

# LinUCB in Recommendation

Radek Bartyzal

MI-GLR

25. 5. 2018

# Recommender system: ratings

<i>users/items</i>	$i_1$	$i_2$	$\dots$	$\dots$	$\dots$	$\dots$	$i_m$
$u_1$	$r_{1,1}$	$\dots$	$r_{1,j}$	$\dots$	$r_{1,k}$	$\dots$	$r_{1,m}$
$u_2$	$r_{2,1}$	$\dots$	$r_{2,j}$	$\dots$	$r_{2,k}$	$\dots$	$r_{2,m}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$u_i$	$r_{i,1}$	$\dots$	$r_{i,j}$	$\dots$	$r_{i,k}$	$\dots$	$r_{i,m}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$u_n$	$r_{n,1}$	$\dots$	$r_{n,j}$	$\dots$	$r_{n,k}$	$\dots$	$r_{n,m}$

# Recommender system: attributes

The image shows a screenshot of the Netflix website interface. At the top, there's a navigation bar with the Netflix logo, a 'Browse' button, a 'DVD' button, a search bar, a notification bell, and a user profile icon labeled 'Frank'. Below the navigation bar, there's a horizontal carousel of featured content, including 'Richie Rich', 'Masters of Sex', 'Daredevil', 'Hawkeye', and 'Rubber'. The 'Daredevil' banner is highlighted with a white cursor. Below the carousel, the 'Daredevil' page is displayed. It features the 'NETFLIX ORIGINAL' logo, the 'Daredevil' title, and a 'SEASON 1' tab. The episode list for Season 1 is shown, with four episodes visible: 'Into the Ring' (53m), 'Cut Man' (53m), 'Rabbit in a Snowstorm' (52m), and 'In the Blood' (52m). Each episode has a thumbnail, a number, a title, a duration, and a brief description. At the bottom of the episode list, there are tabs for 'OVERVIEW', 'EPISODES' (which is selected), 'TRAILERS', 'MORE LIKE THIS', and 'DETAILS'. Below the episode list, there's a section titled 'Popular on Netflix' with a horizontal carousel of other content, including 'The Office', 'Netflix', and 'Parks and Recreation'.

NETFLIX

Browse DVD

Search

Frank

Richie Rich

NEW EPISODES

Masters of Sex

TOGETHER

DAREDEVIL

HAWKEYE

RUBBER

NETFLIX ORIGINAL

DAREDEVIL

SEASON 1

1

Into the Ring 53m

Murdock's vigilante crime fighting and his new law practice find equally dangerous challenges in a murder case tied to a corporate crime syndicate.

2

Cut Man 53m

Murdock makes a near fatal error while trying to save a kidnapped boy, and finds an unlikely ally when he needs saving himself.

3

Rabbit in a Snowstorm 52m

Murdock and Foggy take on a mysterious wealthy client, but Murdock is convinced that there's more to the case than just the facts.

4

In the Blood 52m

Two vicious Russian brothers working for Fisk strike back against Daredevil. Fisk moves to further consolidate his power in the criminal underworld.

