Embedded Ethics — Recommender System Objectives

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Embedded Ethics
Module
Recommender System
Objectives

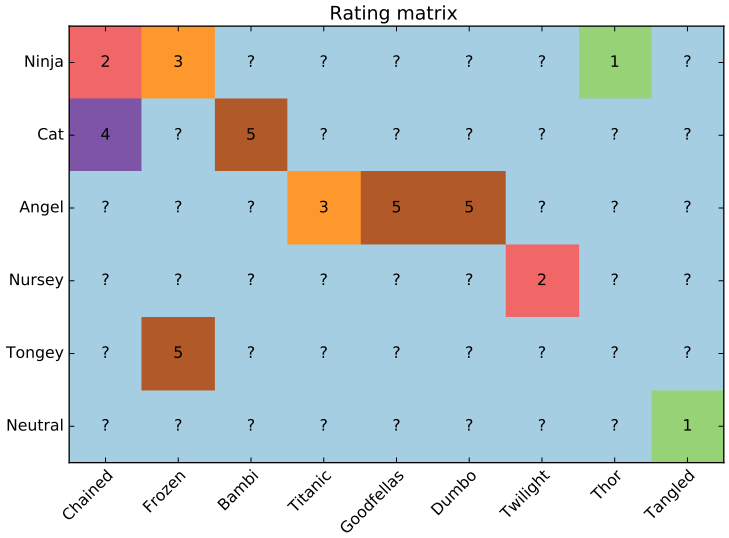
Today

- **Topic:** objective functions for recommender systems
- Two parts
  - **Part 1:** technical challenges in moving beyond regression and classification
  - **Part 2:** ethical challenges, and philosophical tools for reasoning about them

Recap and Motivation

Recap: Netflix Challenge

- We can view collaborative filtering as a matrix completion problem.



- In addition to the learning algorithm, it is important to consider the data and the objective function.

Recommender Systems

- Other kinds of recommendation systems include search engines and social media feeds.
- What are some difficulties you'd run into if you tried to use a Netflix-style algorithm to organize a user's social media feed?

Recommender Systems

- If you were designing an ML algorithm to organize a user's social media feed, what other information might you use?

- As a supervised learning problem, what would be the inputs, and what would be the targets?

Warmup: Open up your social media feeds - shout out some of the topics in the posts that you find.

Challenge 1: Inferring User Preferences

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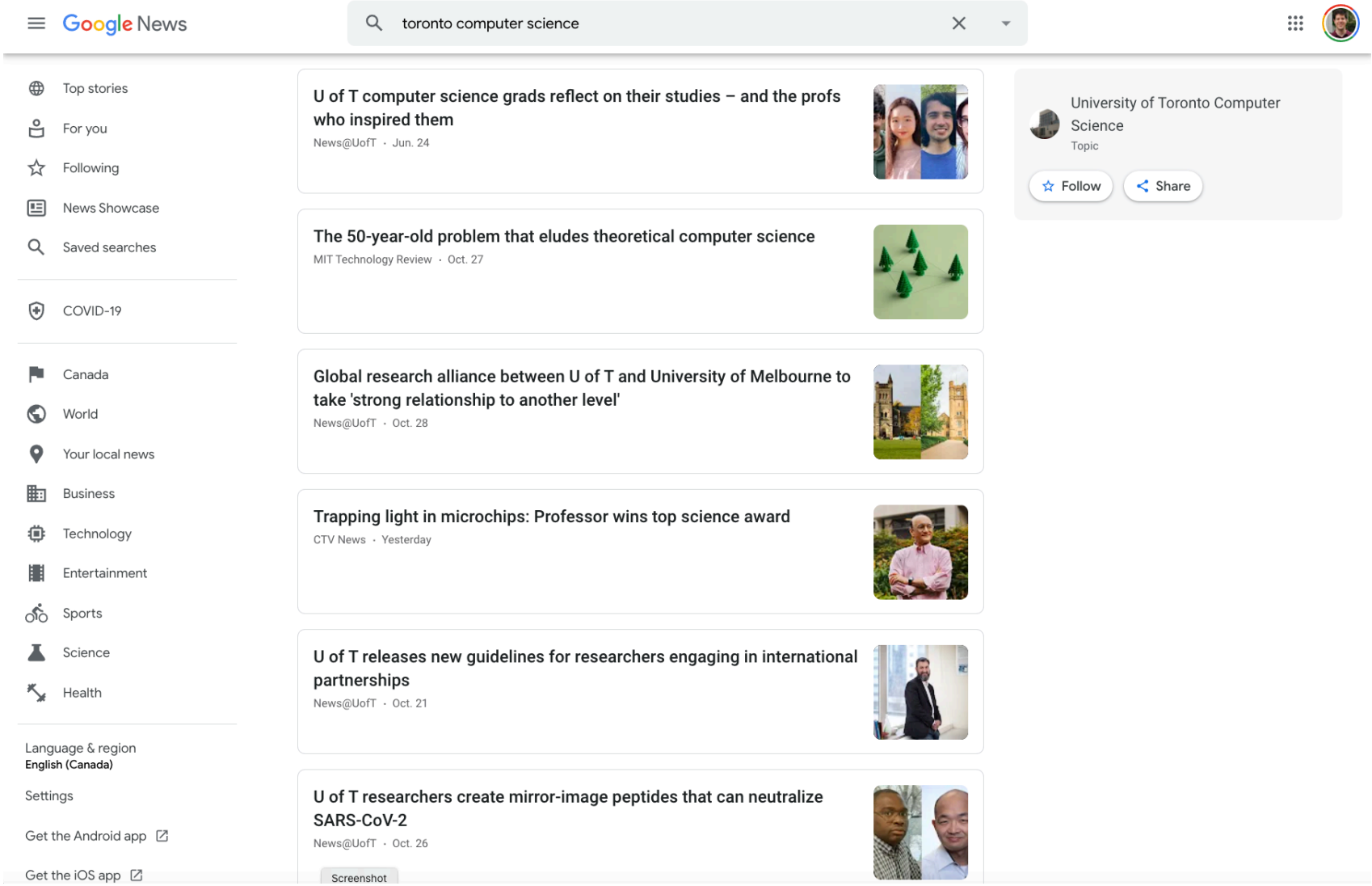
- Google News was an early example of training a model to predict clicks.



