



Embedded Ethics
Module
Recommender System
Objectives

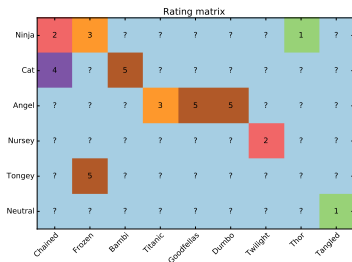
Today

- **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

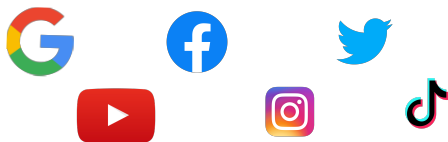
Recap: Netflix Challenge

- 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?

Challenge 1: Inferring User Preferences

Challenge 1: Inferring User Preferences

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

The screenshot shows the Google News interface with a search query of "toronto computer science". The left sidebar contains navigation options: Top stories, For you, Following, News Showcase, Saved searches, COVID-19, Canada, World, Your local news, Business, Technology, Entertainment, Sports, Science, and Health. Below these are options for Language & region (English (Canada)), Settings, and app download links for Android and iOS.

The main content area displays five news items:

- U of T computer science grads reflect on their studies – and the profs who inspired them** (News@UofT · Jun. 24) with a photo of two students.
- The 50-year-old problem that eludes theoretical computer science** (MIT Technology Review · Oct. 27) with a photo of green trees.
- Global research alliance between U of T and University of Melbourne to take 'strong relationship to another level'** (News@UofT · Oct. 28) with a photo of a building.
- Trapping light in microchips: Professor wins top science award** (CTV News · Yesterday) with a photo of a professor.
- U of T releases new guidelines for researchers engaging in international partnerships** (News@UofT · Oct. 21) with a photo of a man in a suit.
- U of T researchers create mirror-image peptides that can neutralize SARS-CoV-2** (News@UofT · Oct. 26) with a photo of two men.

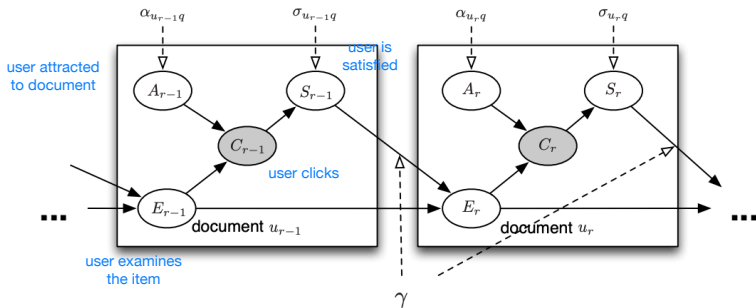
On the right, there is a "University of Toronto Computer Science" topic card with "Follow" and "Share" buttons.

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 naive 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 \Rightarrow clickbait
- Optimizing for time spent reading/watching \Rightarrow favored professional over organic content
- 2017: service changed to reward comments & emojis \Rightarrow 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: Bandit Feedback

Challenge 2: Bandit Feedback

- You only get information about user preferences for the posts you choose to show them. Therefore, the choices you make affect the data you get.
- This is closely related to the [multi-armed bandit problem](#).



- You have a set of slot machine arms, and each arm i pays off \$1 with an unknown probability p_i .
- You are given T trials. You only find out the payoff for the arm that you tried. You want to maximize your total expected payoff.
- Showing the user a post = pulling an arm. Your metric (e.g. likes, clicks) = the payoff.

Challenge 2: Bandit Feedback

Here are the payoffs so far. Which arm should you pull next?

Arm 1: \$ \$ x \$ x \$ \$ x \$ \$

Arm 2: x x x x \$ \$ x x x

Arm 3: x \$

Challenge 2: Bandit Feedback

- Bandit problems are an important example of an **exploration-exploitation tradeoff**
 - “Exploitation”: show the user a post you’re confident they’ll like
 - “Exploration”: show the user a post they may or may not like so that you get information about their preferences

Challenge 3: Evaluating Structured Outputs

Challenge 3: 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?

relevant
irrelevant
relevant
irrelevant
relevant
relevant
irrelevant
relevant

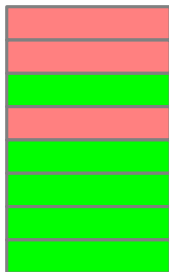
List A

irrelevant
irrelevant
relevant
irrelevant
relevant
relevant
irrelevant
irrelevant

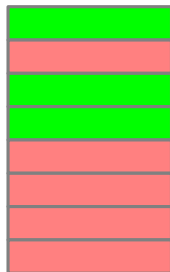
List B

Challenge 3: Evaluating Structured Outputs

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



List A



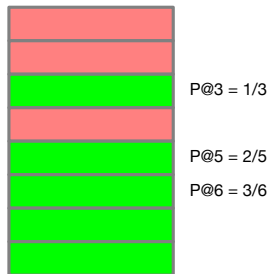
List B

Challenge 3: Evaluating Structured Outputs

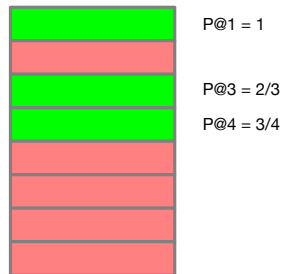
- **Precision@K**: Precision for the list up to the K th item.
- **Average Precision (AP)**: average of Precision@K, where K is taken as the indices of the first N relevant items.
 - Moving a relevant item from position 2 to position 1 is worth more points than moving it from position 8 to position 7.
- **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 3: 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 3: 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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Instructional Team:

Roger Grosse, Steven Coyne, Emma McClure

Faculty Advisors:

Diane Horton¹, David Liu¹, and Sheila McClraith^{1,2}

Department of Computer Science

Schwartz Reisman Institute for Technology and Society

University of Toronto