OVERVIEW EPISODES TRAILERS MORE LIKE THIS DETAILS

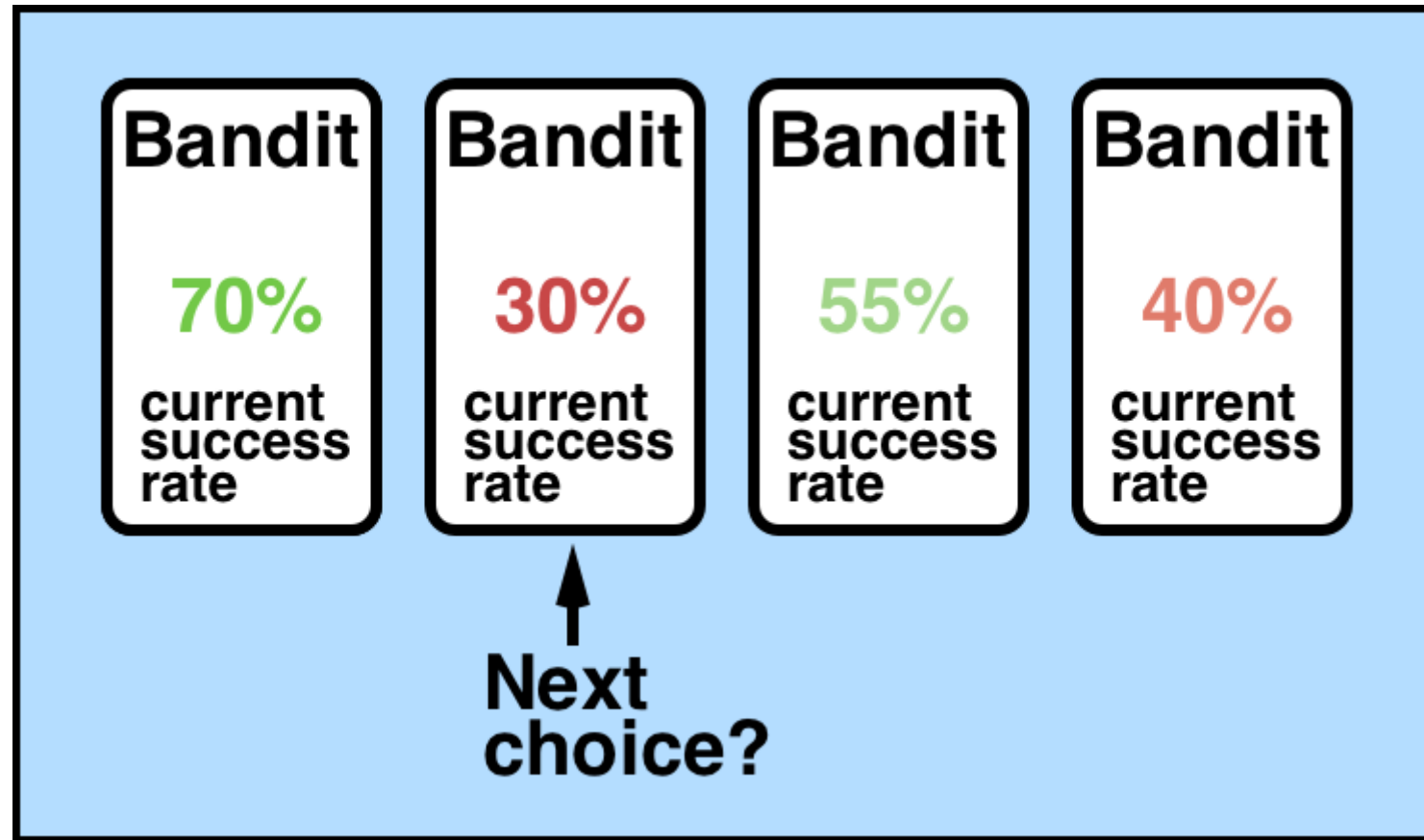
Popular on Netflix

The Office

NETFLIX

Parks and Recreation

# Bandit algorithms



# Contextual Bandit algorithms

- selects articles to serve users
- based on contextual information about the users and articles
- while adapting its article-selection strategy

# Upper Confidence Bound (UCB)

- balance exploration and exploitation
- in trial  $t$ , estimate:
  - mean payoff  $\mu_{t,a}$  of each arm
  - corresponding confidence interval  $c_{t,a}$
  - so  $|\mu_{t,a} - \mu_a| < c_{t,a}$  holds with high probability
- select the arm that achieves a highest upper confidence bound =  $\mu_{t,a} + c_{t,a}$
- with right confidence intervals UCB has logarithmic regret in the total number of trials  $T$  = optimal

# LinUCB with Disjoint Linear Models

We assume the expected payoff of an arm  $a$  is linear in its  $d$ -dimensional feature  $x_{t,a}$  with some unknown coefficient vector  $\theta_a^*$ , namely:

$$E[r_{t,a}|x_{t,a}] = x_{t,a}^T \theta_a^*$$

- $a$  = arm = action = item to be recommended = e.g. article
- $t$  = trial = in this case user ID
- $r_{t,a}$  = reward of action  $a$  in trial  $t$
- $x_{t,a}$  = features describing **both** user and the selected article  $a$  at trial  $t$ . If the features of a user are his ratings, they will change with time.

