Context-aware Co-Attention Neural Network for Service Recommendations

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April 8th, 2019

ICDE'19 Workshop on Recommender Systems with Big Data

Definition of Context

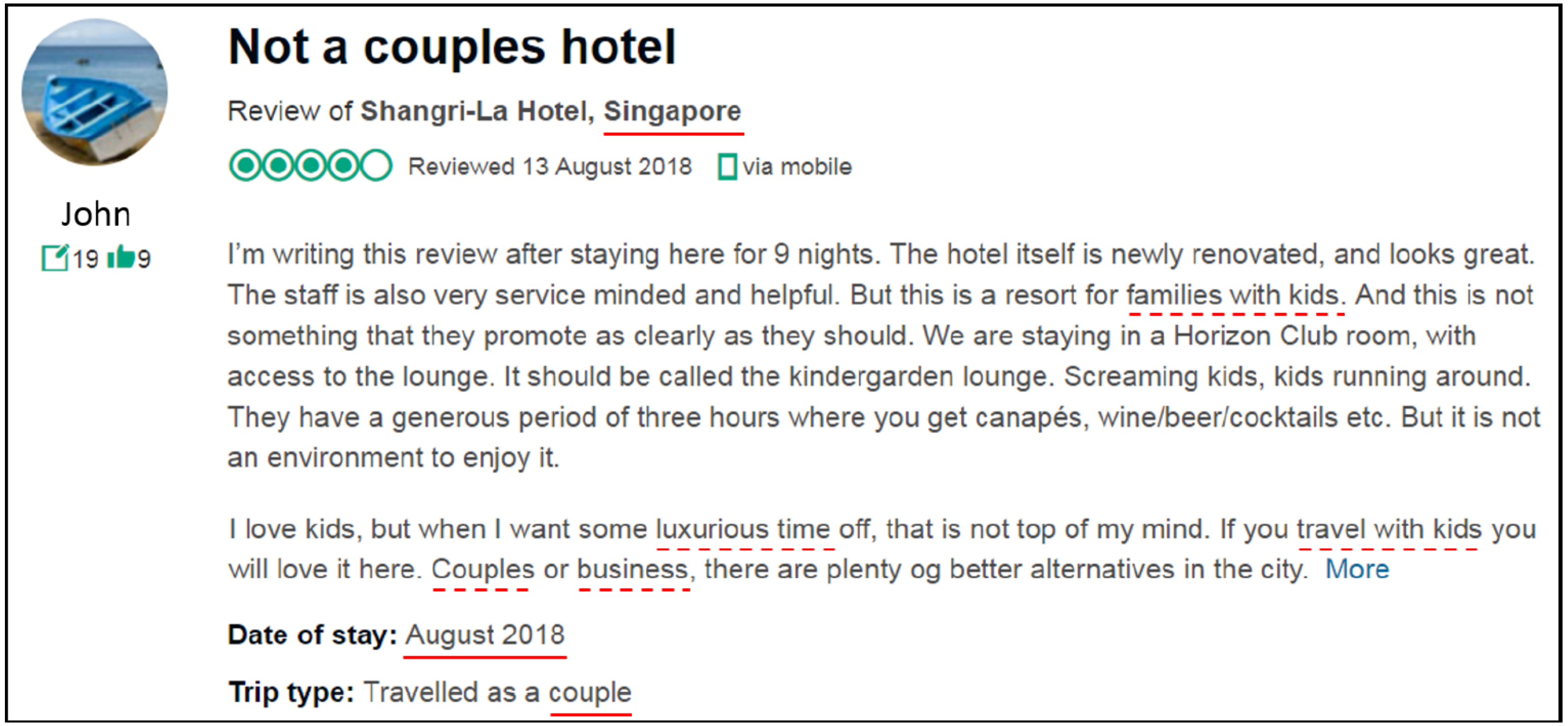
- We adopt the formal definition from (Abowd et al. Springer'99):

> *"Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves."*

- Internal context
  - Personality
  - Emotion
  - Mood
- ***External context***
  - Companion
  - Location
  - Time

Contexts in User Reviews

- Two types of contexts in user reviews
  - Explicit contexts
  - Implicit contexts



Not a couples hotel

Review of **Shangri-La Hotel, Singapore**

Reviewed 13 August 2018 via mobile

John

19 9

I'm writing this review after staying here for 9 nights. The hotel itself is newly renovated, and looks great. The staff is also very service minded and helpful. But this is a resort for families with kids. And this is not something that they promote as clearly as they should. We are staying in a Horizon Club room, with access to the lounge. It should be called the kindergarden lounge. Screaming kids, kids running around. They have a generous period of three hours where you get canapés, wine/beer/cocktails etc. But it is not an environment to enjoy it.

