Accurate and Explainable Recommendation via Review Rationalization

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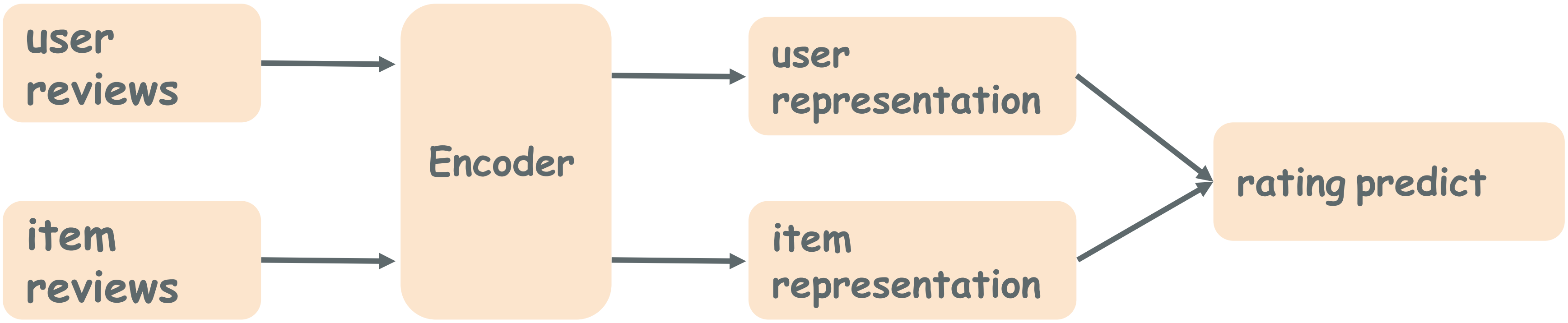
Source : WWW'22

Date : 2022/10/25

Outline

- Introduction
- Motivation
- Method
- Experiment
- Conclusion

Introduction : Review-based recommendation



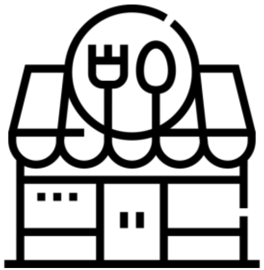
Motivation

Noodles are truly great! The meat sauce and lamb are my favorites!

This is a perfect to-go place near the freeway for a work day including weekends! :-)

taste>convenience

rating predict : 4.3



Input

- user u
- reviews of u : $W_{u,*|\sim tu,v} = \{W_{u,v1}\ ,\ .\ .\ .\ ., W_{u,\sim v}\}$
- user u
- reviews of i : $W_{*,v\ |\sim tu,v} = \{W_{u1,v}, . . . , W_{\sim u,v}\}$