# LinUCB with Disjoint Linear Models

- disjoint = parameters are not shared among different arms
- solution is reached by a simple ridge regression



# LinUCB with Hybrid Linear Models

- arm-specific features as with Distinct
- features shared by all arms – new
  - user may prefer only articles about politics
  - e.g. user prefers items from genre X = feature shared by all arms

$$E[r_{t,a}|x_{t,a}] = z_{t,a}^T \beta^* + x_{t,a}^T \theta_a^*$$

- $z_{t,a}$  = features of the current user/article combination
- $\beta^*$  = an unknown coefficient vector common to all arms

# Dataset

- MovieLens 100k dataset
- 100 000 ratings
- 1000 users
- 1700 movies
- ratings scale 1-5 -> 1 ( $\geq 4$ ) | -1 ( $< 4$ ) | 0 (unknown)
- Used subset: 100 items and 56 users
- randomly added 3 ratings to each user

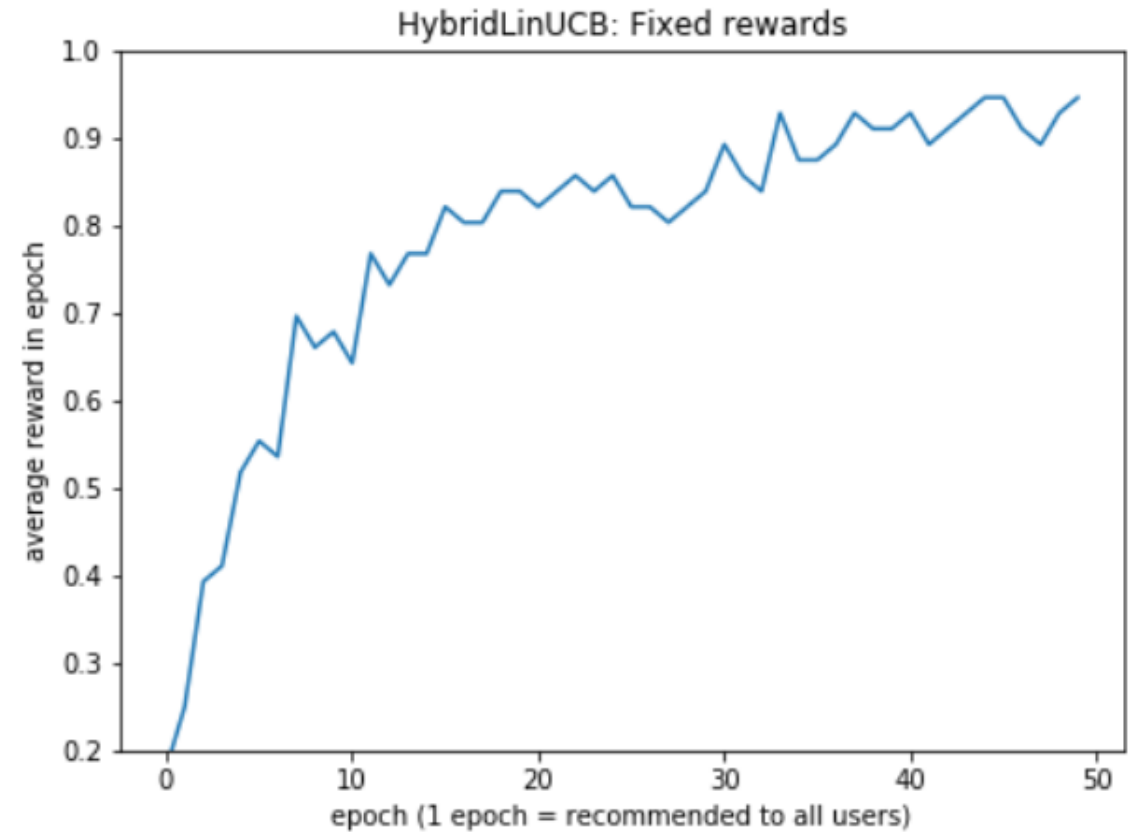
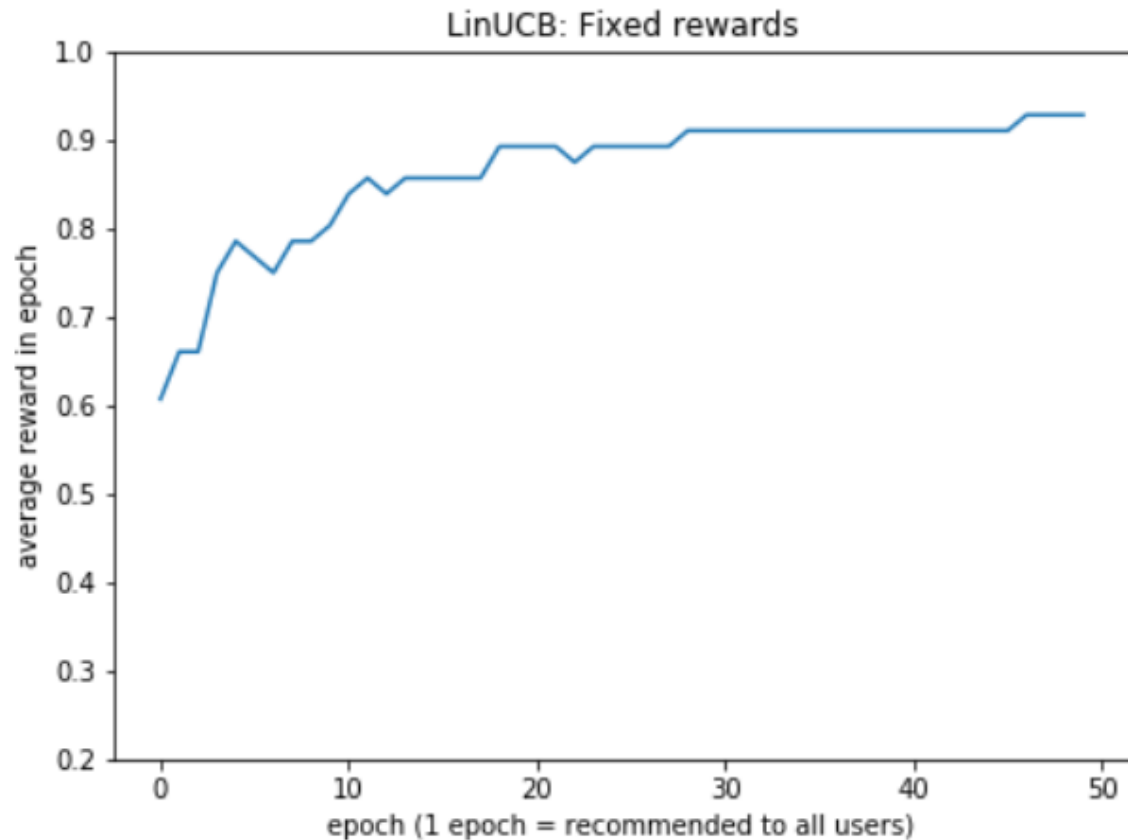
# User modeling

- I need to predict rating for each user/item pair = simulate reaction of real users to recommendations
- Let item  $a$  be recommended to user  $u$ :
  - If the user  $u$  has already rated the item  $a$ , the returned reward will be 1 for positive rating or 0 for negative rating.
  - Else: reward will be sampled from a Bernoulli distribution with  $p$  equal to how much the user likes the genre of item  $a$ .
  - Likability of a genre  $g$  is calculated as a ratio of positive ratings of items belonging to genre  $g$  to a number of negative ratings of items belonging to  $g$ .