I love kids, but when I want some luxurious time off, that is not top of my mind. If you travel with kids you will love it here. Couples or business, there are plenty og better alternatives in the city. More

Date of stay: August 2018

Trip type: Travelled as a couple

A hotel review example from tripadvisor.com

Existing Context-aware Methods

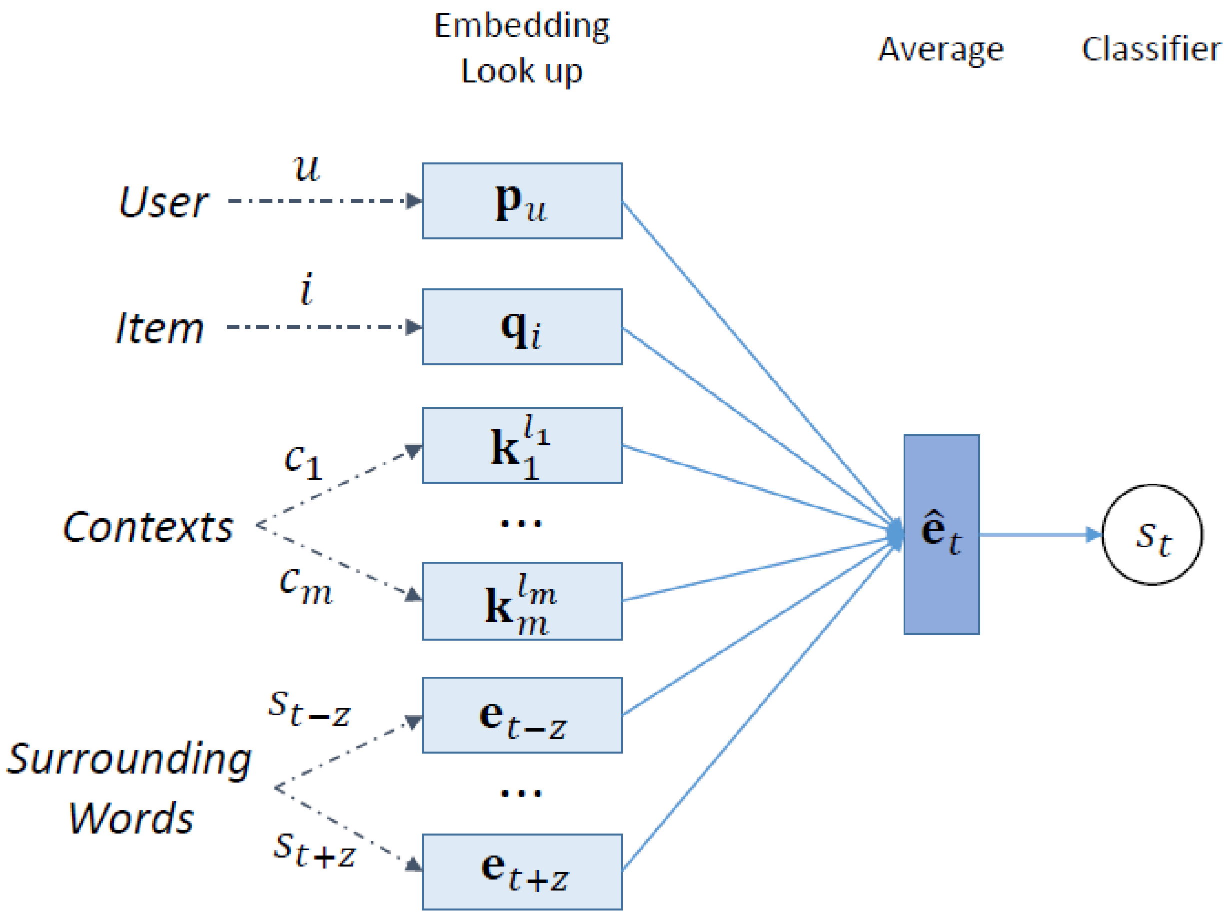
- Implicit context-aware methods
  - The training process is computationally expensive.
  - Recommendations are not accurate enough.
  - Examples
    - ConvMF+ (Kim et al. RecSys'16)
    - DeepCoNN (Zheng et al. WSDM'17)
- Explicit context-aware methods
  - They only characterize relations between two types of entities among users, items and contexts, which may be insufficient.
  - Examples
    - NFM (He and Chua. SIGIR'17)
    - AIN (Mei et al. CIKM'18)

