Towards Conversational Recommender Systems



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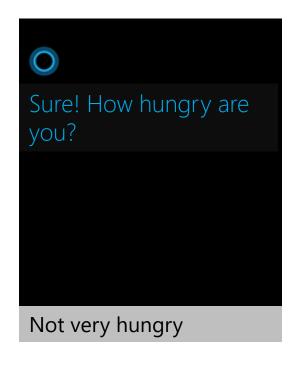
Filip Radlinski

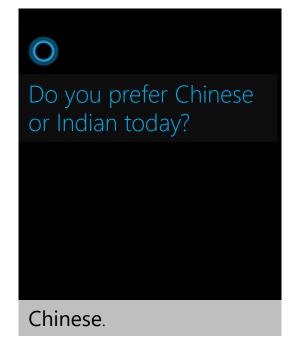


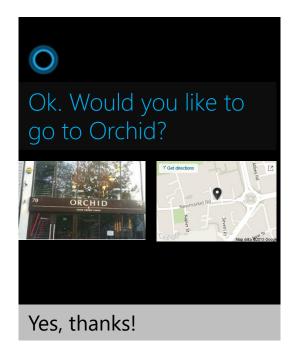
Katja Hofmann



TOWARDS THIS EXAMPLE SCENARIO







ROADMAP

Where should I go for dinner tonight?

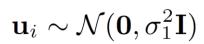
Model exploits implicit structure among items and users to efficiently propagate feedback

Explore/exploit strategy to probe the space of items and allow continuous learning

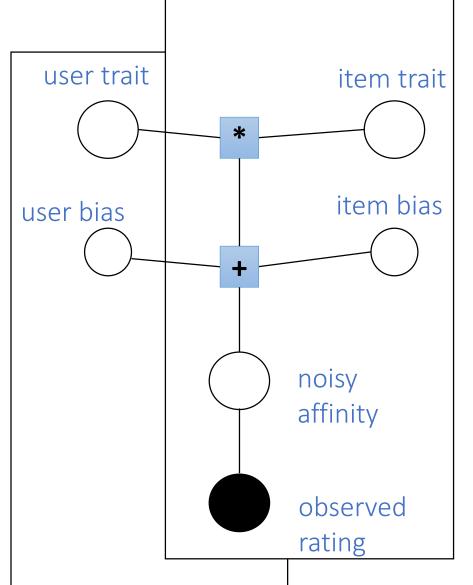
Feedback elicitation mechanism to select **absolute** and **relative** questions.



MODEL: PROBABILISTIC MATRIX FACTORIZATION



$$\alpha_i \sim \mathcal{N}(0, \sigma_2^2)$$



$$\mathbf{v}_j \sim \mathcal{N}(\mathbf{0}, \sigma_1^2 \mathbf{I})$$

$$\beta_j \sim \mathcal{N}(0, \sigma_2^2)$$

$$\mathcal{N}(y_{ij},\epsilon_{ij})$$

$$y_{ij} = \alpha_i + \beta_j + \mathbf{u}_i^T \mathbf{v}_j$$

$$\hat{r}_{ij} = \mathbf{1}[\hat{y}_{ij} > 0]$$
 (5, 1)





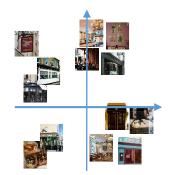




INITIALIZATION FROM OFFLINE DATA

Learn offline embedding from logged observations

1. Initialize prior of every item j from corresponding trait posterior \mathbf{v}_j and bias β_j



2. For cold-start user

$$\mathbf{u}^{cold} \sim \mathbf{E}_{i=1,...,M}[\mathbf{u}_i]$$

$$\alpha^{cold} \sim \mathbf{E}_{i=1,...,M}[\alpha_i]$$



QUESTION SELECTION STRATEGIES

Thompson Sampling (TS):

BANDIT LEARNING

Pick item with max. sampled noisy affinity

Upper Confidence (UCB):

Pick item with highest mean plus variance

Max. Variance:

ACTIVE LEARNING

Explore-only, variance reduction.

