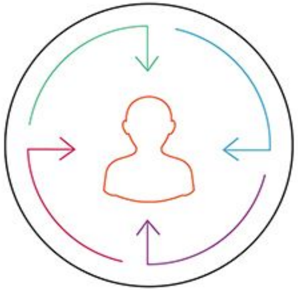
Collaborative Filtering
LinUCB for MovieLens dataset



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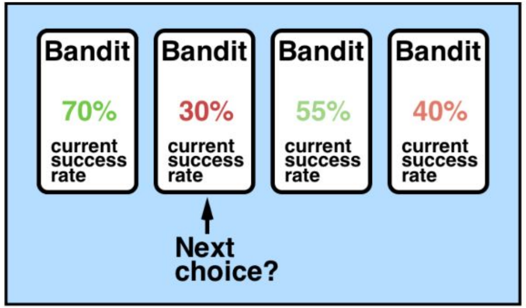
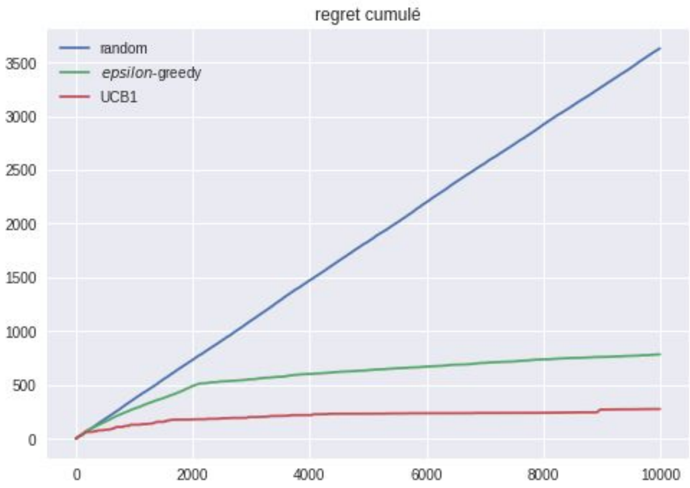
Bandit problem introduction





Goal: minimize the expected total regret

$$R(T) = \mathbb{E}_{I_t}\left[\sum_{t=1}^{T} r_{i^*,t}\right] - \mathbb{E}_{I_t}\left[\sum_{t=1}^{T} r_{i,t}\right]$$

Implemented UCB vs e-greedy vs random

LinUCB Disjoint

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

LinUCB Hybrid

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

Movielens dataset & Data processing

Dataset: Movielens 1M

1 million votes of 6000 users on 4000 films

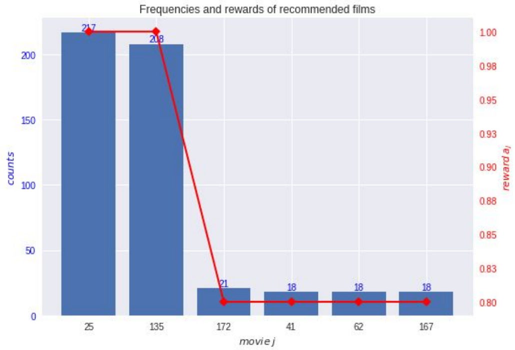
$users/items$	i_1	i_2	$\cdots$	$\cdots$	$\cdots$	$\cdots$	i_m
u_1	$r_{1,1}$	$\cdots$	$r_{1,j}$	$\cdots$	$r_{1,k}$	$\cdots$	$r_{1,m}$
u_2	$r_{2,1}$	$\cdots$	$r_{2,j}$	$\cdots$	$r_{2,k}$	$\cdots$	$r_{2,m}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
u_i	$r_{i,1}$	$\cdots$	$r_{i,j}$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

Pre-processing:

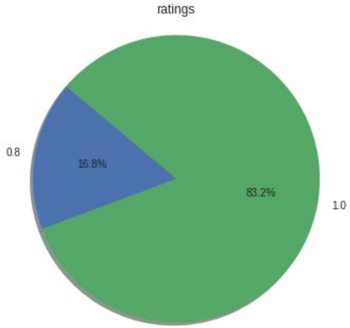
- Resized ratings between 0 and 1
- Selected the movies watched by more than 1000 users
- Selected users who watched more than 150 movies
- Selected 30 most important features