Motivation

- Efficiency
  - Pre-train embeddings of different entities using user reviews
  - Build recommendation model using MLP with only a few hidden layers
- Effectiveness
  - Leverage two types of contexts, i.e., explicit and implicit contexts
  - Dynamically infer complex relations between three types of entities
  - Enable richer interaction between users' preferences and items' aspects

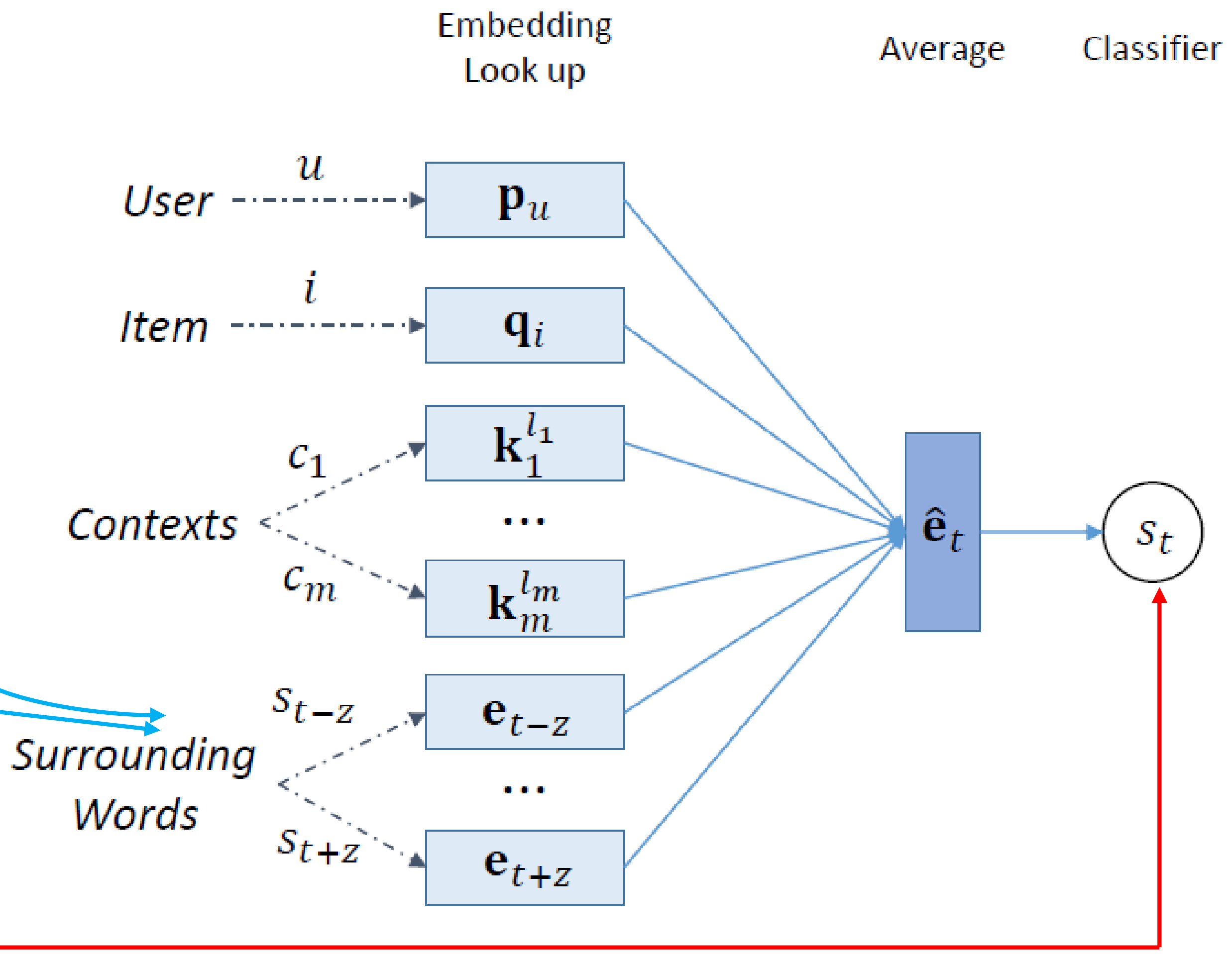
Embedding Method

- Intuitively, within a certain contextual situation, a user is more likely to discuss her/his experiences related to this context in the review.
- To learn embeddings of different entities, we propose to put all of them in one model named Entity2Vec, which is based on Word2Vec (Le and Mikolov, ICML'14).



