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Designing for Diversity: Online Polarization Control in Recommender Systems

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Abstract

With the widespread use of algorithmic curation systems in recent years – the automated, personalized selection and ranking of online content – growing concern over the nature and implications of their biases has been voiced by both their creators and users worldwide. Social networks in particular have been accused of exhibiting some form of bias, resulting in damaging filter bubbles and large scale misinformation spreading.

In this work, we make the case for a systematic approach towards mitigating polarization in personalized recommendation systems using concepts from reinforcement learning theory. To this end, we investigate multi-armed bandits and their more complex variation, contextual bandits, which factor in user information and can dynamically adjust rewards and future recommendation accordingly. We also examine recommendation independence, a set of statistical methods which ensure fair representations in curation systems where sensitive data is involved. Our frameworks are illustrated on three curated datasets (YOW, MovieLens and a synthetically-generated one for the purposes of this dissertation). Through extensive experimentation and comparison with state-of-the-art techniques, we show that our described frameworks provide adequate balance between user satisfaction and diversity of content.

Keywords: Recommender systems, algorithmic depolarization, multi-armed bandits, recommendation independence, differential privacy.

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Chapter 1

Introduction

We begin this chapter by motivating the necessity of algorithmic debiasing and describing the increasingly prevalent issues derived from belief polarization in online communities. We then trace the technical and social context for the occurrence of online biases as well as the risks they pose to information diversity (notably the technical challenges behind filter bubbles). Lastly, we outline the aims and contributions of this work, with an overview of our experiments, main models and overall structure of the report.

1.1 Algorithmic Bias: Why Should We Care?

Personalized content recommendation is deeply ingrained in the modern online browsing experience. From social media to entertainment, news outlets and education, each recommendation shapes our individual model of the world and contributes to our understandings, decisions and beliefs.

1.2 A Brief History of Bias

1.3 Overview of this Dissertation

Chapter 2

Background and Related Work

This chapter lays the foundations for understanding the online polarization problem. In the first section, we focus on the general notion of bias from an ethical standpoint before introducing formal ways of detecting and measuring it in algorithms. Next, we introduce the online recommendation setting, outlining various sources of bias likely to emanate from personalized curation and exploring multi-armed bandits, which are commonly used in modelling recommendation dynamics. The chapter ends with an overview of current algorithmic approaches to recommendation debiasing and establishes the mathematical groundwork which will be built upon in the rest of the dissertation.

2.1 The Anatomy of Polarization

2.1.1 The ethical framework

2.1.2 Quantifying online biases

2.2 The Online Recommendation Setting

2.2.1 Overview

2.2.2 Shades of bias in recommendation

2.2.3 Multi-armed bandits

2.3 Current Approaches to Depolarization

2.3.1 Regularization and noising

2.3.2 Constrained bandit optimization

Chapter 3

Designing for Diversity

In this chapter, we conduct a formal study of combating polarization in online personalization algorithms. We begin by reviewing a general framework which employs a modified version of the bandit algorithm to ensure that balanced sets of items are displayed to each user. This is achieved through polarization constraints, which are shown to attain state-of-the-art regret bounds. We then explore contextual bandits, which factor in user information and can dynamically adjust rewards and future recommendation accordingly. Lastly, we look into recommendation independence, a set of statistical methods which ensure fair representations in curation systems where sensitive data is involved.

3.1 Simple Multi-Armed Bandit Approaches

3.2 The Dynamic Setting: Contextual Bandits

3.3 Recommendation Independence with Sensitive Data

Chapter 4

Experiments

This chapter explores our various implementations of the models described in chapter 3. We start by providing a detailed analysis of the datasets used – MovieLens, YOW and a synthetic dataset generated for the purposes of this dissertation. We then report, for each experiment, the values of any parameters and constraints used and the methodology employed to determine them.

4.1 Methodology

4.1.1 Datasets

4.1.2 Choice of metrics

4.2 Baseline

4.3 Contextual Bandits

4.4 Recommendation Independence

Chapter 5

Results

In this chapter, we report the outcomes of the experiments described in chapter 4, for each model and each dataset. We then visualize polarization over time for the best group in each algorithm, so as to better understand how polarization can be avoided and diversification enforced in our models. We further assess the overall performance and robustness of our models in a cross-comparison and discuss the intuition behind each. Lastly, we discuss time and memory considerations along with elements of optimization and expose the limits of our implementations.

5.1 Baseline

5.2 Contextual Bandits

5.3 Recommendation Independence

5.4 Discussion

Chapter 6

Conclusion

This chapter concludes the dissertation by epitomizing its key concepts and findings, as well as highlighting the main contributions. We also provide insights into the future of content depolarization techniques in personalized curation engines, with a glimpse into neural methods and differential privacy.

6.1 Summary

6.2 Contributions

6.3 Forward

Bibliography