- Overview of multidomain recommender systems (Liang Hu, 25 mins)
- Multi-item domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-user domain recommender systems (Qi Zhang, 20 mins)
- Multi-data domain recommender systems (Z. Y. Lai, 20 mins)
- Multi-spatial domain recommender systems (Qi Zhang 20 mins)
- **Multi-temporal domain recommender systems (Z. Y. Lai, 20 mins)**
- Multi-goal domain recommender systems (Liang Hu, 20 mins)
- Summary (Liang Hu, 5 mins)

Multi-temporal domain recommender systems

- Preliminary of multi-temporal domain recommender systems
- Multi-session modeling for multidomain recommendation
- Multi-time-period modeling for multidomain recommendation

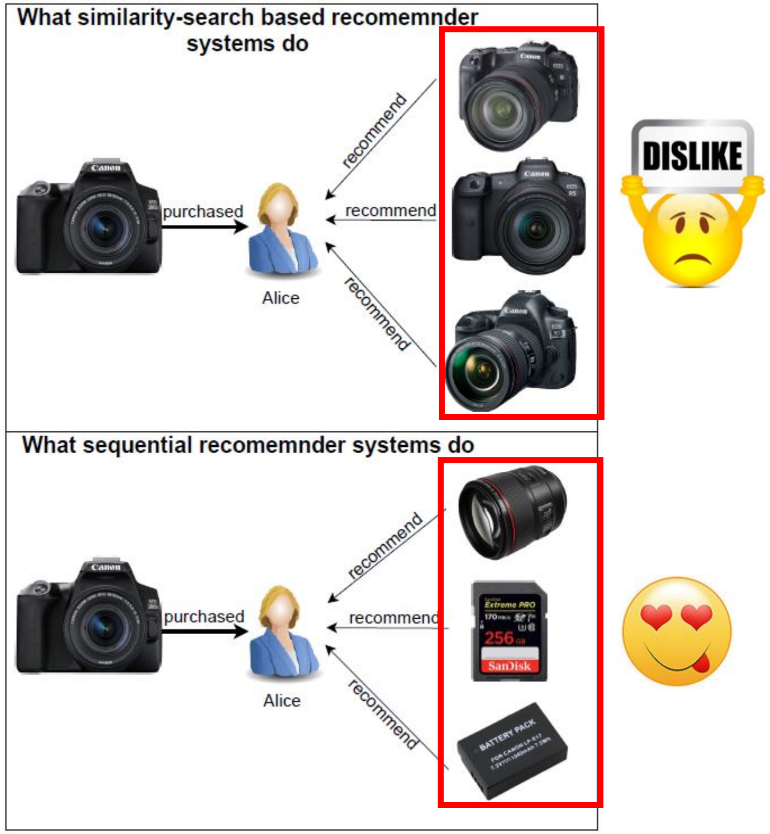
What is a session?

- A **session** is a list of **user-item actions**, e.g., view (items), click, purchase, generated by a user in one visit of an online platform (e.g., amazon.com).
- There is dependency between the interactions within a *session context*.

Shoujin Wang, Longbing Cao, Yan Wang, Quan Z. Sheng, Mehmet Orgun & Defu Lian (2021). **A survey on session-based recommender systems**. *ACM Computing Surveys (CSUR)*.

Why session-based recommender systems?

- Why we need session-based recommender systems?
  - Traditional similarity search-based recommender systems (RSs) (e.g., content-based, collaborative filtering) usually repeatedly recommend identical or similar items to a user without considering her/his dynamic demand.
  - Session-based recommender systems recommend items relevant to but different from the items purchased by a user to satisfy the user's current demand.
  - Obviously, session-based recommender systems generate more preferable recommendation results.