Embedding Example

- User: John
- Item: Shangri-La Hotel
- Contexts
  - August
  - Couple
  - Singapore
- Review content
  - *Couples or business, there are plenty of better alternatives in the city.*



Multi-class Classification

- Compute the average of input vectors

$$\hat{\mathbf{e}}_t = \mathrm{avg}(\mathbf{p}_u, \mathbf{q}_i, \mathbf{k}_1^{l_1}, ..., \mathbf{k}_m^{l_m}, \mathbf{e}_{t-z}, ..., \mathbf{e}_{t+z})$$

- Use the resultant vector as features to predict the target word

$$\mathbf{y} = \mathbf{W}^e \hat{\mathbf{e}}_t + \mathbf{b}^e \qquad p_t = \frac{\exp(y_t)}{\sum_{t'} \exp(y_{t'})}$$

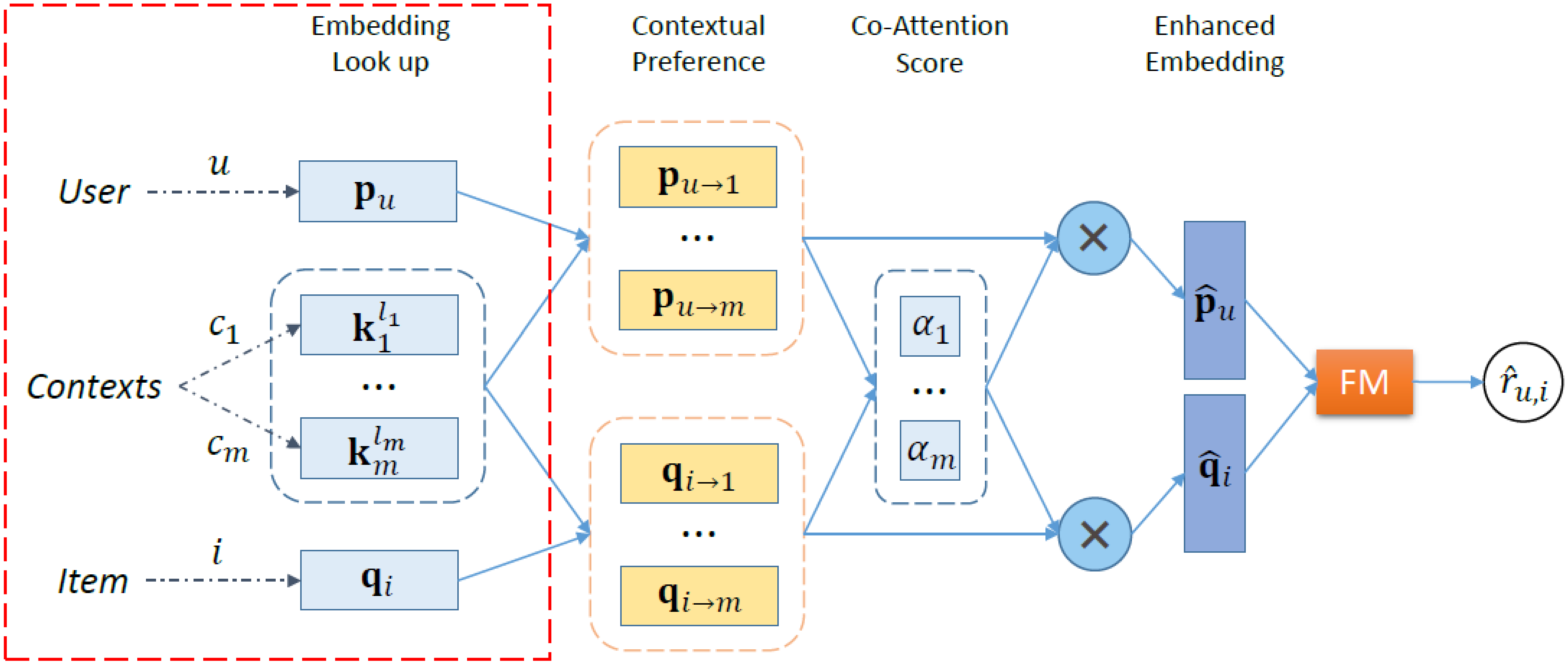
- Minimize the loss function for multi-class classification task

