AMENDED Exhibit 1173

PLAINTIFFS' OMNIBUS OPPOSITION TO DEFENDANTS' MOTIONS FOR SUMMARY JUDGMENT

Produced in Native

YouTube Recommendations Overview

Last updated: Nov 2023

go/yt-recs-overview

[redacted] (WN), [redacted] (Home)

YouTube

[redacted]

Hi everyone, let's get started. Welcome to our "bring up to speed" presentation for [redacted]! Our new Eng VP.
[redacted] and I prepared a joint presentation on Recommendations.
This is meant to be informal. We do have slides though to help the flow.
Questions are welcome and everyone should feel free to chime in to make a point or help answer questions.

Goals of Today's Session

- Understanding YouTube Recommendations: where it fits and what we value.
- Discuss the business problems and how we approach them at a high level.
- Understanding the high-level recommendations flow.
- Discuss the broad challenges and opportunities in the space.
- Generally focus on the "why" and only briefly mention the "how"
    - *Future sessions will go deeper into specific design and technology choices.*
    - *We focus more on Home and Watch Next recommendations today.*

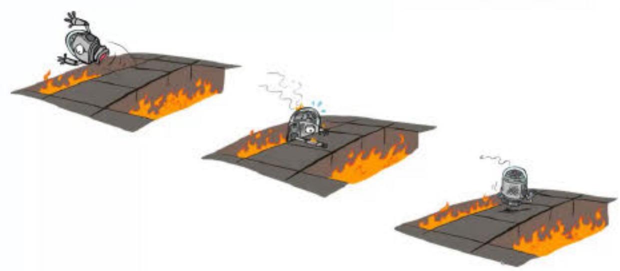
Quick goals of sessions:

- We are only going to cover very high-level: how recommendations fit into YT, business problems they solve, high-level system architecture and flow, broad challenges and opportunities.
- We will have deep dives in the future for different aspects that would go into more details of models, algorithms, and generally infra and ML techniques and technologies we use.

As for format:
I will cover the first half of this deep dive and [redacted] will cover the second half

Challenge: Recommendations is a Reinforcement Learning problem

- Average user watches [redacted] videos per day (median = [redacted])
- Any change in the recommendation leads to [redacted]



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Consequences of “Recommendations is RL problem”

- Unintended behavior
  - on-policy vs off-policy training
  - a model with better loss can result in worse online performance
- Strong feedback loops
  - system gets better by training on its own data (focuses on what matters the most)
  - hard to measure full consequences of a system change
  - need to account for experiment leakage

[redacted]

YouTube