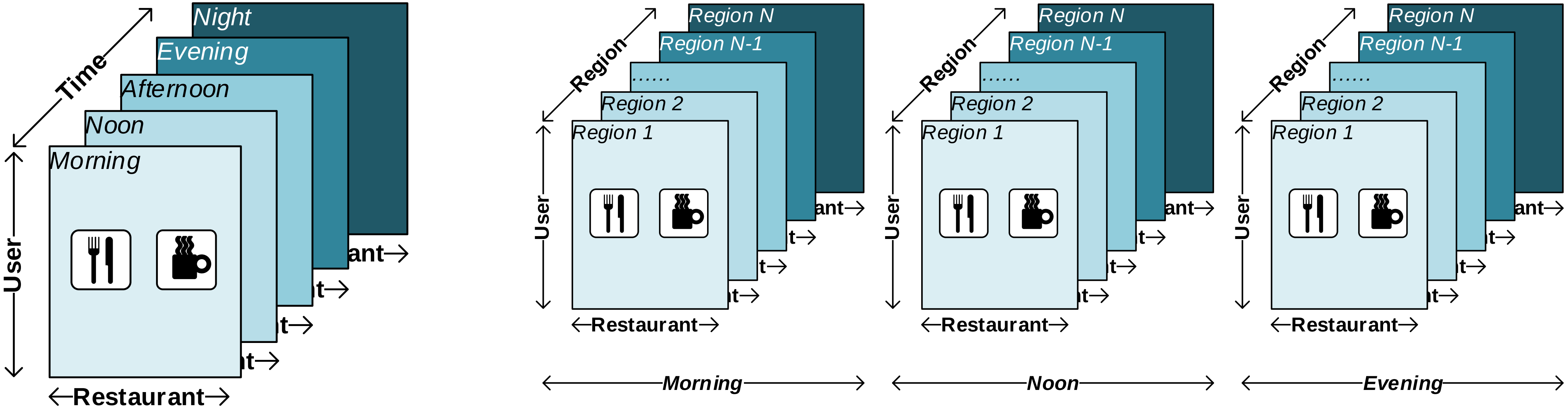


Traditional RSs vs sequential RSs

Shoujin Wang, Liang Hu, Yan Wang, Longbing Cao and Quan Z. Sheng, Mehmet Orgun. "Sequential recommender systems: challenges, progress and prospects." In Proceedings of the *28th International Joint Conference on Artificial Intelligence*, ***IJCAI 2019***, 2019.

Time-aware recommender systems

- Time-Aware Recommender System (TARS) is a type of Context-Aware RS that consider time for recommending items.



Multi-temporal domain recommender systems

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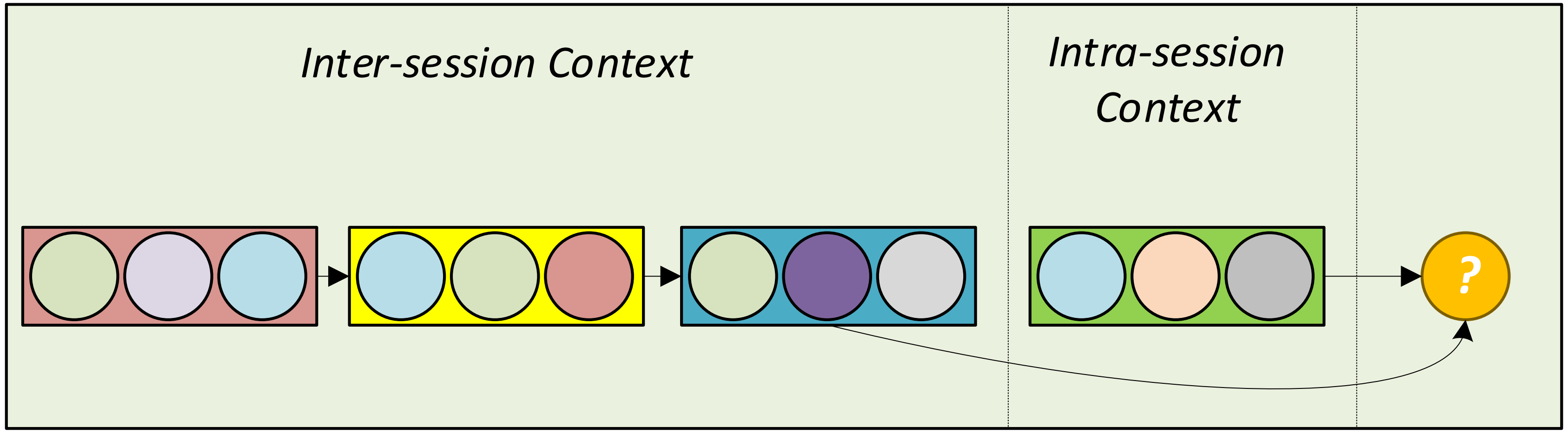
Multi-session recommender systems

