# Towards Conversational Recommender Systems

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There are too many options
for where to eat dinner tonight…

If you asked a local:

# TOWARDS THIS EXAMPLE SCENARIO

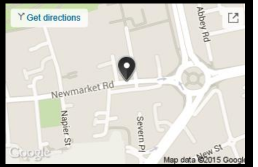
Sure! How hungry are you?

Not very hungry

Do you prefer Chinese or Indian today?

Chinese.

Ok. Would you like to go to Orchid?


Yes, thanks!

# ROADMAP


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

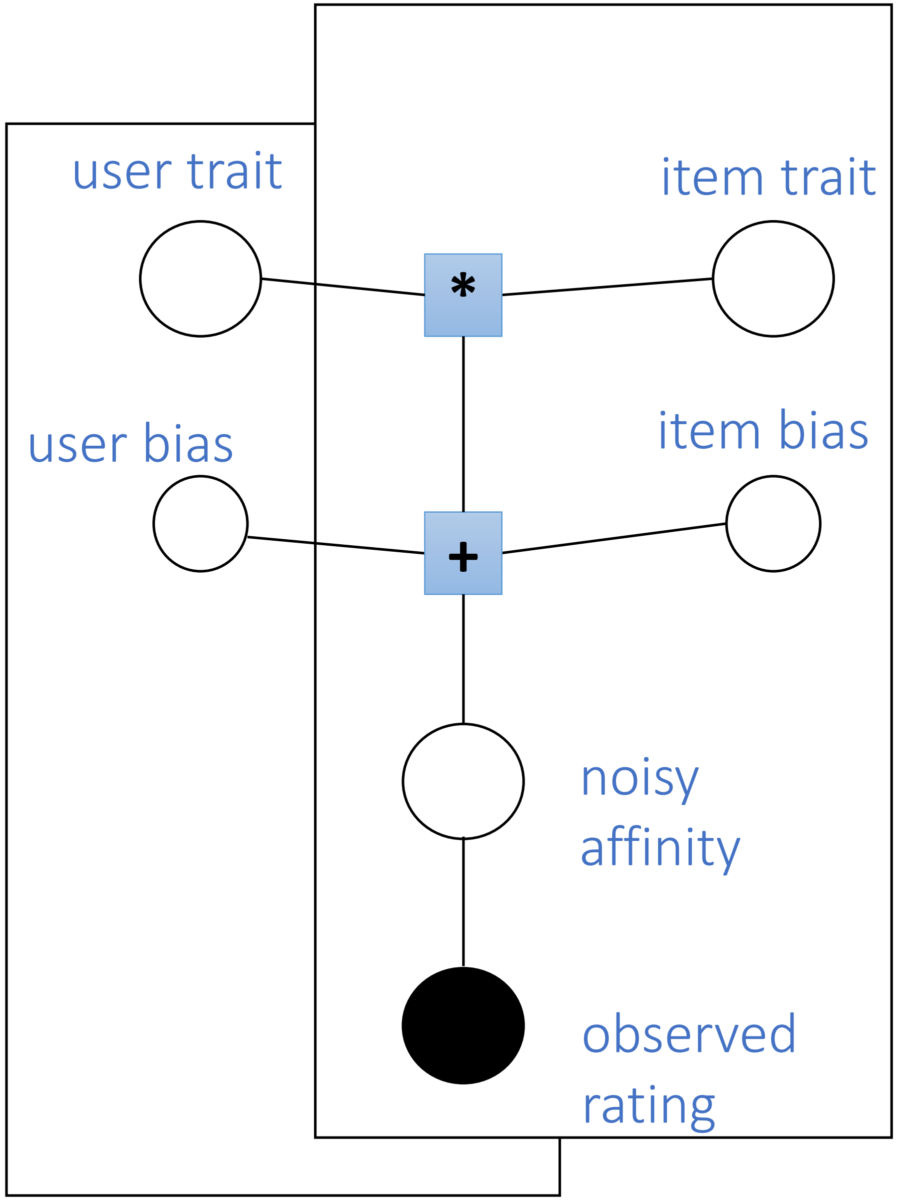
Feedback elicitation mechanism to select absolute and relative questions.

