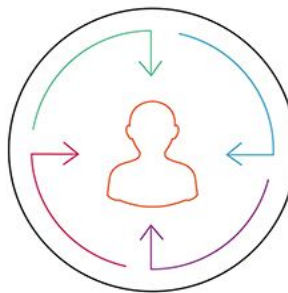


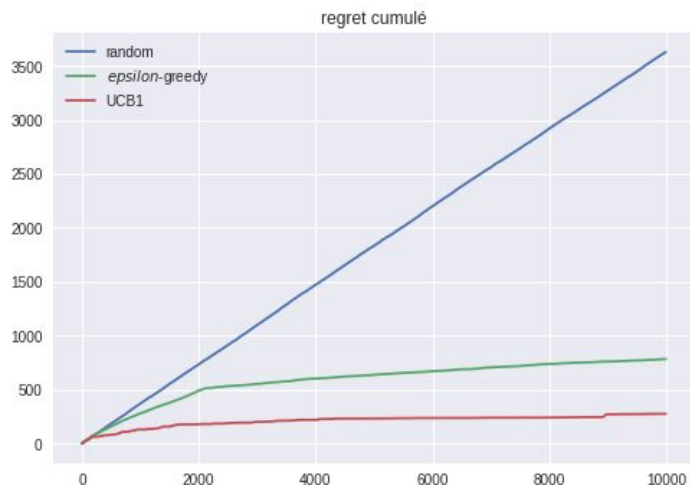
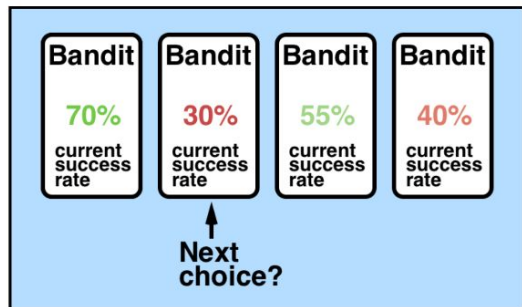
Collaborative Filtering

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

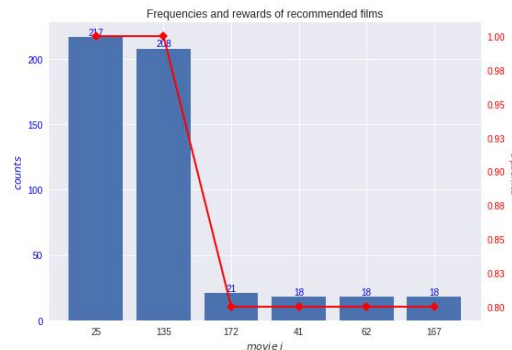
Pre-processing:

- 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

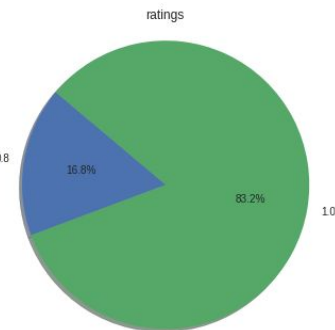
Matrix factorization (SVD): $M = \phi_u^T W \phi_a$

=> Feature user matrix and film (item) matrix

<i>users/items</i>	<i>i</i> ₁	<i>i</i> ₂	<i>i</i> _{<i>m</i>}
<i>u</i> ₁	<i>r</i> _{1,1}	...	<i>r</i> _{1,<i>j</i>}	...	<i>r</i> _{1,<i>k</i>}	...	<i>r</i> _{1,<i>m</i>}
<i>u</i> ₂	<i>r</i> _{2,1}	...	<i>r</i> _{2,<i>j</i>}	...	<i>r</i> _{2,<i>k</i>}	...	<i>r</i> _{2,<i>m</i>}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
<i>u</i> _{<i>i</i>}	<i>r</i> _{<i>i</i>,1}	...	<i>r</i> _{<i>i</i>,<i>j</i>}	...	<i>r</i> _{<i>i</i>,<i>k</i>}	...	<i>r</i> _{<i>i</i>,<i>m</i>}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
<i>u</i> _{<i>n</i>}	<i>r</i> _{<i>n</i>,1}	...	<i>r</i> _{<i>n</i>,<i>j</i>}	...	<i>r</i> _{<i>n</i>,<i>k</i>}	...	<i>r</i> _{<i>n</i>,<i>m</i>}