Output

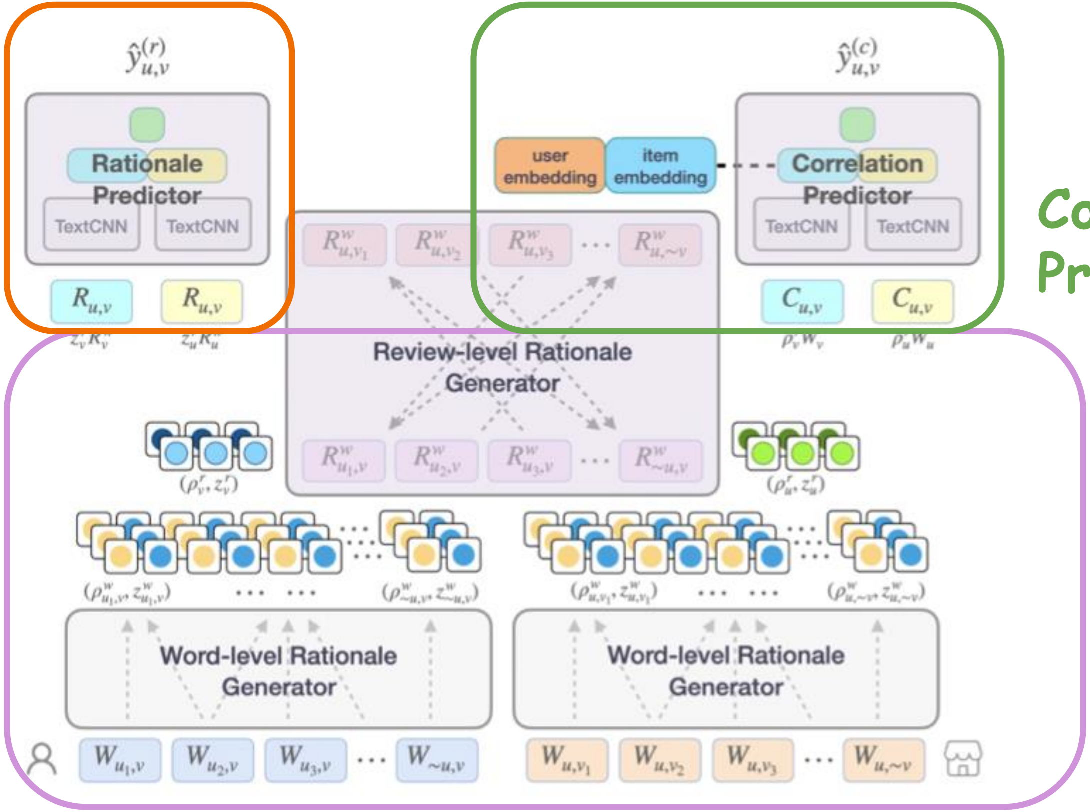
- ratings score

Goal

- Extract the rationales R from reviews that is the direct cause of the rating Y .
- Predict the rating $y\hat{}_{u,v}$ that reflects how much u likes v.

Method ： RECOMMENDATION VIA REVIEW RATIONALIZATION(R3)

Rationale Predictor

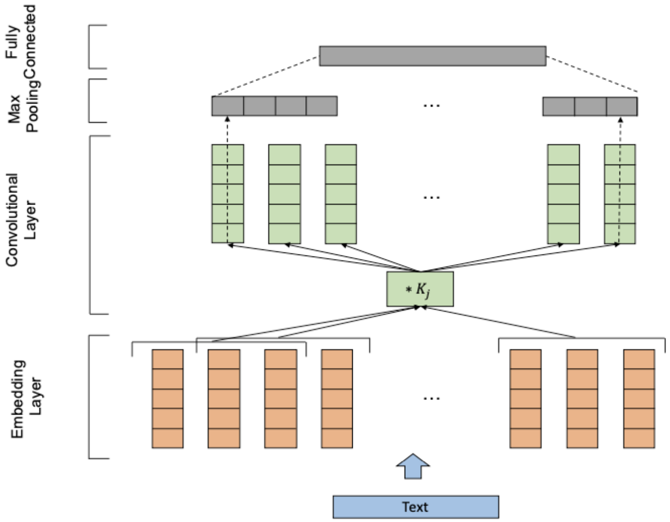


Correlation Predictor

Rationale Generator

1.1 Rationale Generator - Word level

- **Input** : each **word** of a **review**
- **output** : the **probabilities** of the words being selected as **rationales**
- **text processor**



$$\boxed{\rho} = \sigma(cW + b)$$

1.1 Rationale Generator - Word level

- To specifically choose rationales
- transform probabilities ρ to binary signals z
  - $\lfloor \cdot \rceil$ is the rounding function

$$\boxed{z} = \rho + f_d(\lfloor \rho \rceil - \rho).$$

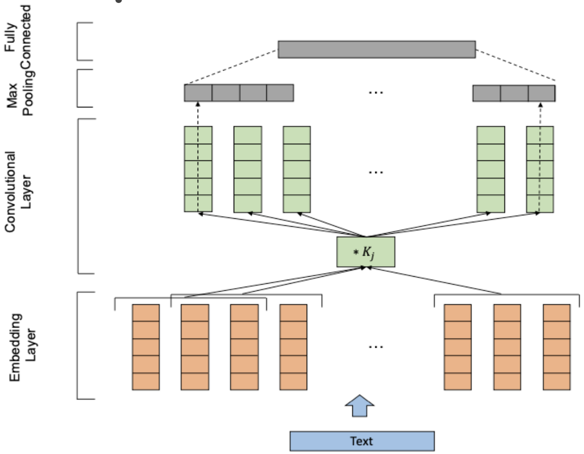
$$\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