$$L_c = \frac{1}{|\mathcal{T}|} \sum_{u,i \in \mathcal{T}} \frac{1}{T_{u,i}} \sum_{t=z}^{T_{u,i}-z} -\log p_t$$

- To capture the semantic meaning of different entities

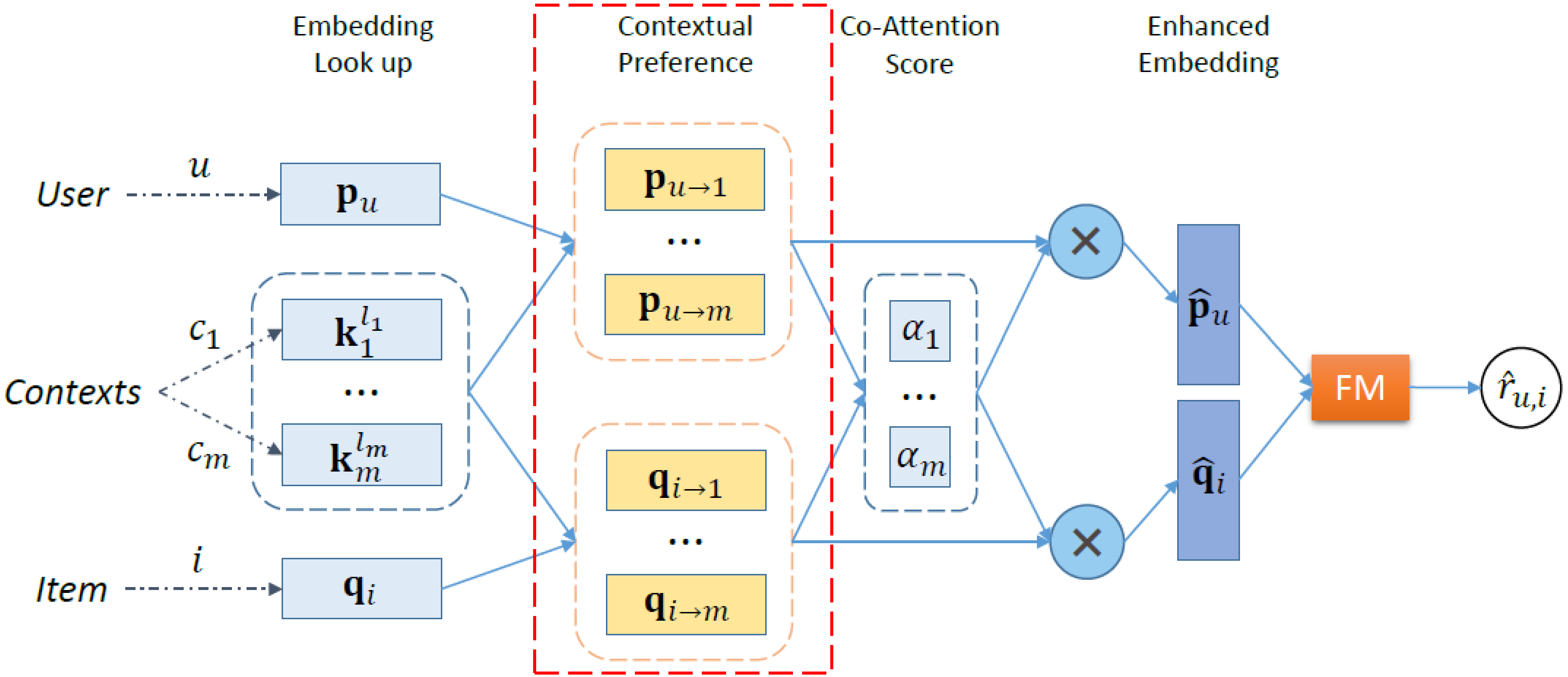
Context-aware Recommendation (1)