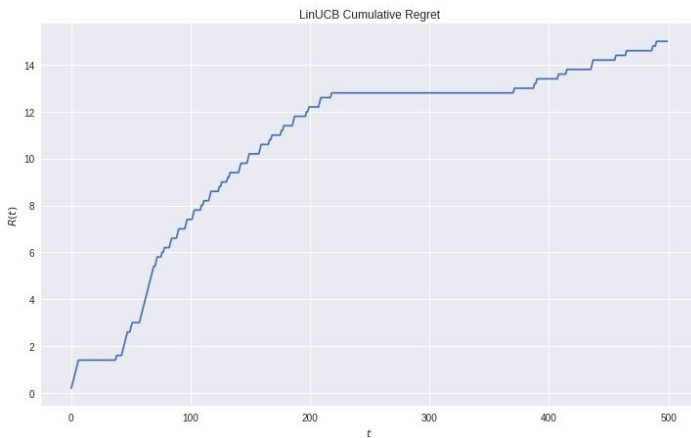


Most frequently recommended films

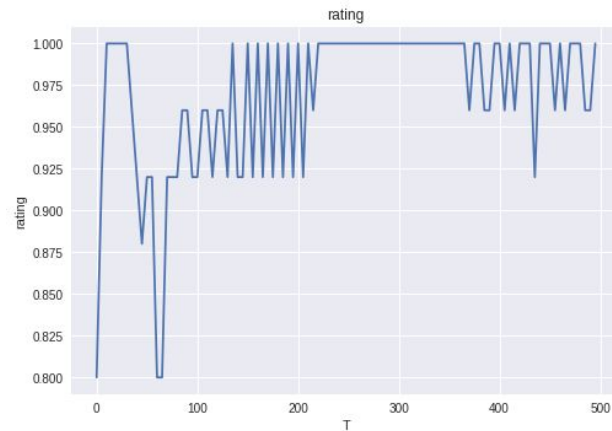


Rating percentages