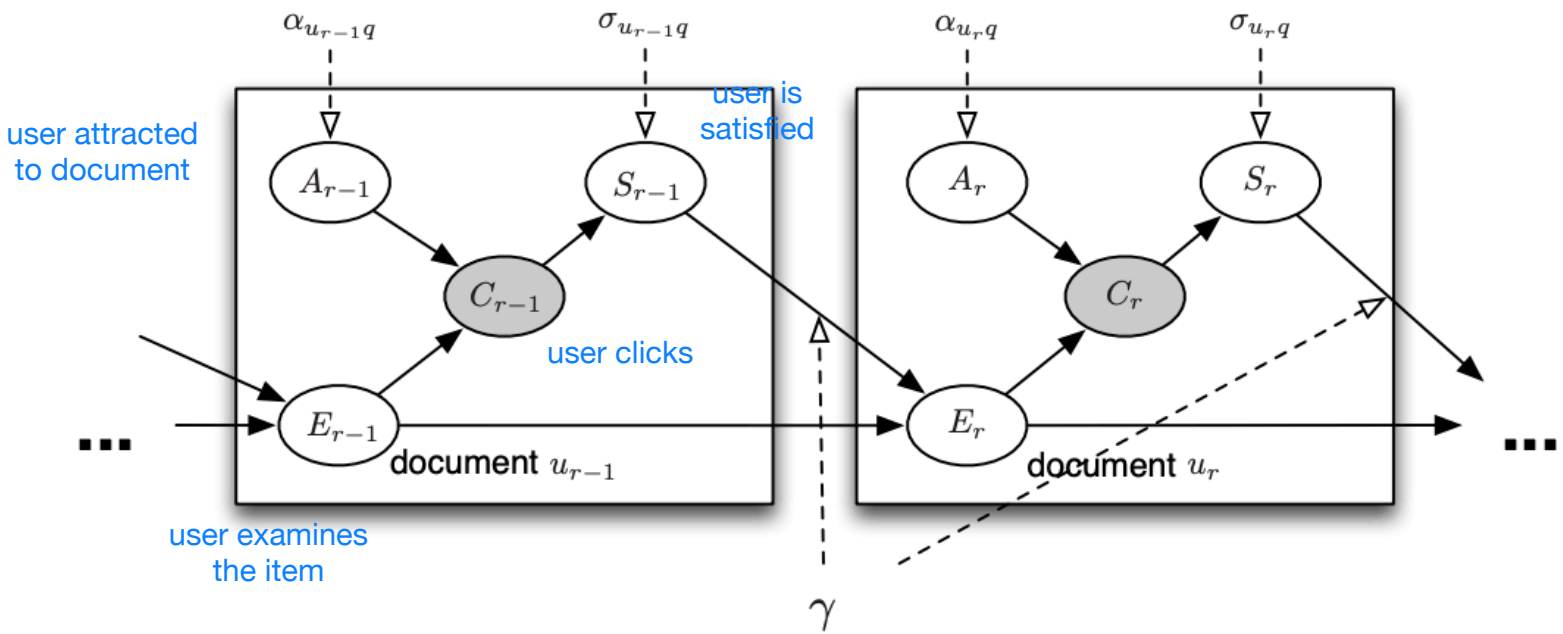
Challenge 1: Inferring User Preferences

- Why are clicks a useful signal?