Table 2. A comparison of different sub-areas in SBRSs

Sub-area	Input	Output	Typical research topic
Next interaction recommendation	Mainly known part of the current session	Next interaction (item)	Next item recommendation, next song/movie recommendation, next POI recommendation, next web page recommendation, next news recommendation, etc.
Next partial-session recommendation	Mainly known part of the current session	Subsequent part of the session	Next items recommendation, session/basket completion
Next session recommendation	Historical sessions	Next session	Next basket recommendation, next bundle recommendation, etc.

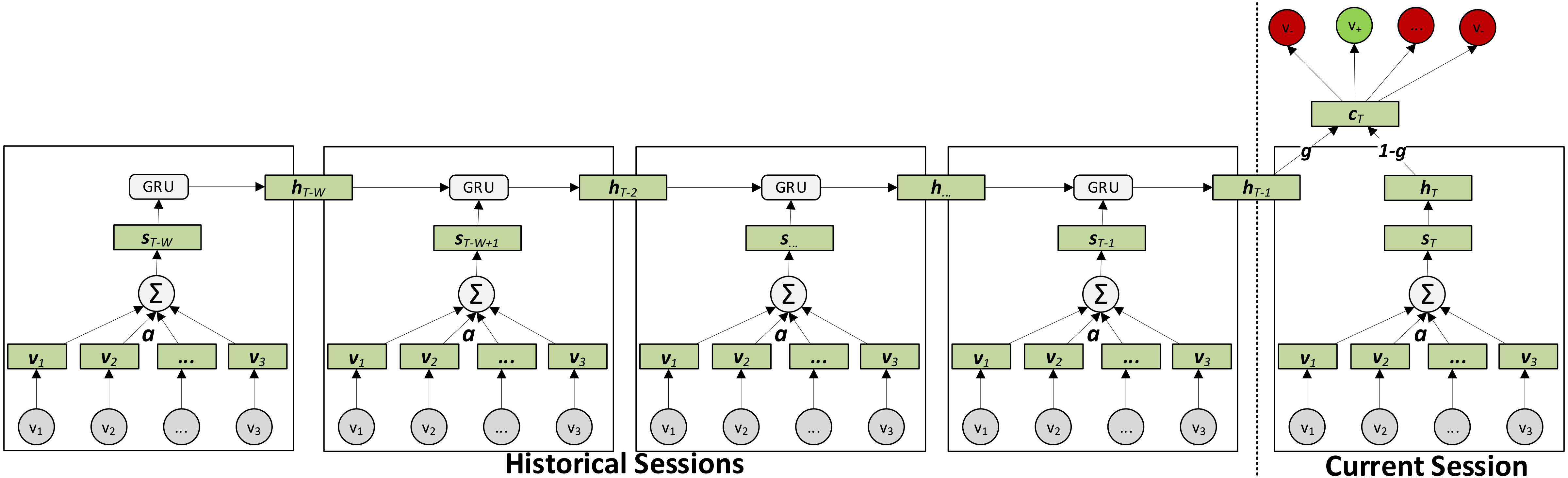
Next partial session recommendation

- The cross-session filtering conducts next-item recommendation under intra-session context with jointly considering inter-session context



Hu L, Chen Q, Zhao H, Jian S, Cao L, Cao J. Neural cross-session filtering: Next-item prediction under intra-and inter-session context. IEEE Intelligent Systems. 2018 Nov 15;33(6).