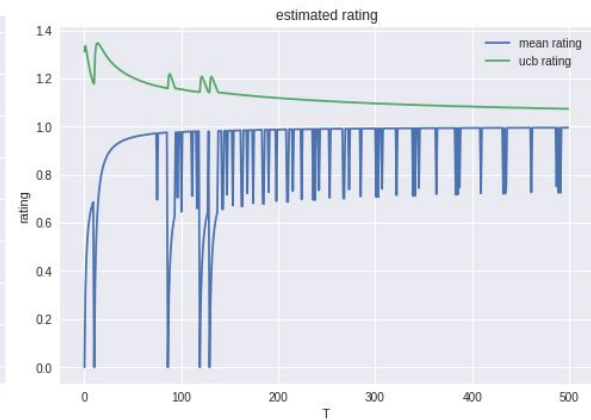
LinUCB Disjoint



Accumulated regret for one user

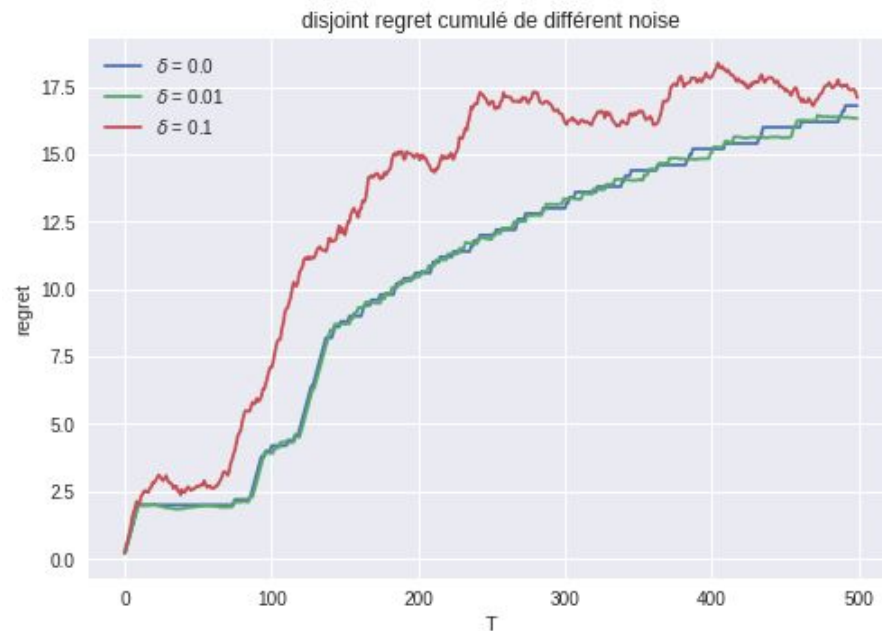
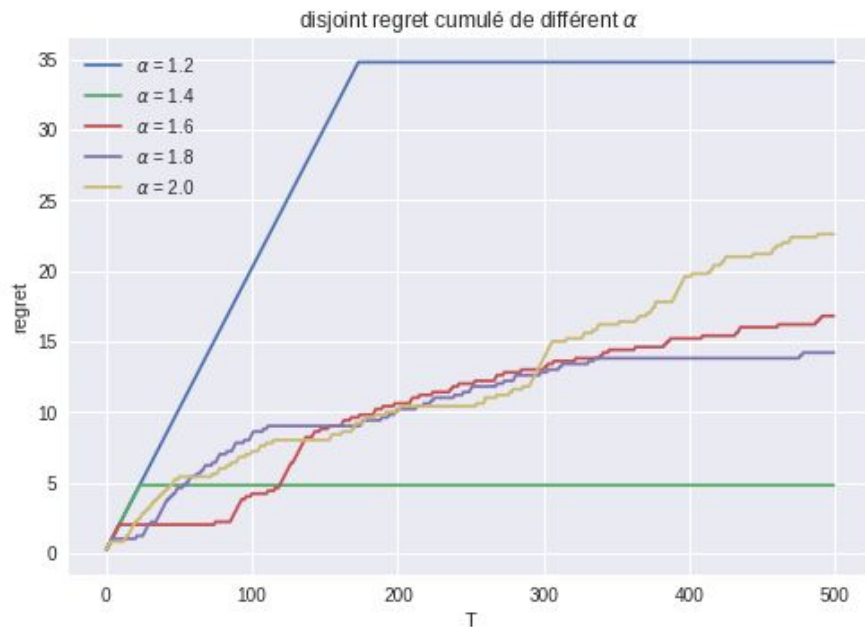