**WHAT TO ASK & HOW TO ASK IT?**

# MODEL: PROBABILISTIC MATRIX FACTORIZATION

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

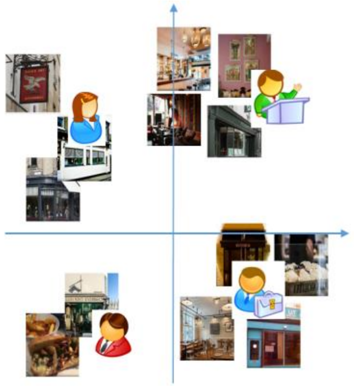
$$\alpha_i \sim \mathcal{N}(0, \sigma_2^2) \qquad \beta_j \sim \mathcal{N}(0, \sigma_2^2)$$

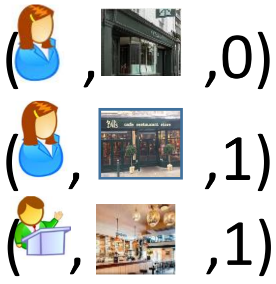



$$\mathcal{N}(y_{ij}, \epsilon_{ij})$$

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

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

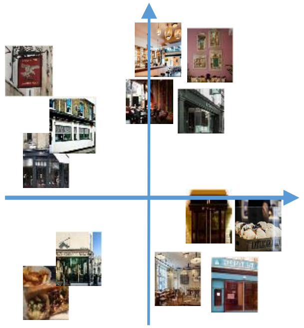




# INITIALIZATION FROM OFFLINE DATA

Learn offline embedding from logged observations

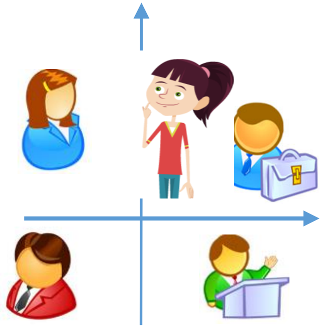
1. Initialize prior of every item j from corresponding trait posterior $\mathbf{v}_j$ and bias $\beta_j$



2. For cold-start user

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

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



# QUESTION SELECTION STRATEGIES

**BANDIT LEARNING**

- Thompson Sampling (TS):
  Pick item with max. sampled noisy affinity
- Upper Confidence (UCB):
  Pick item with highest mean plus variance

