

Introduction

- **Slate recommendation:** Task of recommending a collection of *K* items at once to the user.
- Two pieces of feedback:
 - Was the slate clicked? (reward signal)
 - If it was clicked, which of its items was clicked? (rank signal)
- **Example: 3 products,** phone, couscous and beer.

Slate	non-clicks	clicks on 1	clicks on 2
phone, couscous	661	10	29
phone, beer	644	9	47
couscous, beer	626	46	28

IMPACTFUL

Reward Model - Intuition

Original Data:

Slate	non-clicks	clicks on 1	clicks on 2
phone, couscous	661	10	29
phone, beer	644	9	47
couscous, beer	626	46	28

Reward Model: Ignores items ranking and only uses the reward signal.

Slate	non-clicks	clicks
phone, couscous	661	39
phone, beer	644	56
couscous, beer	626	74

Rank Model - Intuition

Original Data:

Slate	non-clicks	clicks on 1	clicks on 2
phone, couscous	661	10	29
phone, beer	644	9	47
couscous, beer	626	46	28

Rank Model: Ignores the reward signal and only uses items ranking.

Slate	clicks on 1	clicks on 2
phone, couscous	10	29
phone, beer	9	47
couscous, beer	46	28

Full Model - Intuition

• Full Model: Uses both reward and rank signals. It takes data in its raw form.

Slate	non-clicks	clicks on 1	clicks on 2
phone, couscous	661	10	29
phone, beer	644	9	47
couscous, beer	626	46	28

• It is intuitive that both the reward and the rank signals shall contain important information of user preferences.

Bayesian Models: Formulation

Models formulation in the case of slates of size 2:

$$\phi \sim \Gamma(1,1)$$
 $\theta_i \sim \Gamma(1,1), i \in [N]$

Model	Description
Full	$nc, c_1, c_2 I, \phi, \theta, a_1, a_2 \sim \text{Multinomial}\left(I, \frac{\phi}{\phi + \theta_{a_1} + \theta_{a_2}}, \frac{\theta_{a_1}}{\phi + \theta_{a_1} + \theta_{a_2}}, \frac{\theta_{a_2}}{\phi + \theta_{a_1} + \theta_{a_2}}\right)$
Reward	$nc, c I, \phi, \theta, a_1, a_2 \sim \text{Multinomial}\left(I, \frac{\phi}{\phi + \theta_{a_1} + \theta_{a_2}}, \frac{\theta_{a_1} + \theta_{a_2}}{\phi + \theta_{a_1} + \theta_{a_2}}\right)$
Rank	$c_1, c_2 I_c, \theta, a_1, a_2 \sim \text{Multinomial}\left(I_c, \frac{\theta_{a_1}}{\theta_{a_1} + \theta_{a_2}}, \frac{\theta_{a_2}}{\theta_{a_1} + \theta_{a_2}}\right)$

• Remark: These models can be extended smoothly to arbitrary slate sizes.

TOGETHER

Experiments

- Synthetic data: We generate n samples of users interaction with each slate, using a multinomial distribution with known parameters Φ and θ .
- Evaluation: Models ability to estimate the probability of a click on the first item in the slates

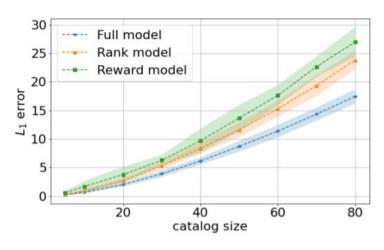
$$L_1(p_{\hat{\theta}}, p_{\theta}) = \sum_{\text{all slates } a} \left| \frac{\hat{\theta}_{a_1}}{\sum_{j \in [K]} \hat{\theta}_{a_j}} - \frac{\theta_{a_1}}{\sum_{j \in [K]} \theta_{a_j}} \right|$$

 Additional Experiment: Models ability to estimate the probability of a non-click on the slates.

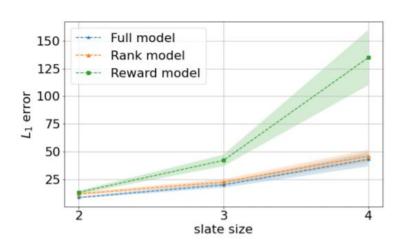
$$L_1(\hat{q}, q) = \sum_{\text{all slates } a} \left| \frac{\hat{\phi}}{\hat{\phi} + \sum_{j \in [K]} \hat{\theta}_{a_j}} - \frac{\phi}{\phi + \sum_{j \in [K]} \theta_{a_j}} \right|$$

Experiments

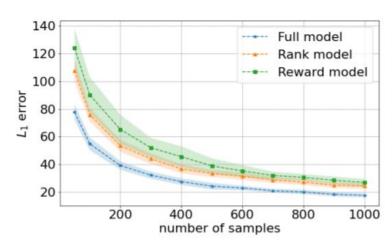
Results



(a) Varying catalog size.



(b) Varying slate size.



(c) Varying N° of samples.

Conclusion

- Three Bayesian models for non-personalized slate recommendation.
- Combining both information is beneficial in slate recommendation, especially as the catalog size and slate size grow.
- Future Work: Extend the Full model to personalized slate recommendation.