envisioned modern AI making life easier, many are experiencing increased confusion and costs in data manipulation, model selection, monitoring, censoring, and decision making. This reality is not surprising: without handy theoretical tools, we often lack principled knowledge of the pattern recognition model’s expressivity, optimization property, generalization guarantee, and our decision-making process has to rely on over-simplified assumptions and human judgments from time to time.

Facing all the challenges, we started researching advanced theoretical tools emerging from various domains that can potentially resolve modern IR problems. We encountered many impactful ideas and made several independent publications emphasizing different pieces. Time is now to bring the community a systematic tutorial on how we successfully adapt those tools and make significant progress in understanding, designing, and eventually productionize impactful IR systems. We emphasize systematicity because IR is a comprehensive discipline that touches upon particular aspects of learning, causal inference analysis, interactive (online) decision-making, etc. It thus requires systematic calibrations to render the actual usefulness of the imported theoretical tools to serve IR problems, as they usually exhibit unique structures and definitions. Therefore, we plan this tutorial to systematically demonstrate our learning and successful experience of using advanced theoretical tools for understanding and designing IR systems. See our webpage for detail: https://moderntoolsfornextgenirs.github.io/

CCS CONCEPTS
• Information systems → Information retrieval; • Computing methodologies → Machine learning; • Theory of computation → Theory and algorithms for application domains.

KEYWORDS
Information retrieval, Theory, Machine Learning, Pattern Recognition, Decision making, Causal inference, Bandit, Reinforcement learning

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1 OUTLINE
Our tutorial consists of three sections focusing on pattern recognition with deep learning, causal inference analysis, and interactive decision making with bandits and reinforcement learning. We first give an overview of the contents in Figure 1, including the major topics, theoretical tools, and their connection with the widespread domain practices and our production examples.

1.1 Pattern recognition with deep learning
There are two critical stages for designing and understanding pattern recognition models: the pre-designing stage where we generate a comprehensive inductive bias for the model, and the post-training stage where we diagnose the model to understand why it behaves in certain ways. To build up the intuition, image we employ a linear regression model. It immediately becomes clear:

(1) what the model is capable of expressing: the family of linear functions;
(2) the optimization properties: gradient descent (GD) will lead to the global optimum of convex objectives;
(3) how the model may generalize to unseen data: it will interpolate and extrapolate linearly in the loss-optimal fashion;
(4) why the model would perform in particular ways: the coefficients directly reflect the feature importance.

However, for deep learning models, these questions are incredibly challenging to answer. It causes debates and confusion, such as in [8] where the effectiveness of using neural networks for collaborative filtering (CF) is questioned. In our recent works [2, 15], we provide comprehensive and systematic answers to the expressivity, optimization property and generalization guarantee using advanced theoretical tools such as neural tangent kernel, implicit bias of GD and...
1.2 Causal inference analysis

The interventional nature of IR system is not only reflected in A/B testing, but also the exposures we make (e.g. search result, recommendation, ads displacement) since they can influence users’ behavior. According to whether the intervention target is (at least partly) controlled, we have the experimental and observational settings. The IR community may find the experimental setting more familiar for causal inference analysis, but recently there has been growing interest in using the passively collected observational data for counterfactual reasoning. In both settings, we find Pearl’s do-calculus and structural equation framework [6] extremely powerful for systematically studying causal problems. For example, we rigorously reveal the fundamental limitations of treating observational feedback with the data missing-not-at-random (MNAR) and the domain-adaptation view. These two domain practices are gaining high popularity, and we also provide promising directions for fixing their issues by discovering invariant mechanisms that comprise causality. Towards this end, we introduce advanced optimization and learning tools for causal discovery (e.g. continuous directed acyclic graph (DAG) optimization) and learning from interventional data. Observational study is not the only focus of our tutorial. We mentioned earlier that existing online experiment frameworks often rely on oversimplified assumptions. By presenting the prominent instrumental variable (IV) and mediation analysis tools, we demonstrate how to lift the assumptions and conduct more robust inferences for IR experiments.

1.3 Interactive (online) decision making

Modern IR systems intrinsically build on the understandings of interaction between the information consumer and provider. The exploration-exploitation dilemma thus stands out as a major challenge because there are explicit or implicit costs associated with each interaction. Many are motivated to characterize the underlying dynamics using such as bandits and reinforcement learning (RL). Setting the practicality issues aside, there are critical conceptual challenges unsettled for both approaches. Notably, there is model-based and model-free options for optimizing the policy in each setting, and while many empirical comparisons have been conducted, there is no rigorous conclusion on what conditions
We mentioned previously that our tutorial is the first of its kind. During our investigation, we find the optimal control an extraordinary tool and testbed for revealing the strength and weaknesses of many solutions. On the other hand, some empirical studies have found inferior performances from bandits and RL, though they are conceptually more suitable for the tasks. We reveal that this phenomenon is caused by the robustness issue: compared with the static counterparts, online decision-making methods are much more sensitive to the algorithmic uncertainty since they tend to accumulate during the process. Therefore, we introduce the advanced theoretical tools from robust optimization and present real-world examples of how to use them to enhance the robustness of our design.

2 RELEVANCE TO WSDM

WSDM is a prestigious conference hosting the most advanced research work, workshop and tutorial in search and web data mining. Information retrieval, which broadly concerns the process of obtaining the demanded information from a collection of resources produced by information systems, lies at the heart of web search and data mining applications. While developing IR systems is predominantly an engineering effort, the quality of design and the depth of understanding, for both pattern recognition and decision-making procedures, decide the success of any deployment and the sustainability of the development cycle.

As deep learning and other inventions open the door to more complex learning tasks and data-driven decision making, the challenge occurs to the IR community that existing theoretical understandings may not apply to some new technologies. It has thus become a pressing issue to update the methodological tools such that IR enthusiasts can find justifications and support when working on new technologies.

As researchers and practitioners in the IR community, we have spent considerable efforts in the past few years establishing novel tools, understandings, and theoretical justifications for both pattern recognition and decision making problems, e.g. [13, 15–17, 19, 20]. We also design industrial IR systems powering the online businesses of Walmart and Instacart in the critical applications of search, recommendation, and advertising [4, 12, 14, 18]. Some of the tutorial’s content, including arguments, theoretical tools, design ideas, and production examples, are adapted from our previous publications. We further include the cutting-edge results and analytical tools, e.g. [5, 9, 21], classical analysis, e.g. [6], as well as novel ideas surveyed from other domains, e.g. [7, 11], just to list a few.

3 FORMAT AND SCHEDULE

The tutorial is a half-day event with three sessions:

(1) pattern recognition with deep learning;
(2) causal inference analysis and experiment design for IR;
(3) interactive (online) decision making with bandits and reinforcement learning.

4 RELATION WITH PREVIOUS TUTORIAL

We mentioned previously that our tutorial is the first of its kind to the best of our knowledge. We systematically introduce the advanced theoretical tools for understanding and designing modern IR systems. Most existing tutorials focus on the application and engineering aspects of the topics we cover, e.g. [1, 3, 10]. While those tutorial gave detailed descriptions and solutions to specific domain problems, the overlap is minimal since they do not provide comprehensive and systematic introductions to the advanced theoretical tools and connect them to real-world production examples. In this regard, our tutorial significantly complements those previous efforts by providing self-contained materials that equip both researchers and practitioners with examples, tools, and guidelines to innovate the future of IR with theoretical support.

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