**ACTIVE LEARNING**

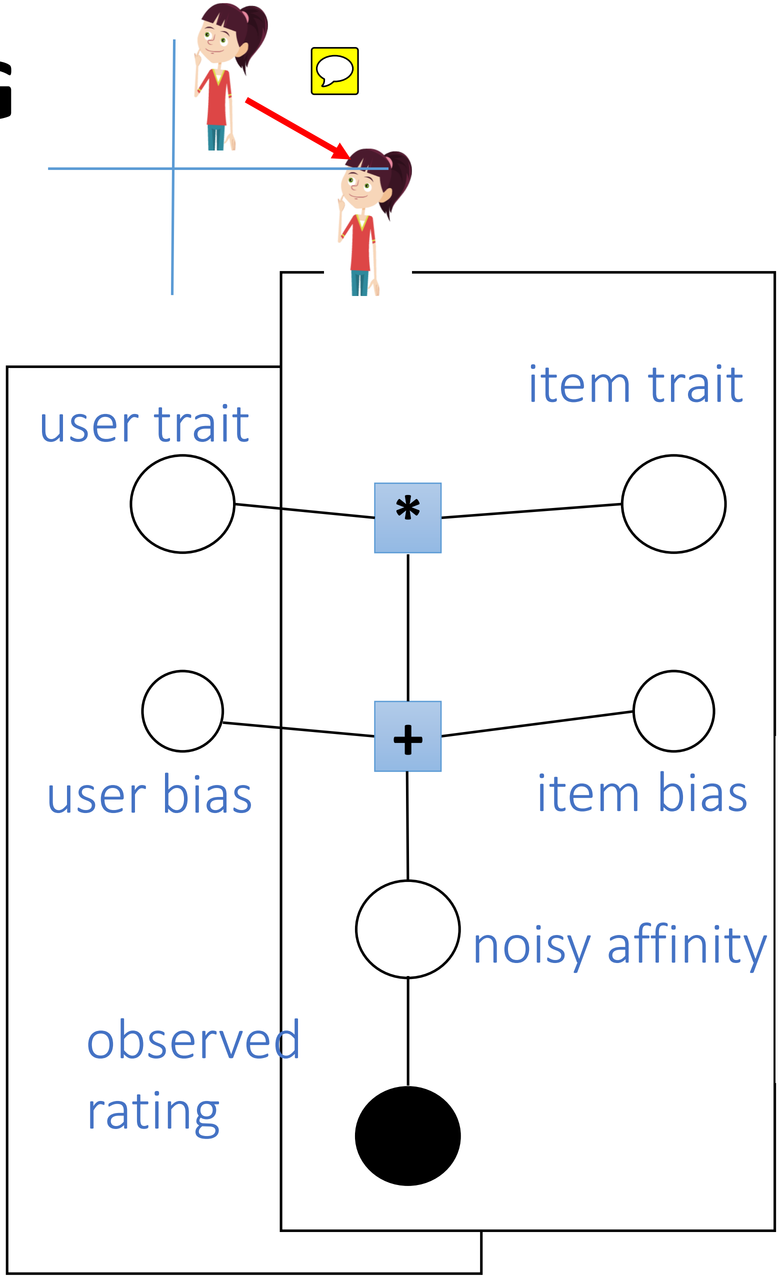
- Max. Variance:
  Explore-only, variance reduction.
  Pick item with highest noisy affinity variance
- Max. Item Trait:
  Pick item whose trait vector contains the most information, (i.e., highest L2 norm)

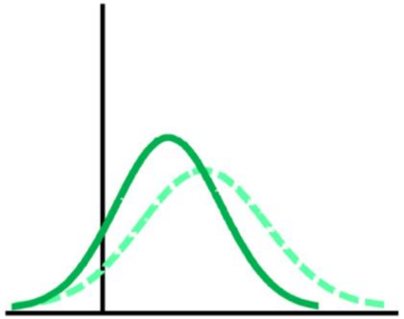
- Greedy: Exploit-only strategy
- Random: Explore-only strategy
- Min. Item Trait: Baseline, least carrying information

# ONLINE UPDATING

Do you like  ?


(  ,  ,0)



# ABSOLUTE MODEL, ABSOLUTE QUESTIONS

Do you like 

?


Generalized Thompson Sampling

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

(  ,  ,1/0)