Neural Cross-session Filtering



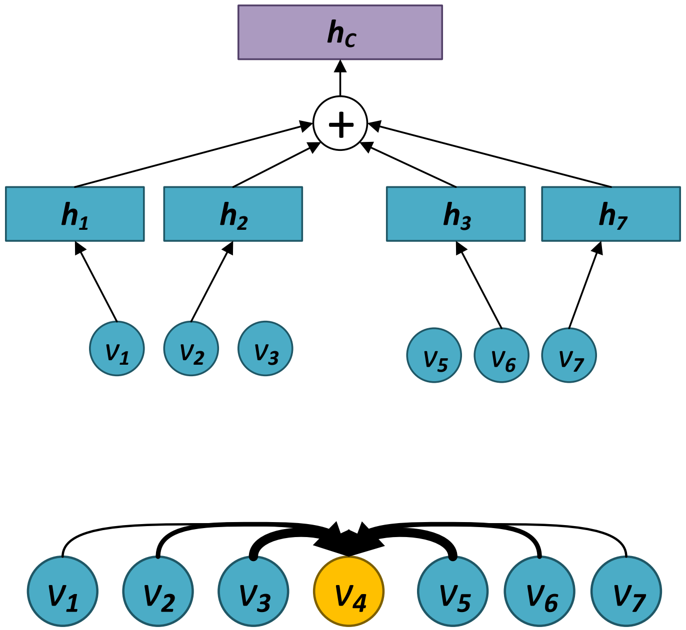
In the left part of split line, historical sessions are used to build inter-session context.

n the right part of split line, the items in the current session are used to build intra-session context.

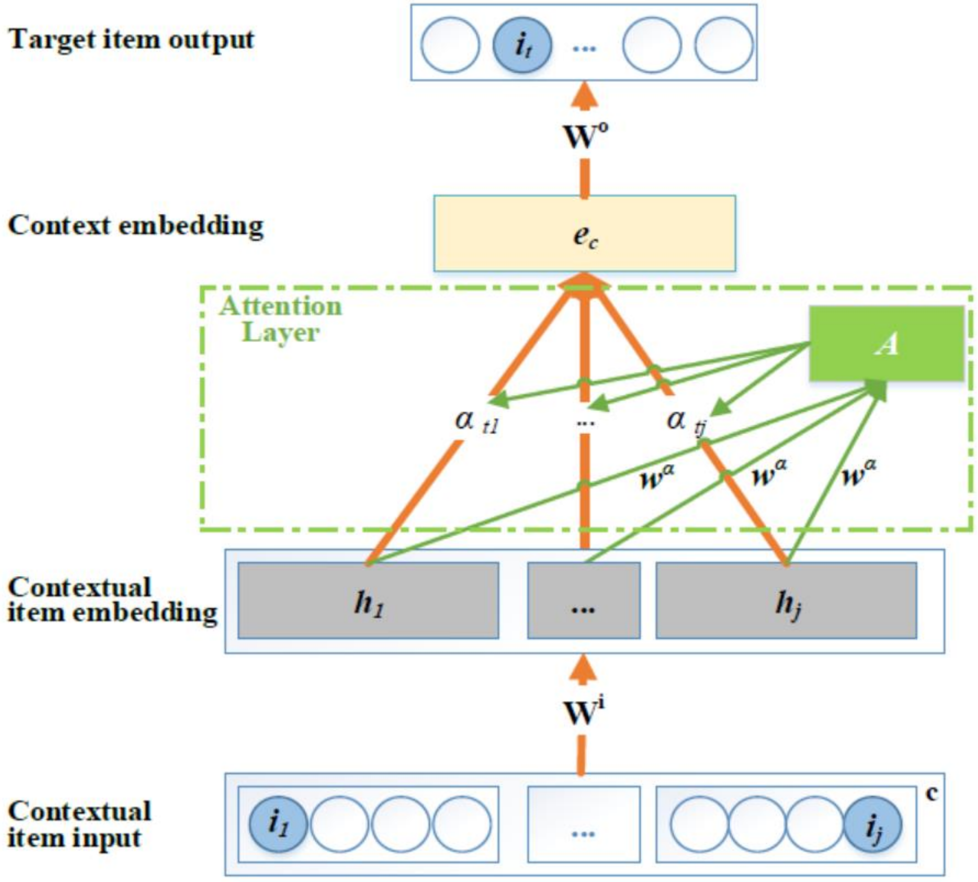
Hu L, Chen Q, Zhao H, Jian S, Cao L, Cao J. Neural cross-session filtering: Next-item prediction under intra-and inter-session context. IEEE Intelligent Systems. 2018 Nov 15;33(6).