Matrix factorization (SVD): $M = \phi_u^T W \phi_a$

=> Feature user matrix and film (item) matrix

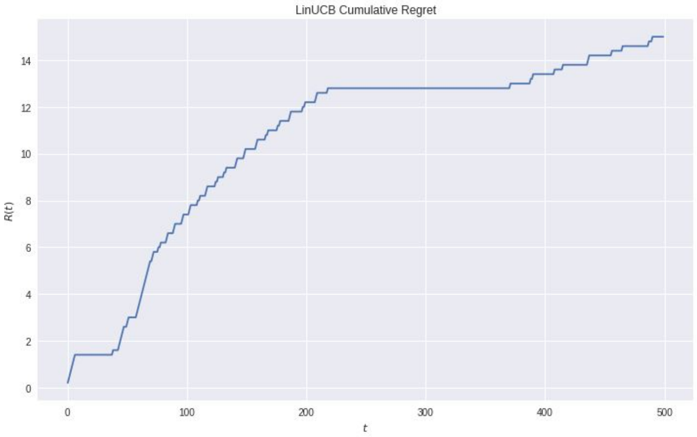


Most frequently recommended films

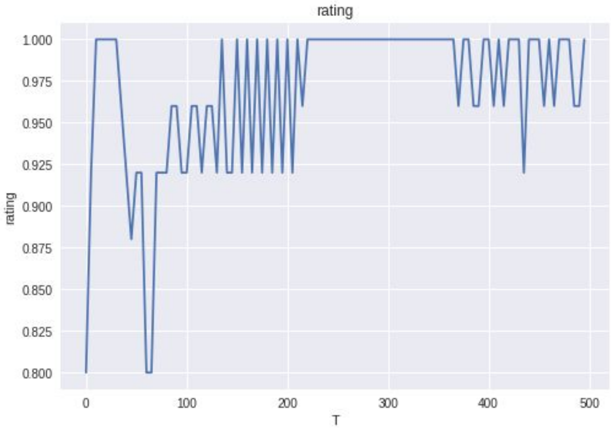


Rating percentages

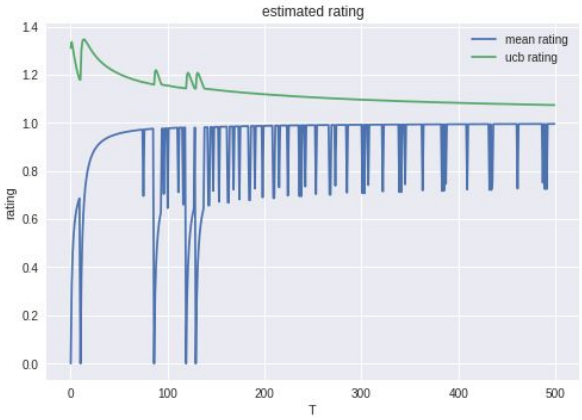
LinUCB Disjoint



Accumulated regret for one user

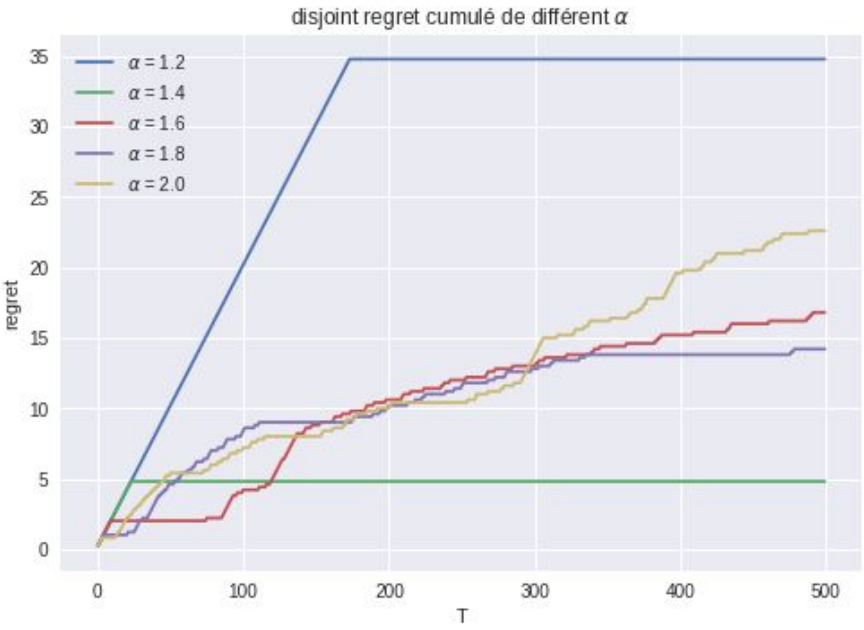


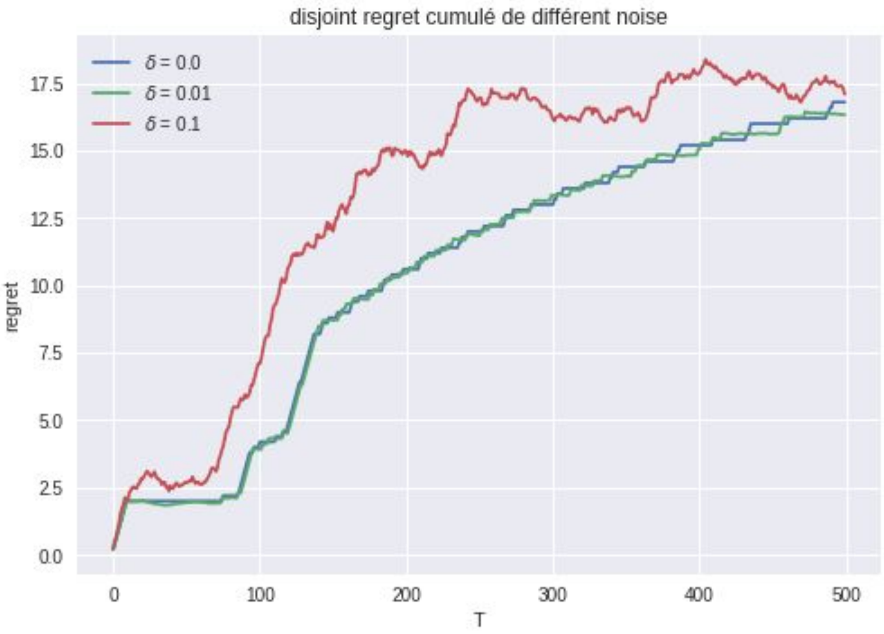