Pick item with highest noisy affinity variance

Max. Item Trait:

Pick item whose trait vector contains the most information, (i.e., highest L2 norm)

- Greedy: Exploit-only strategy
- Random: Explore-only strategy
- Min. Item Trait: Baseline, least carrying information

ONLINE UPDATING



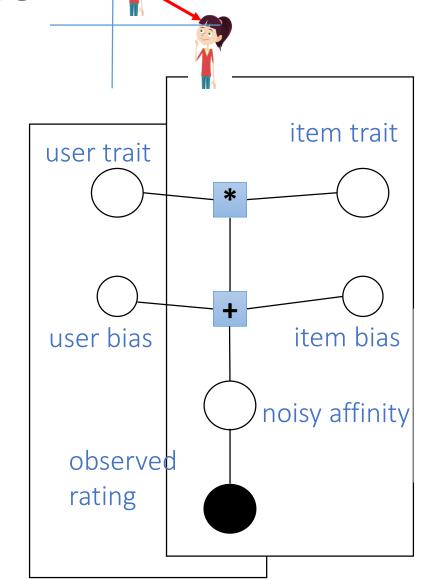




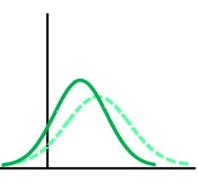












ABSOLUTE MODEL, ABSOLUTE QUESTIONS

Do you like





Generalized Thompson Sampling

$$j^* = \arg\max_{j \in \mathcal{J}} \hat{y}_{ij}$$



FEEDBACK ELICITATION FOR RELATIVE QUESTIONS

People are often better at giving pairwise comparisons instead of absolute judgements



VS



Yes/ No/ I like neither

ABSOLUTE MODEL, RELATIVE QUESTIONS

Insight: Restaurants compared should be far apart in the latent embedding

Do you prefer



over



- 1. Virtual observation (
- , , , 0)
- 2. Virtual prior = posterior after incorporating virtual obs.
- 3. Pick item B: $j^* = \arg \max_{j \in \mathcal{J}} \hat{y}_{ij}$

Abs

$$j^* = \arg\max_{j \in \mathcal{J}} \hat{y}_{ij}$$

Abs Pos

Abs Pos & Neg



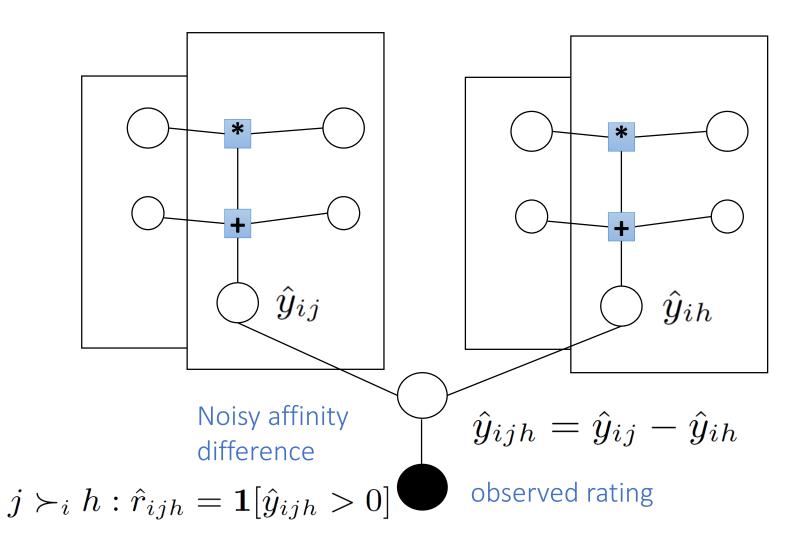




,1)