mask

1.2 Rationale Generator - Review level

- Input : word-level rationales from user historical reviews $R^{w}_{u,*}$

  word-level rationales from item historical reviews $R^{w}_{*,v}$
- output : user preference matrix / item preference matrix
- text processor

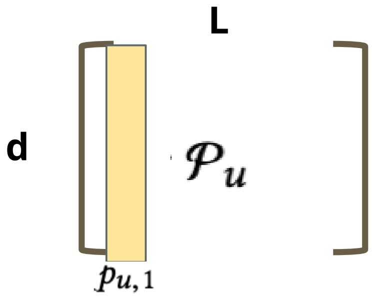


number of reviews from user u

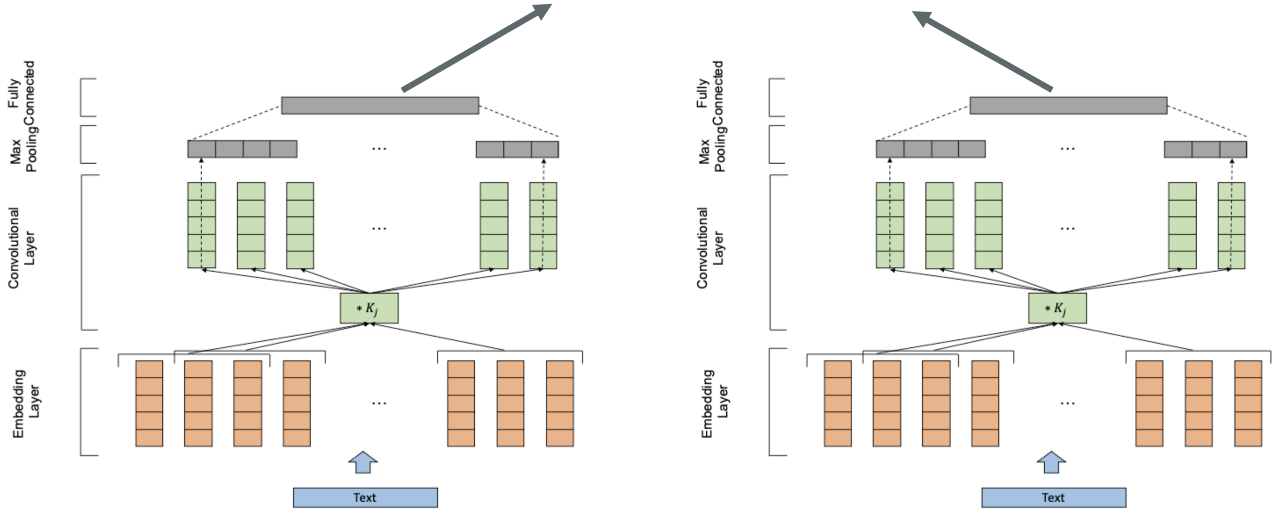
$$\begin{array}{cc} & L \\ d & \left[\quad \mathcal{P}_u \quad \right] \end{array}$$