Average movies rating in iterations



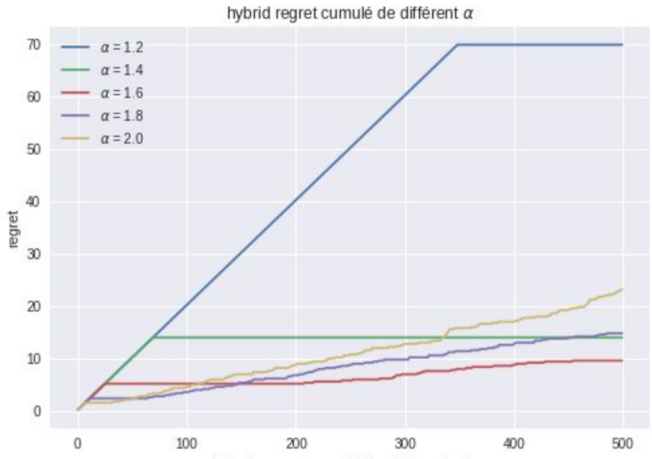
Estimated movies rating

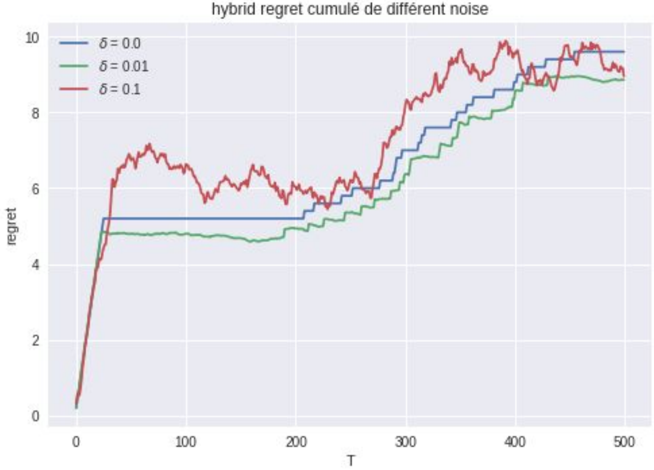
LinUCB Disjoint - Parameters

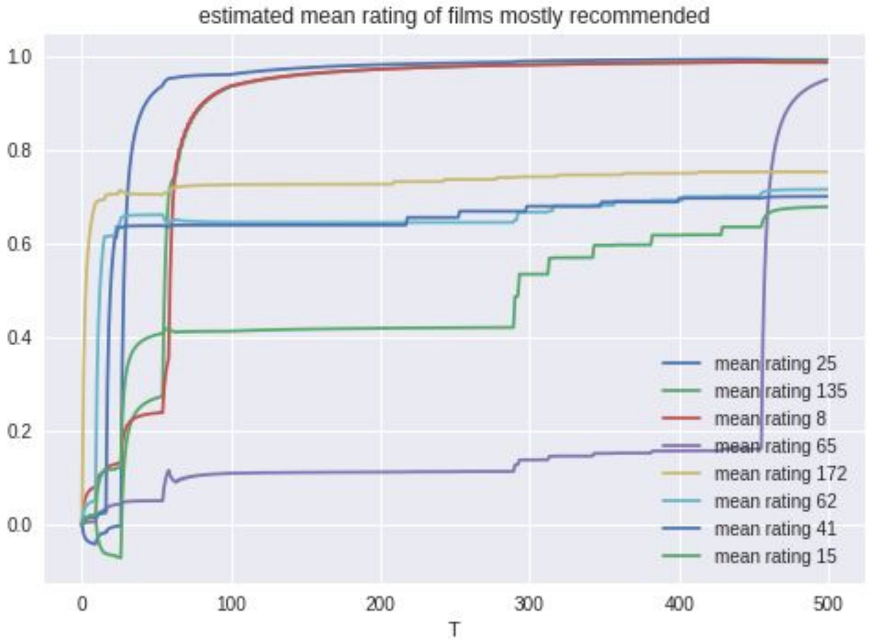




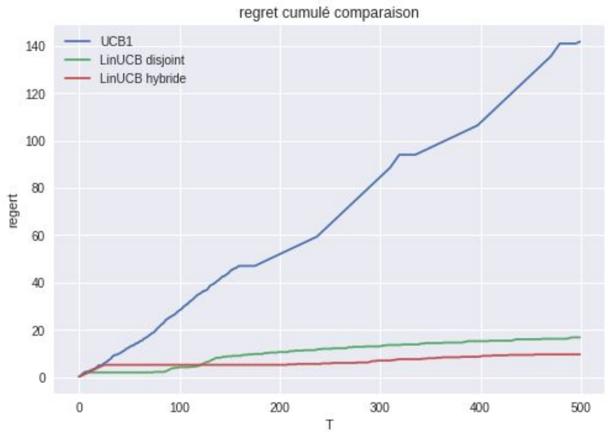
LinUCB Hybrid - Parameters

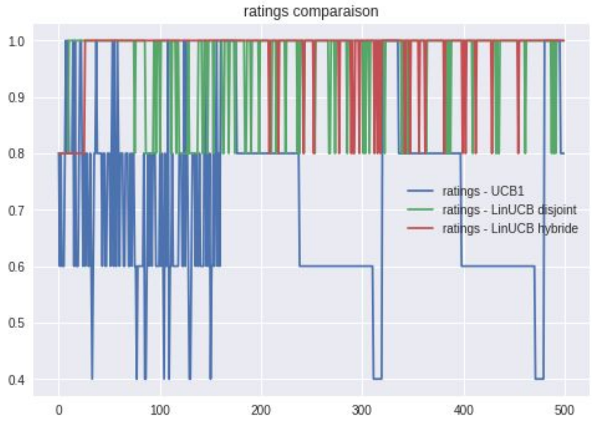






Method comparison and conclusions





iteration	100	200	300	400	500
UCB1	28.2(0%)	52.0(0%)	84.6(0%)	107.6(0%)	141.8(0%)
Reget of lin_dis	4.2(85%)	10.6(79.6%)	13.0(84.6%)	15.2(85.3%)	16.8(88.2%)
Regret of lin_hyb	5.2(81.5%)	5.2(90%)	7.0(91.7%)	8.8(91.8%)	9.6(93.2%)

- LinUCB is much better, especially LinUCB hybrid
- Choice of parameters for the model is important, as we noted that they can drastically impact the results
- Expanding the context with other information would be worthwhile