PAIRWISE MODEL





• • •

PAIRWISE MODEL, RELATIVE QUESTIONS

Do you prefer



over





Abs
$$j^* = rg \max_{j \in \mathcal{J}} \hat{y}_{ij}$$

Pick

item
$$B = h^* = \arg \max_{h \in \mathcal{J}} \hat{y}_{ihj^*}$$

most preferred compared to A









EXPERIMENTS

EXPERIMENTAL SETUP

Offline phase: M users interact with N items → get offline embedding

Online phase: model interacts with cold-start users, asking questions on the N items

Domain: restaurant recommendation

$$AP@k = \sum_{\ell=0}^{k-1} \frac{P@\ell \cdot r_{i[\ell]}^{\text{true}}}{\min(k, \# \text{ of liked items})}$$

Search data for offline embedding

User Study as basis for online evaluation

Obtaining Ground Truth

- 26/12/14 - 26/04/15

search logs: 3,549 cookies

with 289 restaurants \rightarrow

9330 positive observations

 Sample negative observations "Would you consider restaurant X for your next Friday night dinner"?

28 participants

10 restaurants

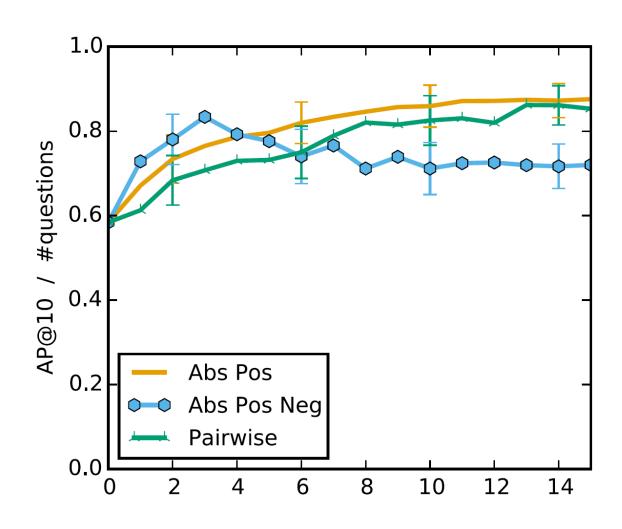
Sample user = one of 28 participants Set user prior = sampled value from **u**i

Observe
user's ratings
on the 10
restaurants

Infer & sample ratings **r**i

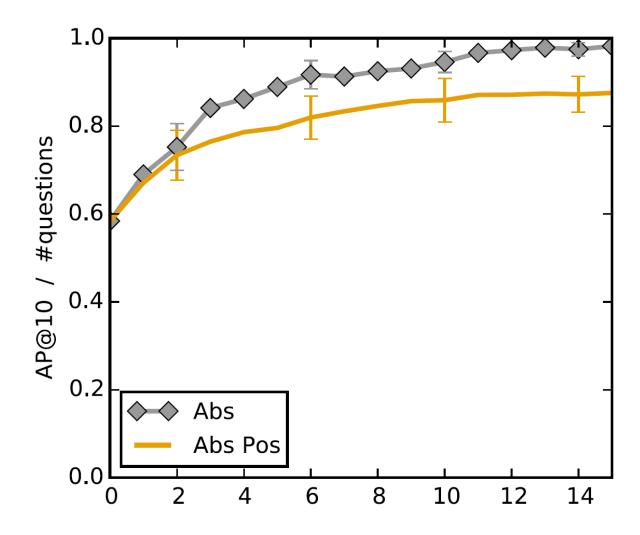
Infer user traits **u**i

Which method for relative questions is better?

