Reinforcement Learning for Recommender Systems

From Contextual Bandits to Slate-Q

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Overview of the tutorial

25 min: Intro to RL and why use RL to solve Recommender Systems?

10 min: Break/ Q&A

25 min: RLlib's Contextual Bandits Algorithms Applied To Recommender

Systems

10min: Break/ Q&A

10 min: RLlib's SlateQ Applied To Recommender Systems





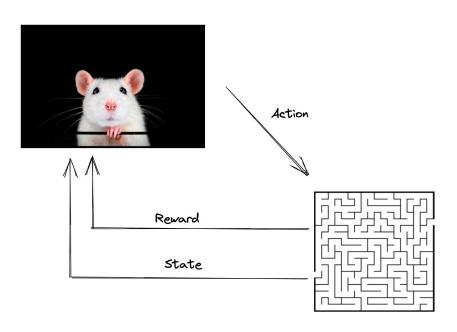
We want to teach a mouse to get to the center of a maze ... how can we do that?

Place bits of cheese in the maze along paths that we **do** want the mouse to take.

Place bits of poison along paths that we **don't** want the mouse to take.

Let the mouse repeatedly explore the maze for a fixed time from different random starting points.

Eventually the mouse learns all paths from everywhere in the maze that maximize cheese and minimize poison.



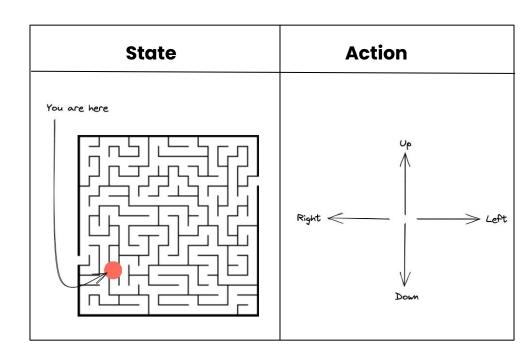


The mouse can be at different positions in the maze. We call this its **state** or observation.

The mouse can move up down left and right in the maze. We call this its **actions.**

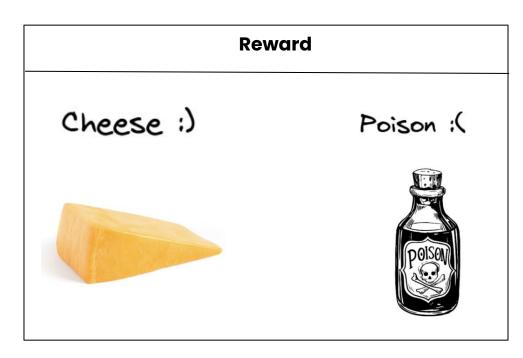
There are terminal states in which the mouse no longer needs to act, such as if the mouse enters the center of the maze.

For every action that mouse takes at its current state to transition into a new state we call this a **time step.**





The mouse gets cheese or poison depending on whether its taking the best action at its state. We call this its **reward.**

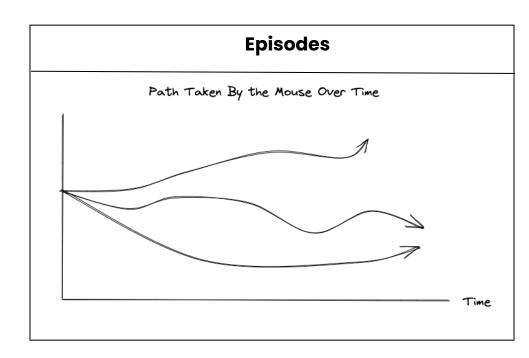




We let the mouse explore and follow the cheese trail for some time but eventually **reset** it to a new random starting state after some time steps.

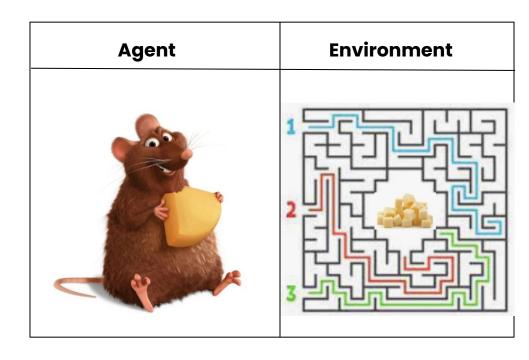
We call the sequence of time steps that the mouse creates from its starting state till we reset it an **episode**.