- Look up pre-trained embedding vectors



Context-aware Recommendation (2)

- Model contextual preferences for users and items



Contextual Preferences

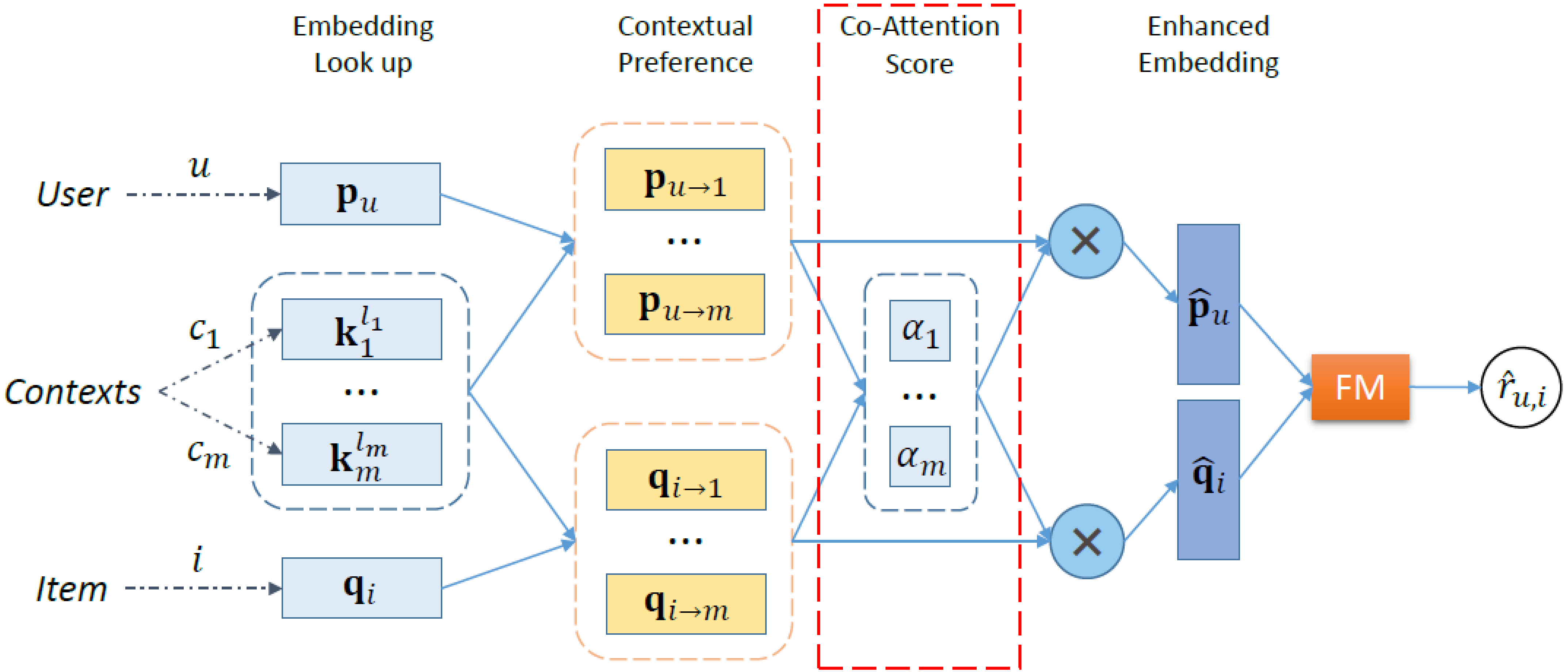
- User's contextual preferences
  - Family -> large bed
  - Business -> Wi-Fi
- Item's context-aware aspects
  - Offer large bed for family trip
  - Provide Wi-Fi for business trip