output size of the FC layer

1.2 Rationale Generator - Review level



FC layer : model user preference on items $p_{u,v}$



user u

item 1

1.2 Rationale Generator - Review level

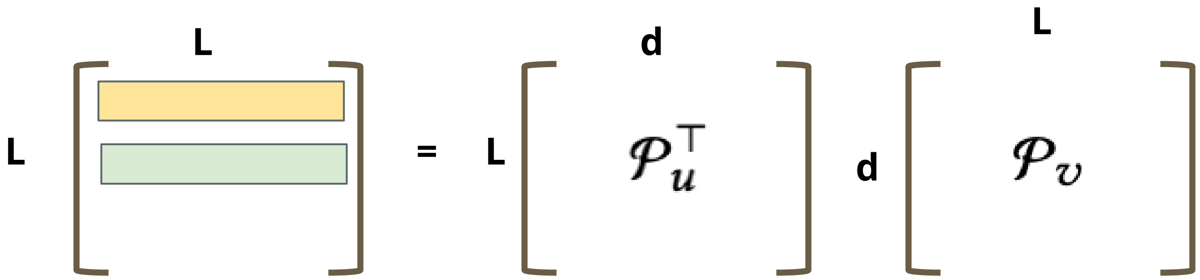
- Input : user preference matrix and item preference matrix
- output : affinity matrix
- to select rationales that match both user interests and item properties

$$s_{u,v} = \mathcal{P}_u^\top \mathcal{P}_v.$$

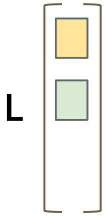
$$\begin{array}{cc} & L \\ L & \begin{bmatrix} \quad s_{u,v} \quad \end{bmatrix} \end{array} = \begin{array}{cc} & d \\ L & \begin{bmatrix} \quad \mathcal{P}_u^\top \quad \end{bmatrix} \end{array} \begin{array}{cc} & L \\ d & \begin{bmatrix} \quad \mathcal{P}_v \quad \end{bmatrix} \end{array}$$

1.2 Rationale Generator - Review level

- obtain the probabilities of potential rationales to become true rationales

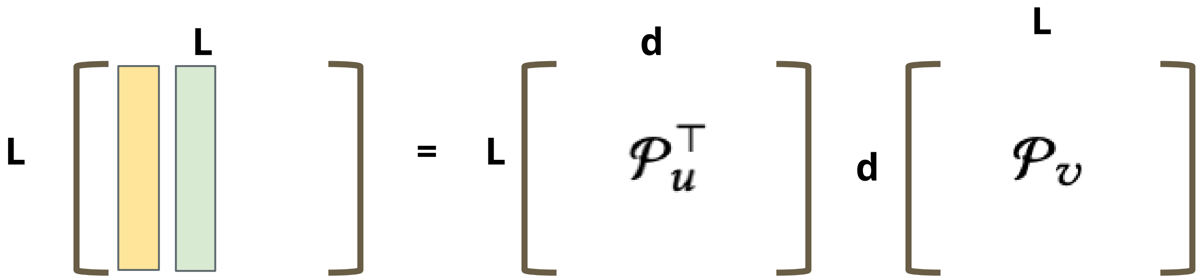


$$\rho_u^r = \sigma\left(\sum_{row} s\right)$$

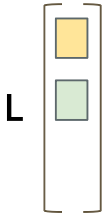


1.2 Rationale Generator - Review level

- obtain the probabilities of potential rationales to become true rationales



$$\rho_v^r = \sigma(\sum_{col} s)$$



2. Rationale Predictor

- predict user ratings on items <u>only by rationale features</u>
- user rationale features :

$$\gamma_u^{(r)} = z_u^{r\top} \mathcal{P}_u$$

- item rationale features :

$$\gamma_v^{(r)} = z_v^{r\top} \mathcal{P}_v$$

- rating prediction :

$$\hat{y}_{u,v}^{(r)} = h_r([\gamma_u^{(r)}, \gamma_v^{(r)}]) + b_u + b_v + \mu$$

3. Correlation Predictor

- predict user ratings by utilizing both <u>rationale features</u> and <u>non-rationale features</u>

$$\gamma_u^{(c)} = \rho_u^{r\top} \mathcal{P}_u, \quad \gamma_v^{(c)} = \rho_v^{r\top} \mathcal{P}_v$$

$$\hat{y}_{u,v}^{(c)} = h_c([\gamma_u^{(c)} + \gamma_u^{(e)}, \gamma_v^{(c)} + \gamma_v^{(e)}]) + b_u + b_v + \mu$$

user embedding and the item embedding trained by <u>**matrix factorization**</u>

4 Model Learning

- Loss:

$$\mathcal{L}_G = \mathcal{L}_R + \lambda \mathbf{ReLU}(\mathcal{L}_R - \mathcal{L}_C) + \alpha(\mathbb{E}[||R||_1] - \gamma).$$