Average movies rating in iterations

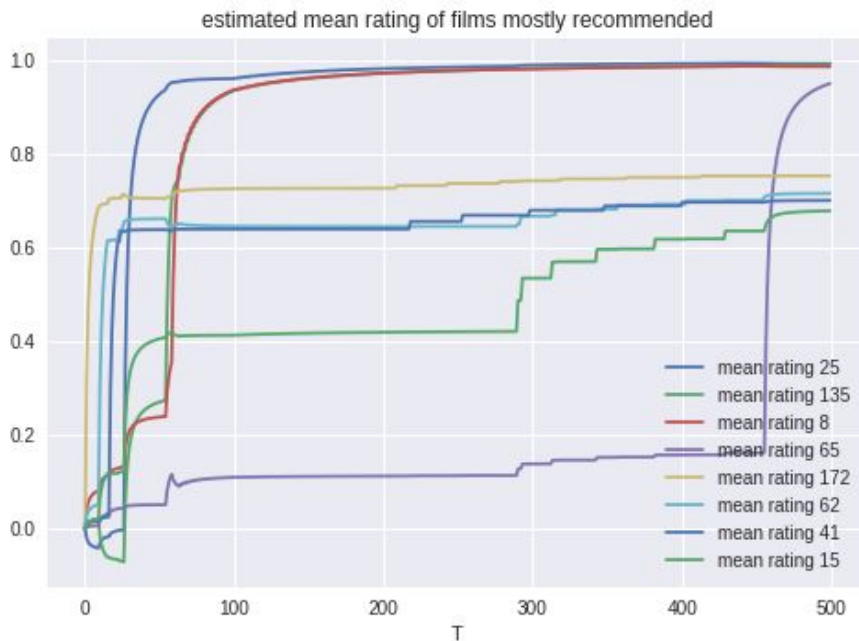
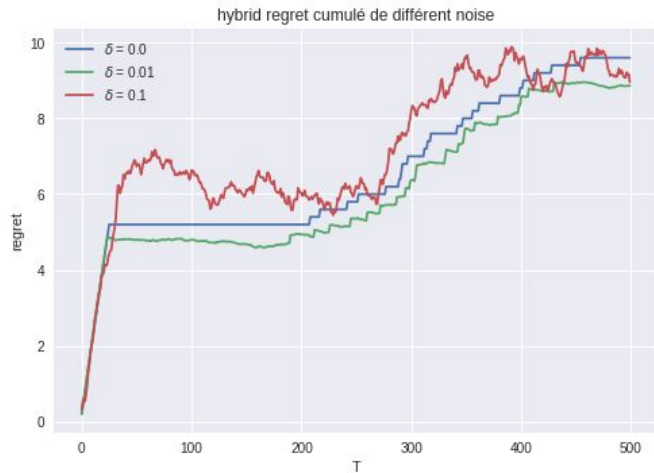
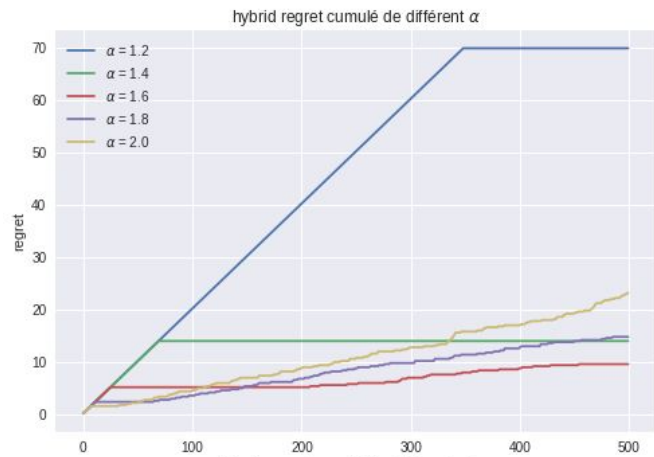


Estimated movies rating

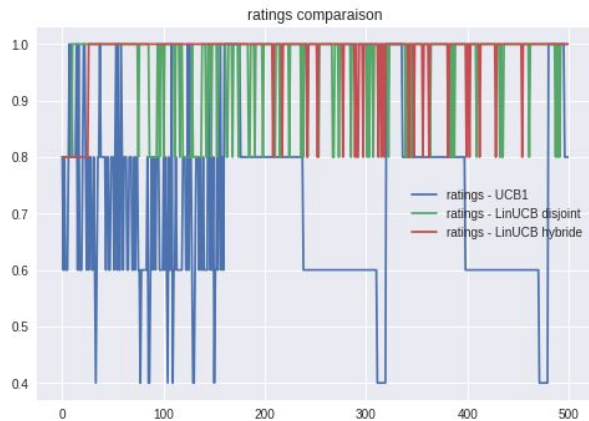
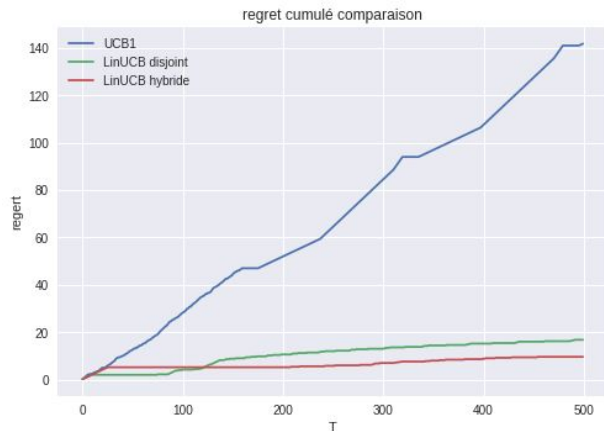
LinUCB Disjoint - Parameters



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%)

The number with a percentage is the reduction of regret compared to UCB1

- 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