When an episode terminates, say from the mouse reaching its exploration time limit, or by reaching the center of the maze, we say that its **done** signal is true.





We can use **Reinforcement Learning** to teach the mouse, or our **agent**, to take the sequence of actions at the states which it visits so that we maximize the total reward per episode in the maze **environment**.



Can We Use The Framework Of The Toy Problem And Relate It To A Real World Problem?





RL and Self Driving

Autonomous Vehicle vision-based controller

State: camera images, lidar sensor readings

Action: steering wheel angle, pressure on brake,

pressure on gas pedal

Reward: +1 driving safely at the current time step,

0 otherwise

Done: when the trip ends or if an unsafe driving incident occurs at the current time step.

Using RL, train the car-agent to maximize the amount of safe driving behavior during a trip



Recommender Systems and RL



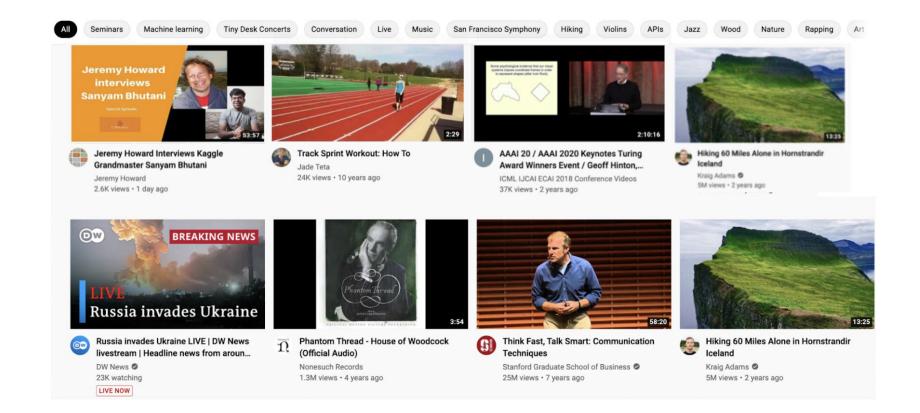


RLIP What Are Recommender Systems?

What	Where
Serve up personalized content, based on users interactions, in order to provide an improved experience for each user.	 Games Rideshare Purchasing apps (B2B, B2C) Websites, web apps Mobile apps Chatbots Call centers



RL and Recommender Systems





RL and Recommender Systems

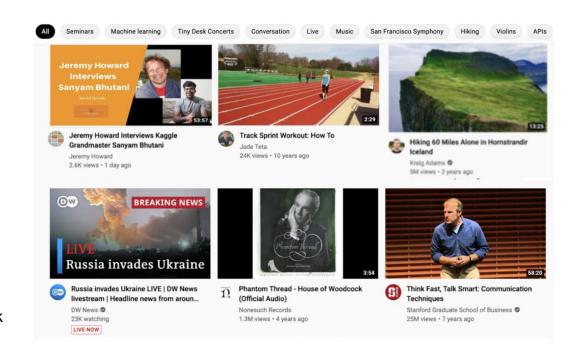
State: user actions, features about the user, user watch history

Action: recommended videos

Reward: +1 if user clicks a piece of content AND long-term satisfaction has increased at the current time step, 0 otherwise

Done: True if we've made the maximum amount of recommendations in a user's session on the website.

Using RL, train a recsys agent to maximize the click through rate and long term satisfaction of users.