- MSE:

$$\mathcal{L}_R = \sum_{u,v \in \mathcal{D}} (\hat{y}^{(r)}_{u,v} - y_{u,v})^2,$$

$$\mathcal{L}_C = \sum_{u,v \in \mathcal{D}} (\hat{y}^{(c)}_{u,v} - y_{u,v})^2.$$

4 Model Learning

- the rationale generator needs to construct a minimal feature set with maximum predictive ability

$$\mathcal{L}_G = \mathcal{L}_R + \lambda \mathrm{ReLU}(\mathcal{L}_R - \mathcal{L}_C) + \alpha(\mathbb{E}[||R||_1] - \gamma).$$

4 Model Learning

- ensures that the size of the selected rationales is small via a sparsity constraint:

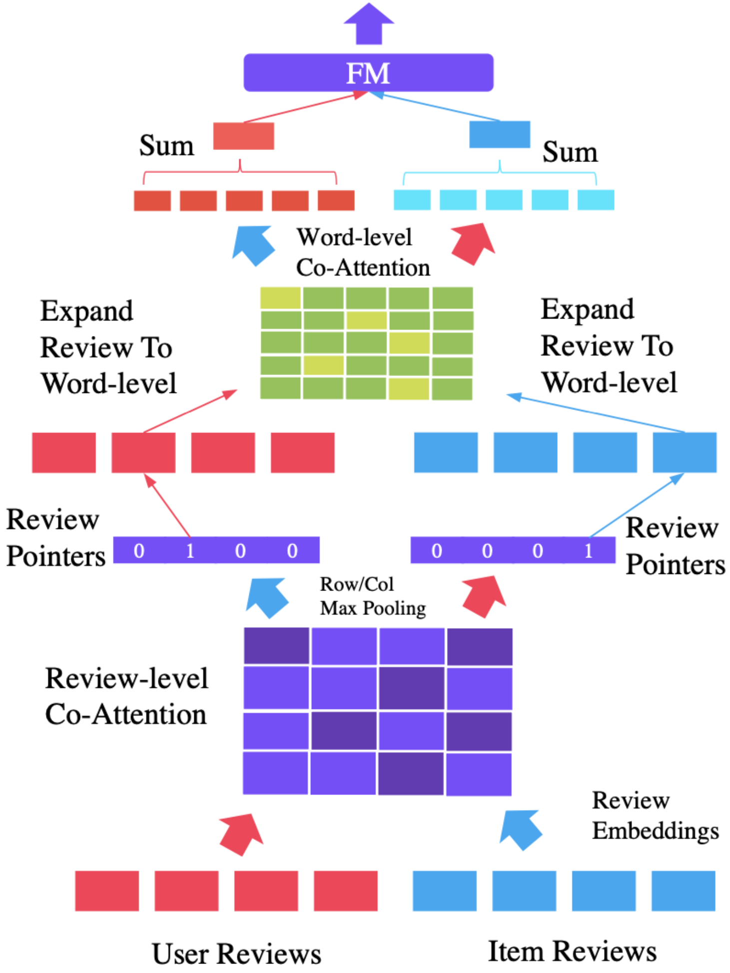
$$\mathcal{L}_G = \mathcal{L}_R + \lambda \mathbf{ReLU}(\mathcal{L}_R - \mathcal{L}_C) + \alpha(\mathbb{E}[||R||_1] - \gamma).$$

Datasets

Datasets	#Users	#Items	#Reviews
Home and Kitchen	35,515	11,843	341,138
Toys and Games	19,385	11,912	167,328
Health and Personal Care	38,577	18,520	346,089
Beauty	22,348	12,095	198,378
Yelp	35,515	11,843	341,138