# FEEDBACK ELICITATION FOR RELATIVE QUESTIONS

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

**VS**

# 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**

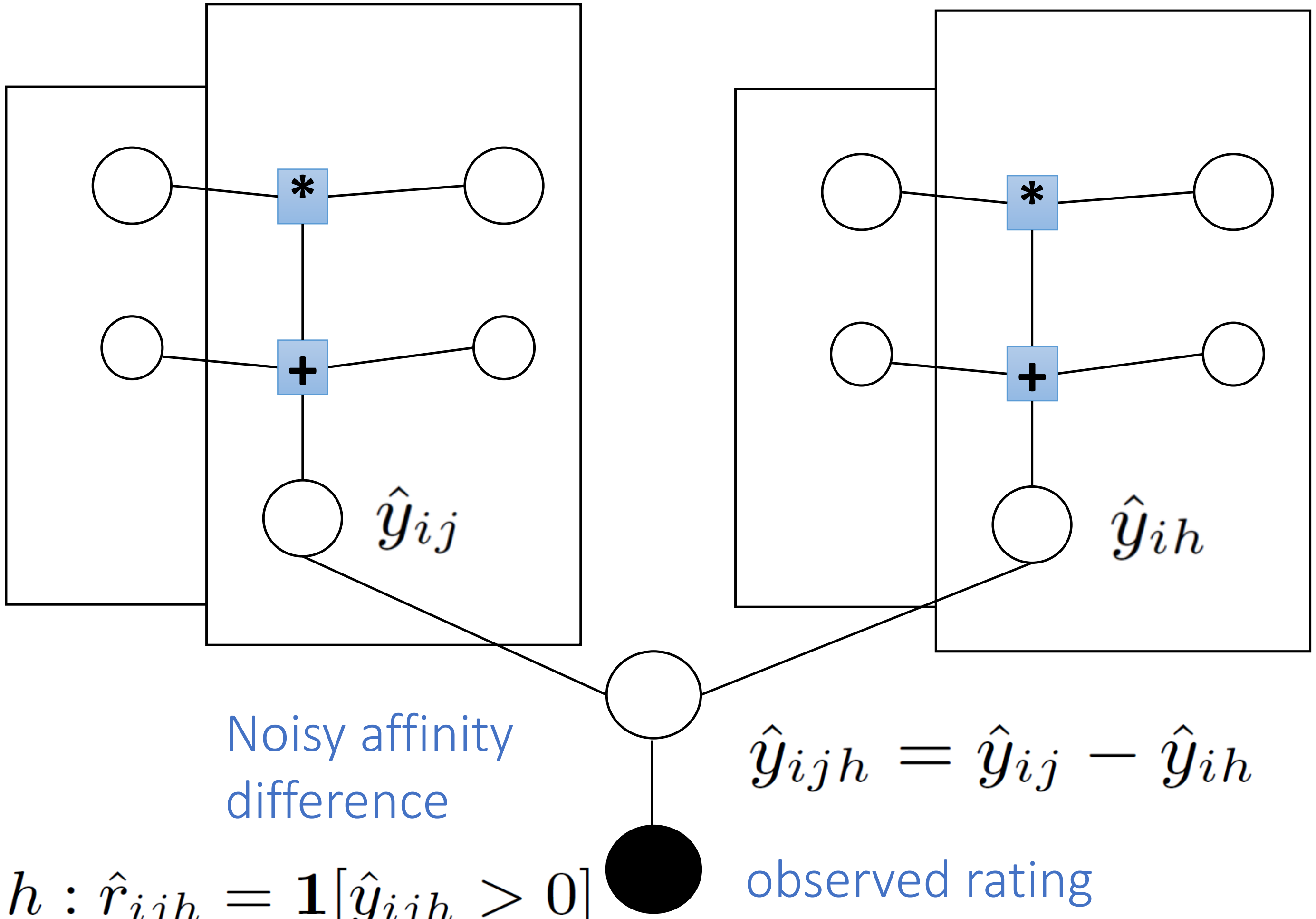
(  ,  ,1)

**Abs Pos & Neg**

(  ,  ,1)

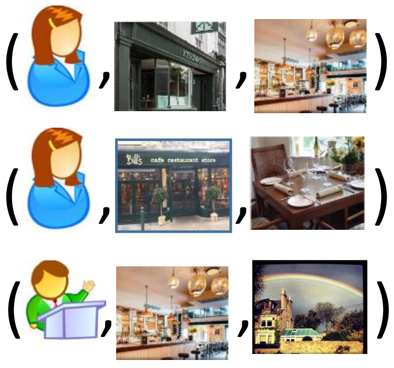
(  ,  ,0)