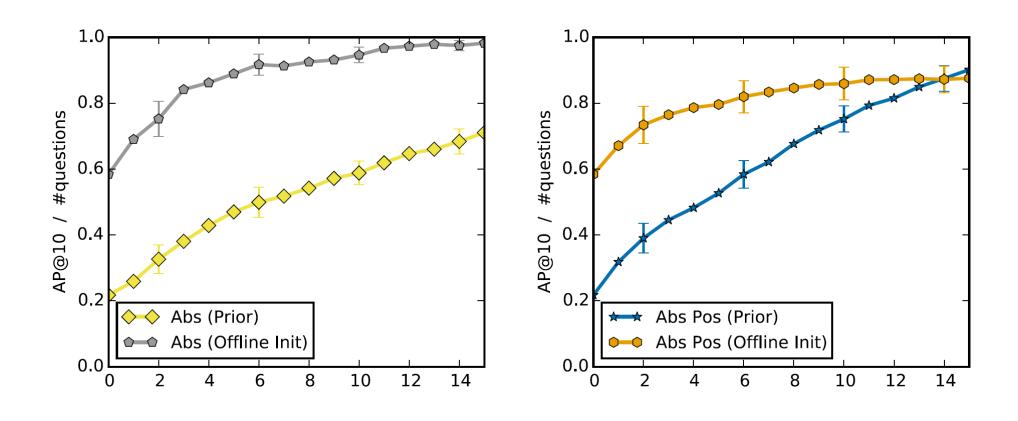


Are absolute or relative questions better?

After only 2 questions, 25% improvement over a static model.

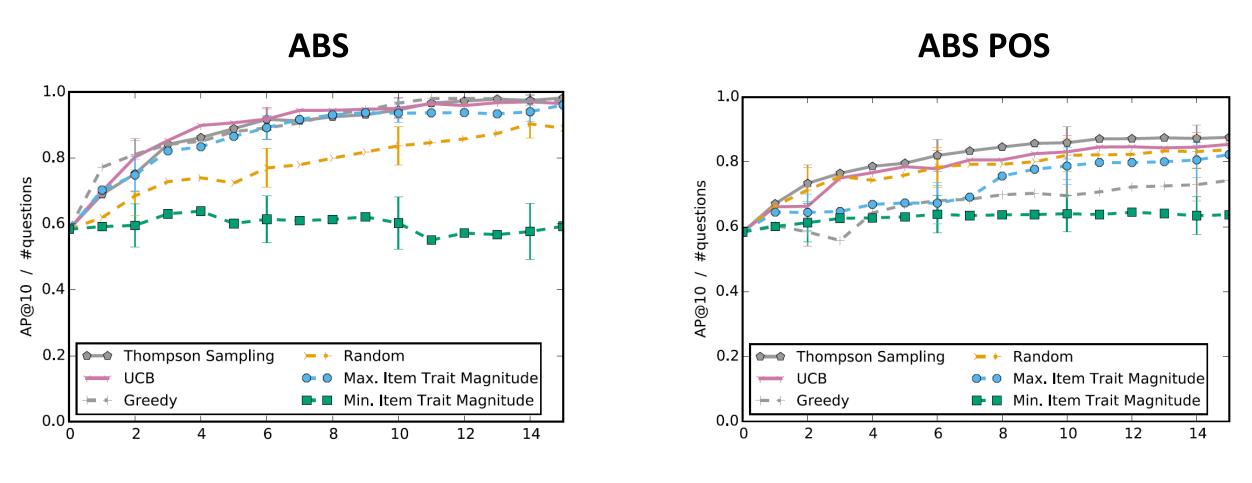


Does offline initialization help?



Dramatic benefits from offline embeddings.

Which question selection strategy is best?



Bandit-inspired strategies perform the most robustly.

CONCLUSIONS

- 1. Envision recommender systems that converse with new users to learn their preferences.
- 2. Fully online learning approach for recommendation -- both using absolute and relative feedback
- 3. Proposed various question selection strategies
- 4. Best performance can be achieved with absolute questions.
- 5. Effective learning with relative feedback is also possible.
- 6. Offline learned embedding greatly boosts initial performance.
- 7. Bandit-inspired question selection strategies are very effective.

Thank you!