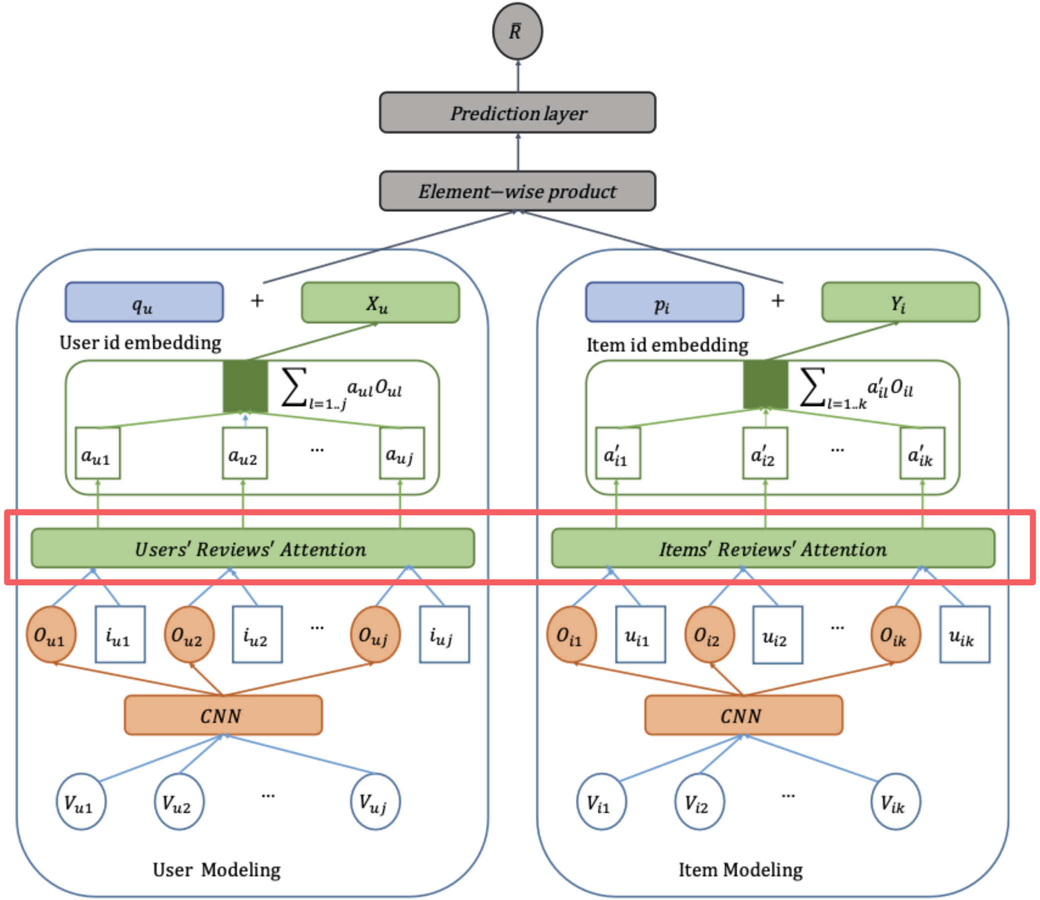
Experiment-Baseline

- MPCN



Experiment-Baseline

- NARRE



Experiment-Baseline

(a) Raw Dataset	MF	D-CoNN	D-CoNN++	MPCN	NARRE	R3-R	R3-C
Home and Kitchen	0.8882	0.8770	0.9895	0.8881	0.8815	**0.8421****	0.8432
Toys and Game	0.6916	0.6799	0.6770	0.6925	0.6862	0.6760*	**0.6537**
Health and Personal Care	0.9239	0.9188	1.0332	0.9531	0.9626	0.8510**	**0.8470**
Yelp	1.0811	1.0796	1.0761	1.1097	1.0672	**1.0603****	1.0638