# Implementation

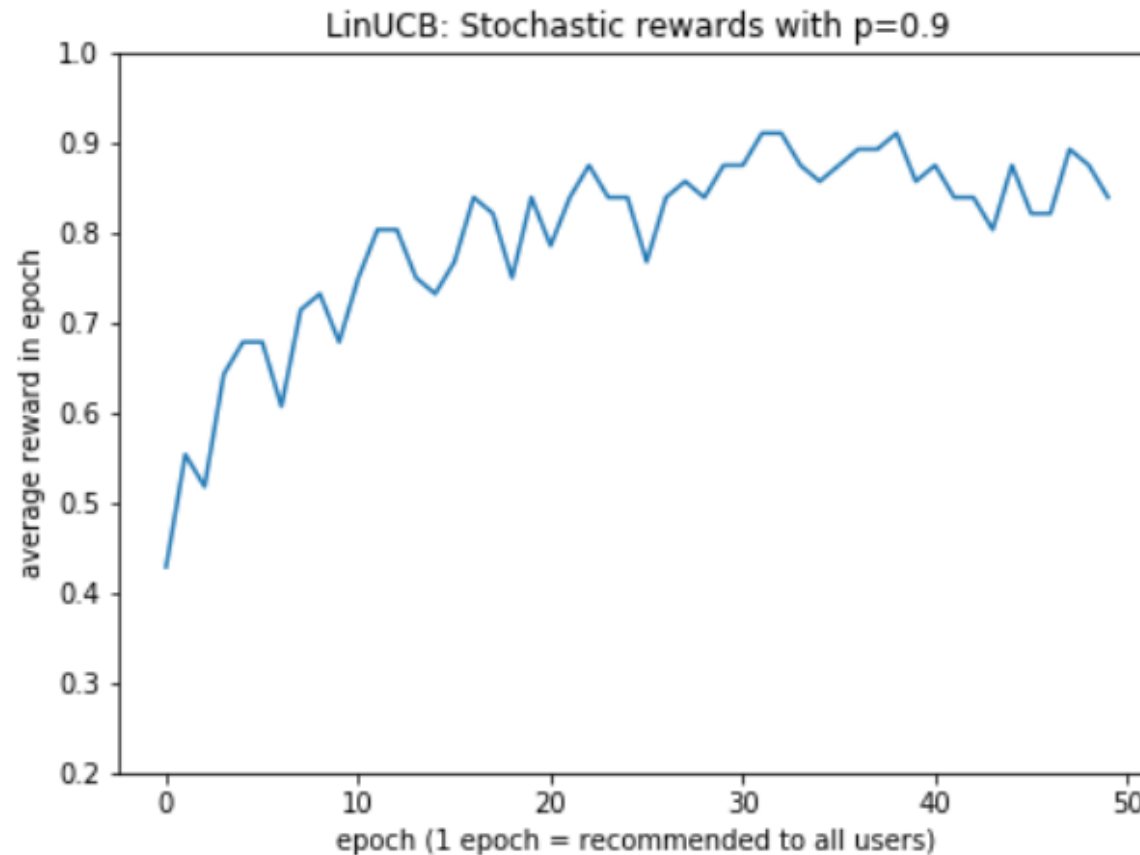
- Features in  $x_{t,a}$  are a concatenation of features of user  $t$  and item  $a$  at the current time
- user features = his ratings of all items =  $R_u$
- item features = movie genres = array of 1/0 describing whether the movie belongs to a genre. There are 19 genres.
- $x_{t,a}$  = user features concatenated with item features
- $z_{t,a}$  = only article features = genre vector

# Experiment with deterministic rewards



# Experiment with stochastic rewards

- Reward 1 is returned with  $p=0.9$



# Experiment with stochastic rewards