# PAIRWISE MODEL




$$\hat{y}_{ijh} = \hat{y}_{ij} - \hat{y}_{ih}$$

$$j \succ_i h : \hat{r}_{ijh} = \mathbf{1}[\hat{y}_{ijh} > 0]$$



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# PAIRWISE MODEL, RELATIVE QUESTIONS

Do you prefer

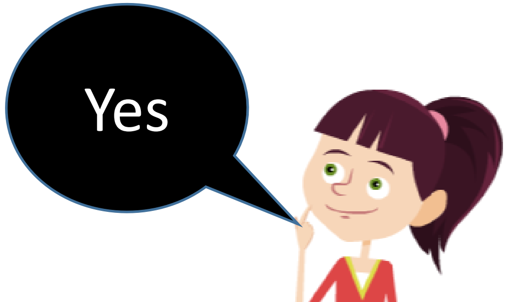

over


?

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

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

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 → 9330 positive observations
- Sample negative observations

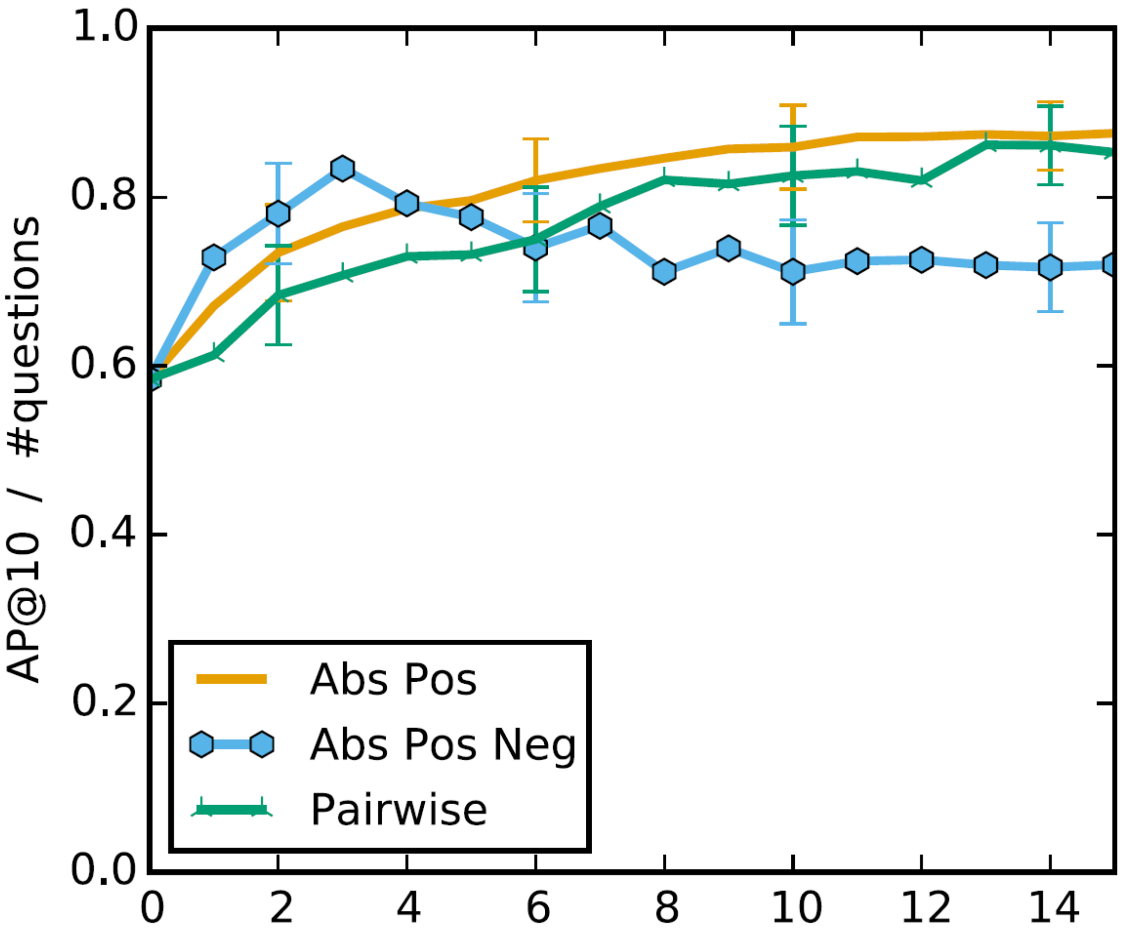
"Would you consider restaurant X for your next Friday night dinner"?