- Multi-layer Perceptron (MLP) for modeling the relations between users/items and contexts

$$\mathbf{p}_{u \rightarrow j} = \sigma(\mathbf{W}_j^p[\mathbf{p}_u, \mathbf{k}_j^{l_j}] + \mathbf{b}_j^p)$$

Context-aware Recommendation (3)

- Measure the matching degree in terms of contexts



Co-Attention

- To measure how much a user's contextual preferences match an item's context-aware aspects
- Co-attention is Leveraged for each contextual variable.

$$\beta_{u,i\to j} = \mathbf{h}^T \sigma(\mathbf{W}_1 [\mathbf{p}_{u\to j}, \mathbf{q}_{i\to j}] + \mathbf{b}_1)$$

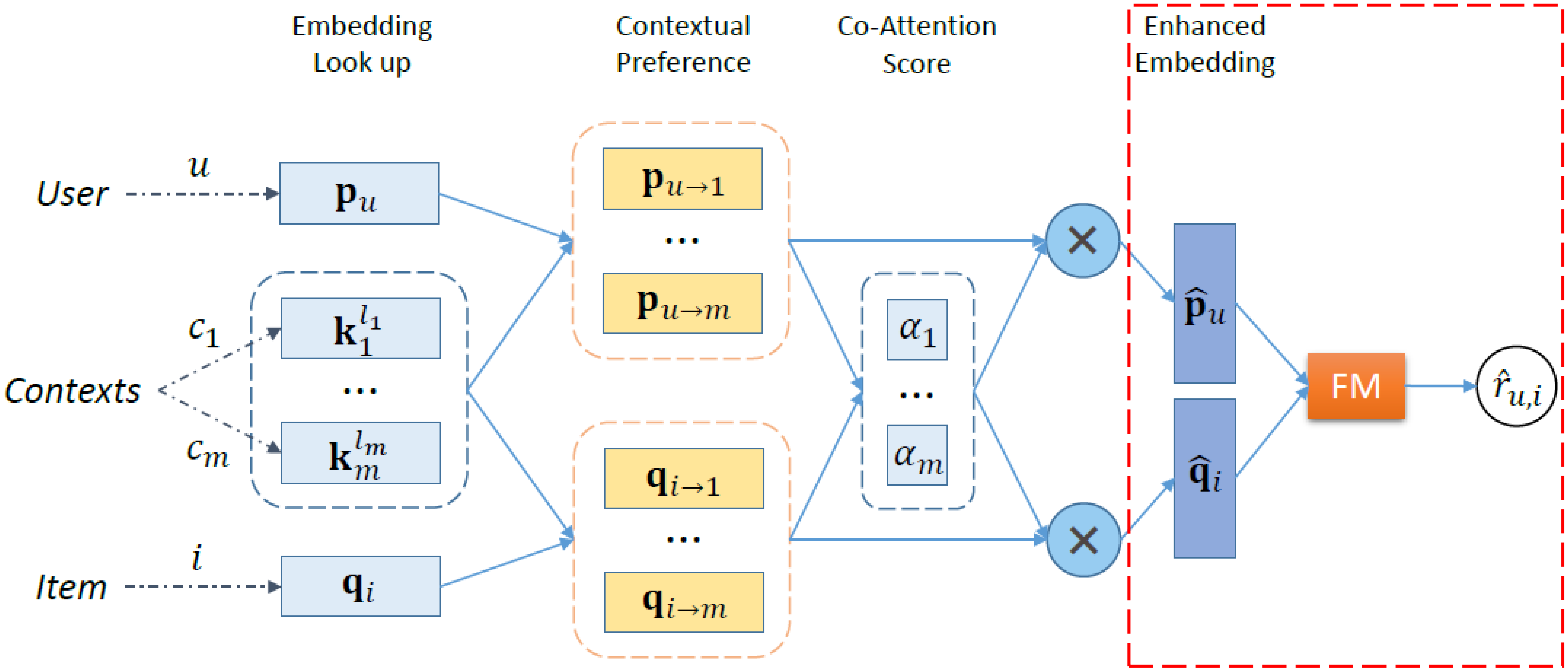
$$\alpha_{u,i\to j} = \frac{\exp\left(\beta_{u,i\to j}\right)}{\sum_{j'=1}^{m} \exp\left(\beta_{u,i\to j'}\right)}$$

- The larger a co-attention score is, the more it contributes to the final prediction.