Experiment-the performance of R3 with data distribution shifts

(a) Raw Dataset	MF	D-CoNN	D-CoNN++	MPCN	NARRE	R3-R	R3-C
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Health and Personal Care	0.9239	0.9188	1.0332	0.9531	0.9626	0.8510**	**0.8470**
Yelp	1.0811	1.0796	1.0761	1.1097	1.0672	**1.0603****	1.0638

(b) Debiased Dataset	MF	D-CoNN	D-CoNN++	MPCN	NARRE	R3-R	R3-C
Home and Kitchen	3.9481	3.8327	4.4353	4.3538	3.8801	**3.0957****	3.1048
Toys and Game	2.8575	2.8244	3.0766	2.7924	2.9847	**2.0158****	2.1809
Health and Personal Care	3.7198	3.8870	4.5853	4.1551	4.1778	**2.8640****	2.9443
Yelp	2.6131	2.8038	2.8559	3.1663	2.8603	2.3466**	**2.3432**

test-u

Experiment

$$\pi_{u,v} = \text{interest} + \text{bias}_{\text{user}} + \text{bias}_{\text{item}} + \text{bias}_{\text{global}}.$$
$$\pi = \text{interest}.$$
$$\pi_u = \text{interest} + \text{bias}_{\text{user}}.$$
$$\pi_v = \text{interest} + \text{bias}_{\text{item}}.$$

$$\text{PCC} = \frac{\sum_{u,v}(\hat{y}_{u,v} - \bar{\hat{y}}_{u,v})(y_{u,v} - \bar{y}_{u,v})}{\sqrt{\sum_{u,v}(\hat{y}_{u,v} - \bar{\hat{y}}_{u,v})^2}\sqrt{\sum_{u,v}(y_{u,v} - \bar{y}_{u,v})^2}};$$

Model	MSE	PCC			
		$\pi_{u,v}$	π	π_u	π_v
benchmark test set					
MF	1.0811	0.3731	0.0470	0.2017	0.3325
NARRE	1.0672	0.3671	0.2810	0.2307	0.3490
R3-R	**1.0603****	0.3696	0.1799	0.1965	0.3290
R3-C	1.0638	0.3677	0.1638	0.2027	0.3280

Experiment

Model	MSE	PCC			
		$\pi_{u,v}$	π	π_u	π_v
benchmark test set					
MF	1.0811	0.3731	0.0470	0.2017	0.3325
NARRE	1.0672	0.3671	0.2810	0.2307	0.3490
R3-R	**1.0603******	0.3696	0.1799	0.1965	0.3290
R3-C	1.0638	0.3677	0.1638	0.2027	0.3280
debiased test set					
MF	2.6131	0.3257	-0.0004	-0.0004	0.3257
NARRE	2.8603	0.3237	0.2603	0.2603	0.3237
R3-R	2.3466**	0.3290	0.3128	0.3128	0.3287
R3-C	**2.3432**	0.3323	0.2209	0.2209	0.3275

Experiment-Explanation via Rationales

Table 4: Rationales (words in boldface) from user and item reviews extracted by R3 for predicting the targeted review and rating. The targeted review is: food has improved recently but service is slow and always pesky flies - gross. its hit or miss.

user historical reviews	item historical reviews
- been here a few times - close location and "burger deals". **service** is **horrible** and **food** is so **slow**, could be better. cute burger ideas, but not worth full price - more **bar** like then food place. - water as beverage - **horrid service** - to get water then food, oh boy then waiting for bill. **food** was **good** , but **service blew**!	have been there multiple times as 1/2 off coupons - **bad food** and **service** 3 out of 4 visits - 1/2 off coupons still available - no thank u. even when empty **service sucked**, **burgers overcooked**, side **dish errors** on plate, bad bad, was great place - bar seems **busy** for happy hour maybe, no more attempts by me.

Conclusion

- extracts rationales from user and item reviews via a rationale generator to alleviate the effects of spurious correlations in recommendation.

- R3 can achieve accurate recommendation and provide causal-aware explanation based on the rationales