28 participants

10 restaurants

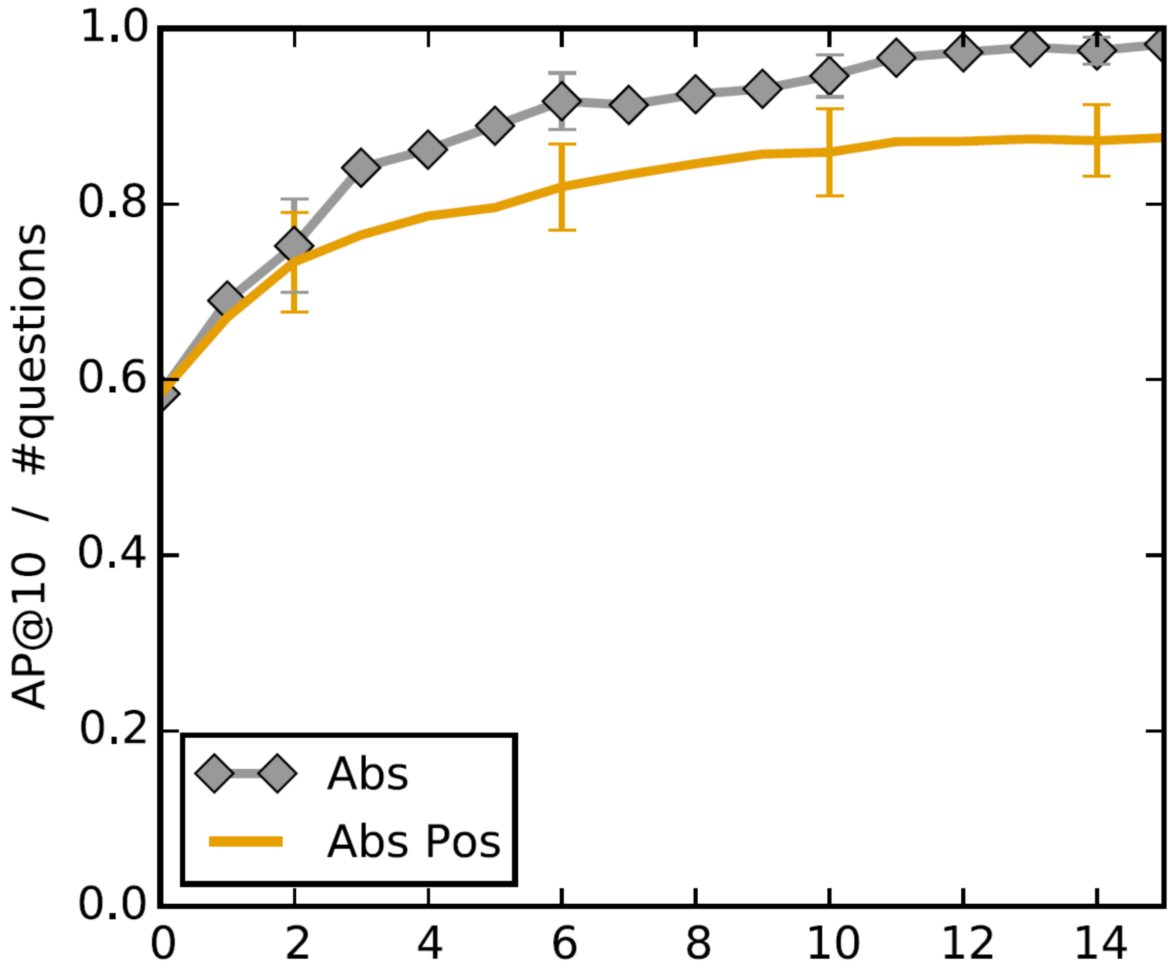
1. Sample user = one of 28 participants
2. Observe user's ratings on the 10 restaurants
3. Infer user traits $u_i$
4. Set user prior = sampled value from $u_i$
5. Infer & sample ratings $r_i$

