Towards Conversational Recommender Systems

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Can you recommend to me a restaurant in Cambridge for tonight?
There are too many options for where to eat dinner tonight...

If you asked a local:

- Do you like seafood?
- Do you have a car?
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!
CONTRIBUTION

1. Novel view of human-like recommenders that converse with new users to learn their preferences

2. Fully online learning approach for recommendation -- both using absolute and relative feedback

3. We propose question selection strategies for deciding which question to ask to a cold-start user
OUR INTERACTIVE RECOMMENDATION PIPELINE

1. Pick a model and a preference elicitation mechanism

2. Model initialized with offline data
   A) Mechanism selects question to ask the user
   B) User answers the question
   C) All model parameters are updated
   D) Remove asked question from allowed questions
OUR INTERACTIVE RECOMMENDATION PIPELINE

- Mechanism selects next question
- User answers the question
OUR INTERACTIVE RECOMMENDATION PIPELINE

Model presents to the user its recommendations

Human in the Loop
WHAT TO ASK?
HOW TO ASK IT?
ROADMAP

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

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

3) **Feedback elicitation** mechanism to select **absolute** and **relative** questions.
LATENT FACTOR MODEL: A principled way of selecting questions

Where should I go for dinner tonight?
user bias \( \alpha_i \in \mathbb{R} \)
item bias \( \beta_j \in \mathbb{R} \)
user trait \( \mathbf{u}_i \in \mathbb{R}^d \)
item trait \( \mathbf{v}_j \in \mathbb{R}^d \)
\( d \ll M, N \)
$$u_i \sim \mathcal{N}(0, \sigma_1^2 I)$$

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

$$v_j \sim \mathcal{N}(0, \sigma_1^2 I)$$

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

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

$$y_{ij} = \alpha_i + \beta_j + u_i^T v_j$$

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

Insight: People are often better at giving pairwise comparisons instead of absolute judgements.
PAIRWISE MODEL

\[
\hat{y}_{ij} - \hat{y}_{ih} = \hat{y}_{ij} - \hat{y}_{ih}
\]

Noisy affinity difference

\[
j \succ i \; h : \hat{r}_{ijh} = 1[\hat{y}_{ijh} > 0]
\]

observed rating
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

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

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
Do you like [image]?

No

(user trait, item trait, user bias, item bias, noisy affinity, observed rating, (1, 0))
ABSOLUTE MODEL, ABSOLUTE QUESTIONS

Do you like [image of food]?

Yes / No

THOMPSON SAMPLING

\[ j^* = \arg \max_{j \in J} \hat{y}_{ij} \]

(1, 1/0)
PREFERENCE ELICITATION FOR RELATIVE PREFERENCES

Do you prefer ?

Absolute Model, Relative Questions
1. Abs Pos
2. Abs Pos & Neg

Pairwise Model, Relative Questions
3. Pairwise

Yes/ No/ I like neither
**ABSOLUTE MODEL, RELATIVE QUESTIONS**

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

**Do you prefer** Restaurant A **over** Restaurant B?

Abs: \( j^* = \arg \max_{j \in \mathcal{J}} \hat{y}_{i,j} \)

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

Two ways of incorporating feedback to the Absolute Model

Do you prefer over ?

Abs Pos

Abs Pos & Neg

\((, ,1)\)

\((, ,1)\)

\((, ,0)\)
PAIRWISE MODEL, RELATIVE QUESTIONS

Use the Pairwise model.

Do you prefer Restaurant A over Restaurant B?

Abs \( j^* = \arg \max_{j \in \mathcal{J}} \hat{y}_{i,j} \)

Pick item \( B = h^* = \arg \max_{h \in \mathcal{J}} \hat{y}_{ih,j^*} \) most preferred compared to A

Yes
EXPERIMENTS
EXPERIMENTAL SETUP

**Offline phase:** M users interact with N items $\rightarrow$ get offline embedding

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

$$AP@k = \sum_{\ell=0}^{k-1} \frac{P@\ell \cdot r_i^{true}[\ell]}{\min(k, \# \text{ of liked items})}$$
• Index of 512 Cambridge restaurants from a restaurant review provider

• Search Logs: For 26/03/15 – 26/04/15 identified 3,549 cookies who clicked/impressed at least one restaurant

• Index of 289 restaurants accessed by at least a user

• 4 months search history of interactions of 3,549 cookies with 289 restaurants → 9330 positive observations

• For negative observations, sample uniformly at random min(10, n+) restaurants as dislikes

• Tune no of traits, variances for highest pairwise accuracy

OFFLINE EMBEDDING BASED ON SEARCH LOG DATA
**Challenge** for online recommender evaluation: Need users’ ground truth on the space of all questions

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

- 28 individuals, varying in age, job level, time spent in Cambridge
- Anonymous questionnaire
- Pool of restaurants: 10 diverse Cambridge restaurants
• Need ground truth for **all 289** Cambridge restaurants
• **Bootstrap cold-start users** from the 28 participants

| Sample user = one of 28 participants | Observe user’s ratings on 10 survey restaurants | Infer user traits $u_i$ (prior: offline embedding) | Set user prior = sampled value from $u_i$ | Infer unknown ratings $r_i$ Ground truth = sample |

**GROUND TRUTH DATA OF ONLINE USERS ON ALL RESTAURANTS**
Which method for relative questions is better?
Are absolute or relative questions better?
Does offline initialization help?
Which question selection strategy is best?

For ABS
Which question selection strategy is best?

For ABS POS
CONCLUSIONS

• Envision recommender systems that converse with new users to learn their preferences.
• Best performance can be achieved with absolute questions.
• Effective learning with relative feedback is also possible.
• Offline learned embedding greatly boosts initial performance.
• Bandit-inspired question selection strategies are very effective.

Thank you!