- What are some problems with optimizing for clicks?

Challenge 1: Inferring User Preferences

- Here is a Bayesian network designed to model user behavior for a search engine.
  - We covered Bayes nets briefly when we discussed naıve Bayes.
- Nodes represent random variables, and edges represent direct influences. Shaded = observed.
- Want to infer user satisfaction (S).



Chuklin et al., "Click models for web search"

Challenge 1: Inferring User Preferences

- User preferences aren't just a matter of reactions to individual items, but also of the user's overall experience.
- Many web services optimize for a criterion called engagement.
  - User's frequency, intensity, or depth of interaction with a product over some time period
  - Not a technical term, but a business term, instantiated in different ways by different companies
  - E.g. Gmail: percentage of active users who visited the site on 5 or more days during the past week Rodden et al., "Measuring the user experience on a large scale"
  - E.g. Facebook: time spent on site, meaningful social interactions

    https://www.washingtonpost.com/technology/interactive/2021/how-facebook-algorithm-works/
- This is not directly optimized by an ML algorithm (as far as I know), but is used to evaluate changes to the system.
  - Sort of analogous to how logistic regression minimizes cross-entropy loss but you might tune hyperparameters based on accuracy.

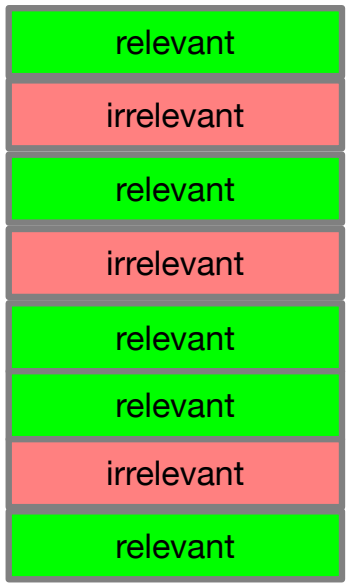
Challenge 1: Inferring User Preferences

- The choice of what to optimize for can have ethical implications.
- The recently published Facebook Papers reveal a lot about unintended consequences of algorithm design
  - My aim isn't to pick on Facebook here. They found these harms and worked to fix them!
- Early years: optimizing for likes and clicks ⇒ clickbait
- Optimizing for time spent reading/watching ⇒ favored professional over organic content
- 2017: service changed to reward comments & emojis ⇒ most successful political posts were the polarizing ones
  - Some political parties consciously shifted their messaging to be much more negative
  - Facebook eventually rolled back this change for health and politics
- `https://www.wsj.com/articles/facebook-algorithm-change-zuckerberg-11631654215`

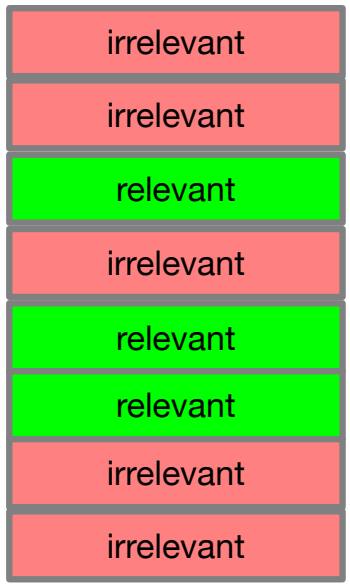
Challenge 2: Evaluating Structured Outputs

Challenge 2: Evaluating Structured Outputs

- Most of this class has focused on classification, where there is a natural metric to use (accuracy).
- In this case, we'd like to produce a feed (an ordered list of items). Problems where we want to predict a structured object are known as structured prediction.
- For now, assume that all items are either relevant or irrelevant.
- Which of the following lists is preferable?