# Which method for relative questions is better?

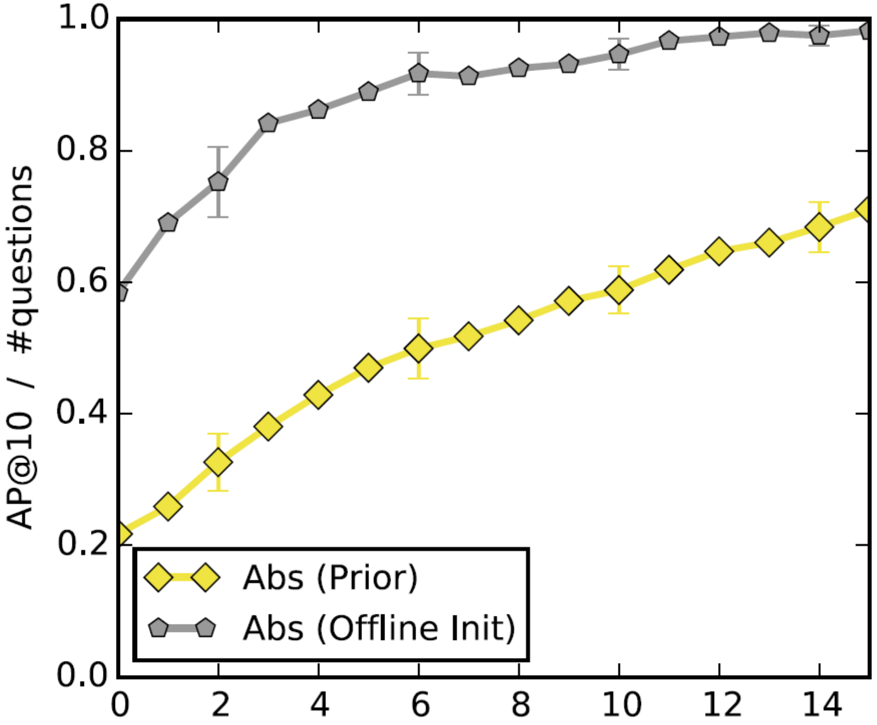


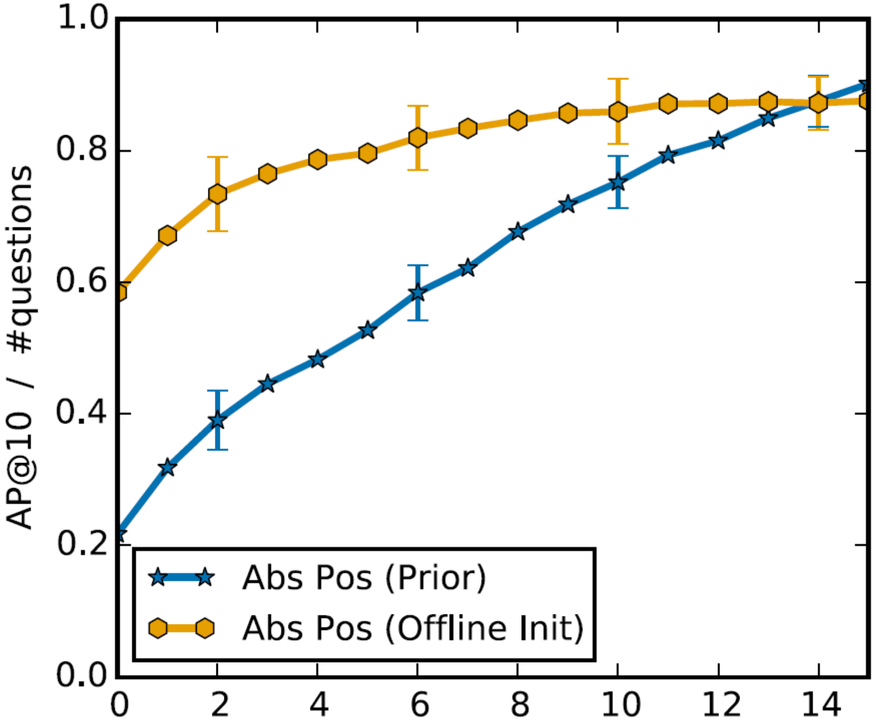
# Are absolute or relative questions better?