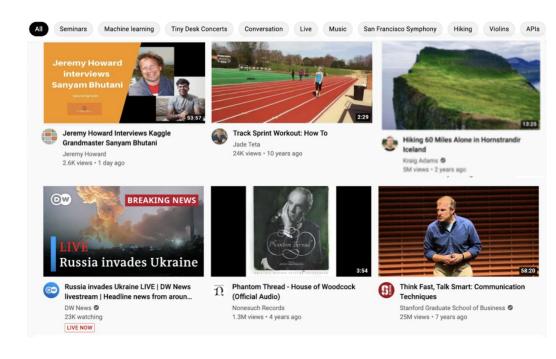




Supervised Learning (SL) Approach to Recommender Systems

High-level steps to build a Recommender System using SL

- 1) Train a model using supervised learning that takes as input some features about the user (demographic, interests) and outputs some categories or topics the user would be interested in.
- Use a search ranking algorithm on the categories to produce video recommendations.





Why use RL over SL for Recommendations?

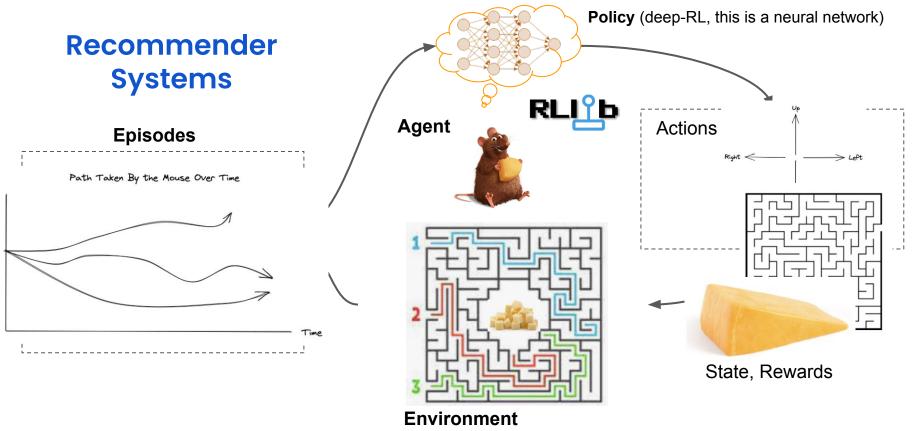
RL Algorithms will train recsys agents that maximize the quality of all the recommendations that are given. SL trains agents to give pointwise recommendations.

With SL there is no concept of long term satisfaction of a user embedded in to training. This must be hardcoded into the recommender system as a heuristic.

RL can be used to train an end to end recommendation system whereas SL will have brittle hand-engineered features in the system.



