# Title

J.T. Cho joncho@

joncho@ seas.upenn.edu Karinna Loo

kloo@
seas.upenn.edu

**Veronica Wharton** 

whartonv@ seas.upenn.edu

#### 1 Introduction

For our CIS 625 final project, our team — JT Cho, Karinna Loo, and Veronica Wharton — took a closer look at the topic of fairness in machine learning. The paper that piqued our interest was Rawlsian Fairness for Machine learning (Joseph et al., 2016), which describes two online algorithms in the linear contextual bandit framework that both learn at a rate comparable to (but necessarily worse than) the best algorithms absent of a fairness constraint and also satisfy a specified fairness constraint. The authors present theoretical and empirical results. Our team sought to reimplement the algorithms presented by Joseph et al. (2016) and then expand upon their empirical analyses. We were also interested in exploring further fairness analyses using real-world data.

## 2 Project overview

Our project consisted of the following steps:

- 1. We read the paper *Rawlsian Fairness for Machine Learning* (Joseph et al., 2016).
- 2. We implemented the TopInterval, IntervalChaining, and RidgeFair algorithms from the paper in Python.
- 3. We ran our implementations on a Yahoo! dataset containing a fraction of the user click log for news articles displayed in the Featured Tab of the Today Module on the Yahoo! Front Page during the first ten days in May 2009 (Yahoo!, 2009), to see how well they performed on real data.
- 4. To empirically evaluate our implementations, we ran experiments similar to those in (Joseph et al., 2016) with randomly-drawn contexts.
- 5. We compiled our findings into a written report.

# 3 Algorithm Implementations

The code for our implementations can be found here: https://github.com/jtcho/FairMachineLearning/blob/master/fairml.py

4 Implementation: TopInterval

5 Implementation: IntervalChaining

6 Implementation: RidgeFair

7 Experimental results: generated data

TODO: Pretty figures

8 Experimental results: real data

**TODO:** Pretty figures

### 9 Conclusion

#### References

[Joseph et al.2016] Matthew Joseph, Michael Kearns, Jamie Morgenstern, Seth Neel, and Aaron Roth. 2016. Rawlsian fairness for machine learning. *CoRR*, abs/1610.09559.

[Yahoo!2009] Yahoo! 2009. Yahoo! front page today module user click log dataset. https://webscope.sandbox.yahoo.com/catalog.php?datatype=r. Accessed: 2017-04-03.