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



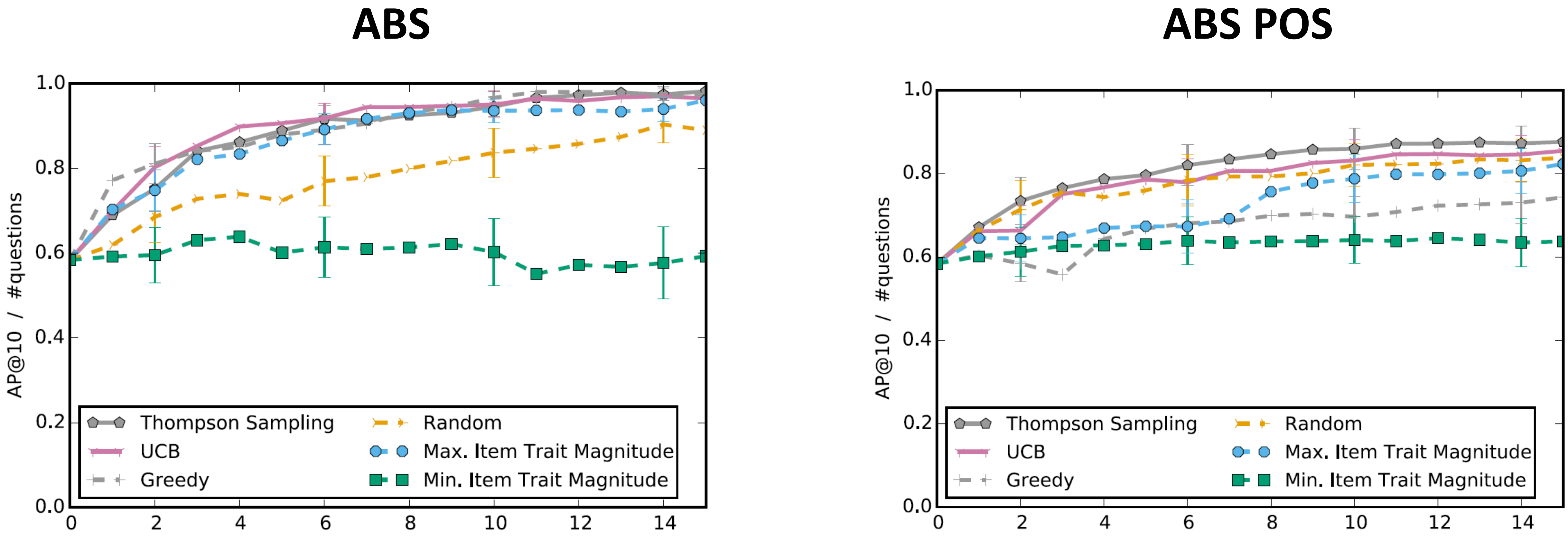
# Does offline initialization help?




**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!**