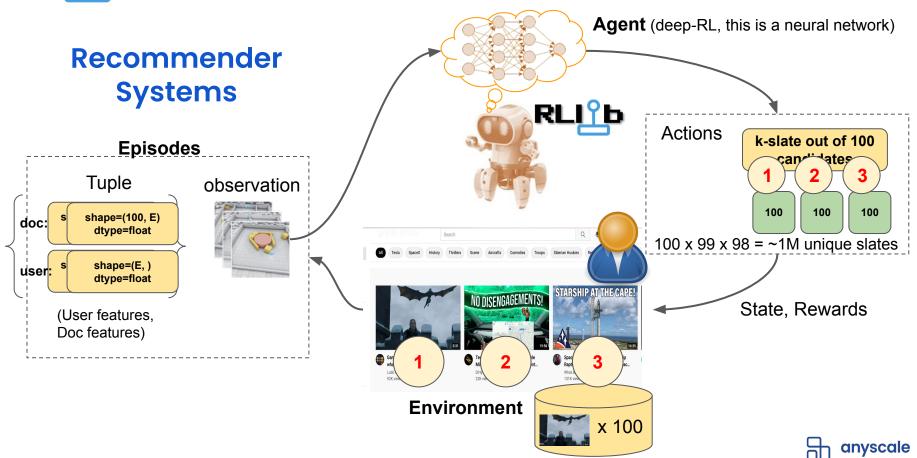
Deep RL and RLlib code abstractions





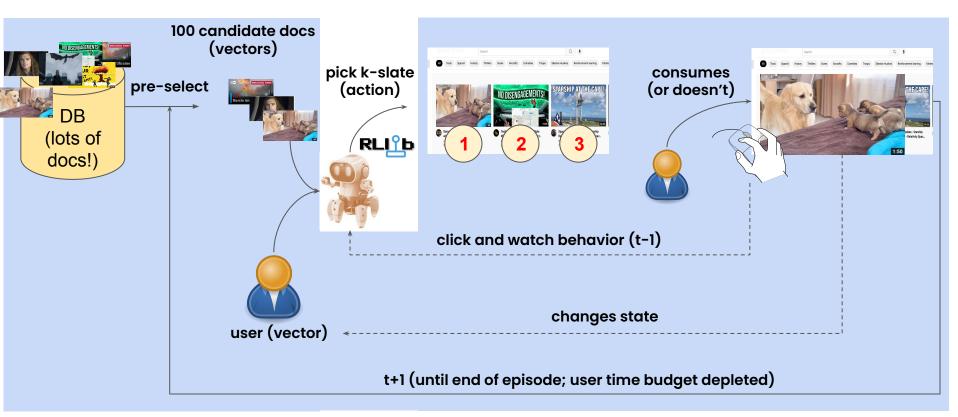


RL Ingredients and RLlib code abstractions





A Recommender System in Action



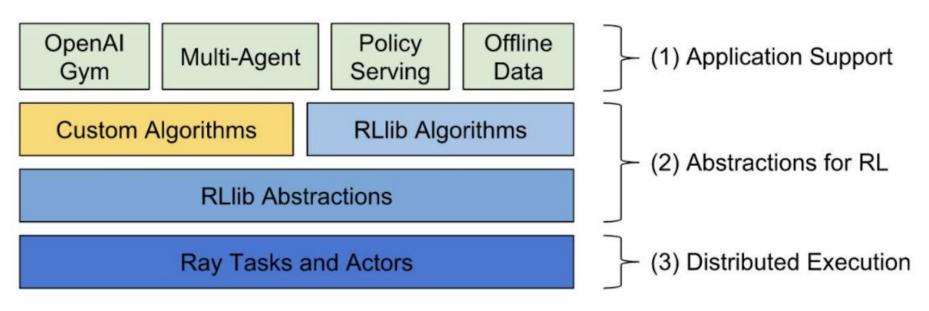
What Software Should I Use To Do RL?





RLlib Parallelize and Distribute at Scale

Ray provides a common framework for distributed RL algorithms using asynchronous parallel Tasks and Actors.





Support for both TF2 and PyTorch





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- Benchmarks and tuned examples. Gives you a leg-up, someplace to start with hyperparameter choices.





And why should I use RLlib?

Because these companies here do!
Thx for presenting at Ray- and RL Summits!













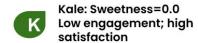






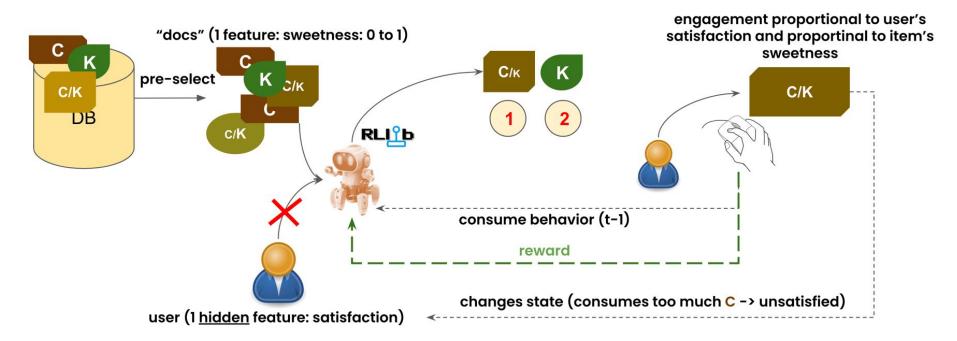






Google RecSim The "Long Term Satisfaction" Problem

Chocolate: Sweetness=1.0
High engagement; low
satisfaction





10 min Break :) Then ... our Colab Notebook

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GOOGLE COLAB LINK: bit.ly/odsc_rllib_tutorial
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