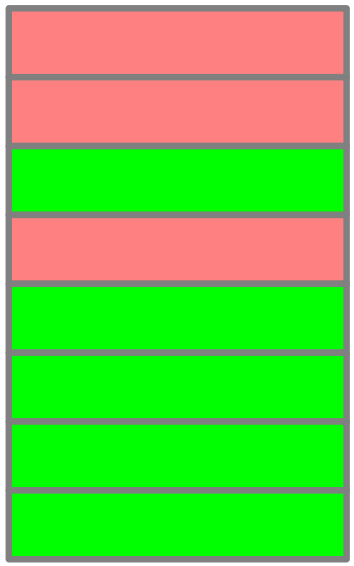
List A



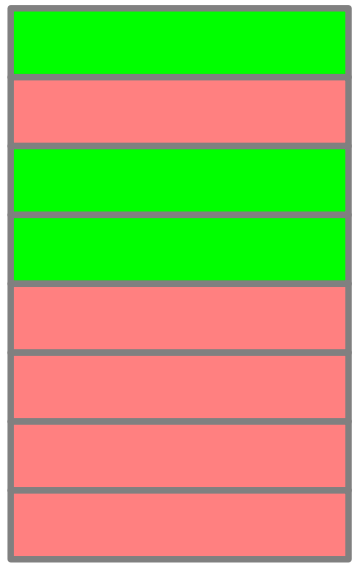
List B

Challenge 2: Evaluating Structured Outputs

- One basic measure is precision: the fraction of items which are relevant.
- Which of the following lists is preferable?



List A



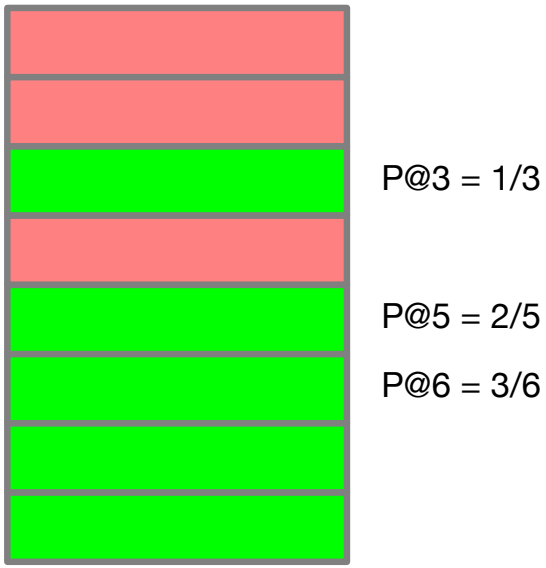
List B

Challenge 2: Evaluating Structured Outputs

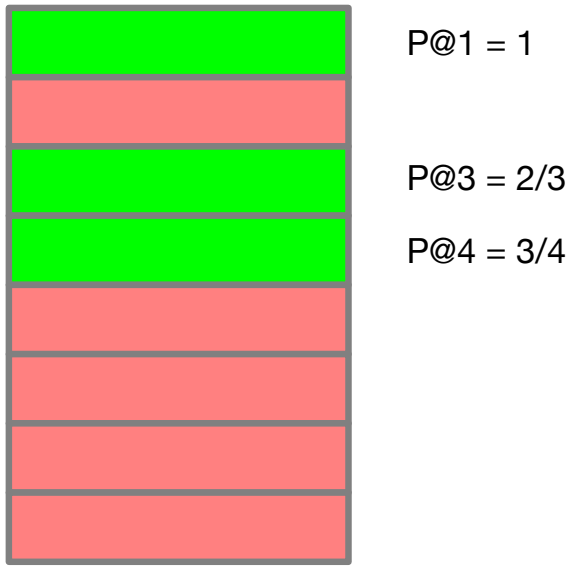
- Precision@K: Precision for the list up to the Kth item.
- Average Precision (AP): average of Precision@K, where K is taken as the indices of the first N relevant items.
  - Moving a relevant item from position 2 to position 1 is worth more points than moving it from position 8 to position 7.
- Mean Average Precision (MAP): mean of the AP over multiple queries.
- Note: in different application areas, there are different (but related) definitions of AP/MAP.

Challenge 2: Evaluating Structured Outputs

An example of calculating AP with $N = 3$.



$$\text{MAP} = \frac{1}{3}\left(\frac{1}{3} + \frac{2}{5} + \frac{3}{6}\right) \approx 0.41$$



$$\text{MAP} = \frac{1}{3}\left(1 + \frac{2}{3} + \frac{3}{4}\right) \approx 0.81$$

Challenge 2: Evaluating Structured Outputs

What other factors might you consider in evaluating a list of recommendations?

Towards Ethics

- We've been discussing challenges that arise when defining optimization objectives beyond the basic classification and regression settings.
- So far, we've focused on challenges of building a useful and engaging system.
- But what we choose to optimize for can have unintended consequences. The rest of the lecture focuses on thinking about optimization objectives from an ethical standpoint.

Acknowledgements

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