$$\hat{\mathbf{p}}_u = \sum_{j=1}^{m} \alpha_{u,i\to j} \mathbf{p}_{u\to j} \qquad \hat{\mathbf{q}}_i = \sum_{j=1}^{m} \alpha_{u,i\to j} \mathbf{q}_{i\to j}$$

Context-aware Recommendation (4)

- Predict the rating using Factorization Machines (Rendle. ICMD’10)



Rating Prediction

- To predict a rating, FM is leveraged to model the second order interactions between the user and item enhanced profiles.

$$\mathbf{x} = [\hat{\mathbf{p}}_u, \hat{\mathbf{q}}_i]$$

$$\hat{r}_{u,i} = w_0 + \mathbf{w}_1^T \mathbf{x} + \frac{1}{2} \sum_{f=1}^{k} [(\mathbf{v}_f^T \mathbf{x})^2 - (\mathbf{v}_f^2)^T \mathbf{x}^2]$$

- Mean squared error loss is adopted as the objective function.

$$L_r = \sum_{u,i \in \mathcal{T}} (r_{u,i} - \hat{r}_{u,i})^2$$

Datasets

- We crawled in total 10 million reviews from tripadvisor.com.

OVERVIEW OF OUR TRIPADVISOR HOTEL REVIEW DATASETS.

	# users	*# items*	*# reviews*	*# reviews per user*	*# reviews per item*
HK (Hong Kong)	137,145	247,889 (618)[a]	2,118,108 (176,840)	15.44 (1.29)	8.54 (286.15)
NYC (New York City)	471,243	297,270 (531)	4,572,716 (583,257)	9.70 (1.24)	15.38 (1098.41)
LDN (London)	639,710	354,841 (1,660)	6,382,831 (870,184)	9.98 (1.36)	17.99 (524.21)

[a] The values given in brackets correspond to sizes of the datasets without users' past reviews.

CONTEXTUAL VARIABLES AND CONTEXT VALUES.

Contextual Variables	**Context Values**
Companion	Families, Couples, Solo, Business, Friends
Time	January, February, March, April, May, June, July, August, September, October, November, December
Place[a]	Hong Kong, Bangkok, Singapore, London, New York City, Dubai, Kuala Lumpur, Shanghai, Paris, Sydney

[a] As examples, we list 10 selected cities with the largest review counts in HK dataset.

Baselines

- Context-unaware: only take user and item IDs into account
  - PMF (Mnih and Ruslan, NIPS'14)
  - FM (Rendle. ICMD'10)
- Implicit context-aware: extract features from user reviews
  - ConvMF+ (Kim et al. RecSys'16)
  - DeepCoNN (Zheng et al. WSDM'17)
- Context-aware: explicitly make use of contexts
  - NFM (He and Chua. SIGIR'17)
  - AIN (Mei et al. CIKM'18)

Experimental Results

- Accuracy

PERFORMANCE COMPARISON IN TERMS OF RMSE.

Category	Methods	HK	NYC	LDN
context-unaware	**PMF**	1.1185	1.1926	1.1923
	FM	1.0140	1.0491	1.0437
implicit context-aware	**ConvMF+**	0.9001	0.9975	0.9832
	DeepCoNN	0.8546	0.8815	0.8805
context-aware	**NFM**	0.8481	0.8727	0.8661
	AIN	0.8469	0.8664	0.8606
ours	**CCANN**$_{rand}$	0.8439	0.8658	0.8598
	CCANN	**0.8409***	**0.8652***	**0.8586***

* denotes the statistical significance for $p < 0.001$ given by student's t-test, compared to NFM.

- Efficiency
  - On HK dataset on an NVIDIA Tesla K80 GPU
  - NFM, AIN, and our CCANN takes ρ to reach the best performance.
  - ConvMF+ and DeepCoNN run approximately at 13ρ and 68ρ, respectively.

Conclusion

- We built an effective and efficient context-aware recommender system using MLP and Co-attention.
- We also proposed an embedding method to jointly learn different entities' embeddings from user reviews.

- Future Work
  - We will conduct a live-user study to investigate the matching contexts for explanation purposes.
  - We are also interested in the techniques of automatic text generation for producing customized explanations in human-readable text.

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Q&A

Thank you!