Modeling session embedding with attention mechanism

Context items contribute differently to the next choice

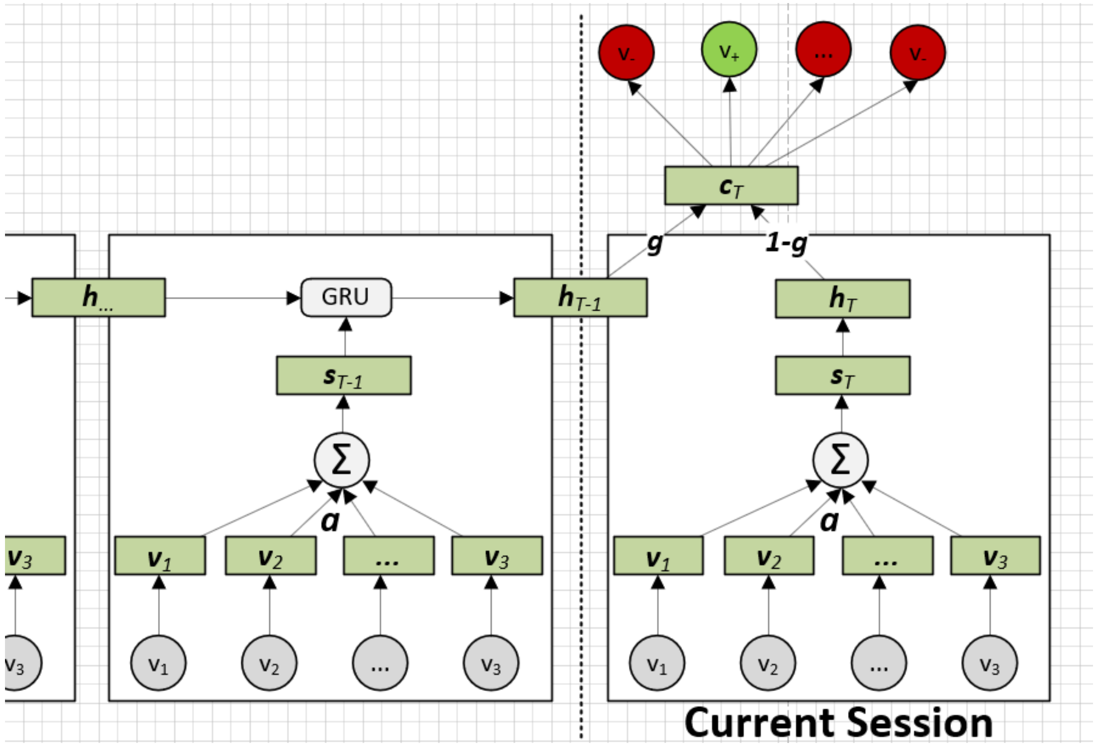


ATEM



Wang, S., Hu, L., & Cao, L. *Attention-based Transactional Context Embeddings for Next-Item Recommendation*. AAAI2018

Intra- and Inter-session Context Encoding



- A gate vector $\mathbf{g}$, to filter the information from historical session context embedding $\mathbf{h}_{T-1}$ and current session context embedding $\mathbf{h}_T$.

$$\mathbf{g} = \sigma(\mathbf{W}^g[\mathbf{h}_{T-1}; \mathbf{h}_T] + \mathbf{b})$$

- We integrate $\mathbf{h}_{T-1}$ and $\mathbf{h}_T$ into a joint context embedding $\mathbf{c}_T$ in terms of $\mathbf{g}$

$$\mathbf{c}_T = \mathbf{g} * \mathbf{h}_{T-1} + (1 - \mathbf{g}) * \mathbf{h}_T$$

Dataset

- IJCAI-15 Dataset: https://tianchi.aliyun.com/datalab/dataSet.htm?id=5
  - This real-world dataset was collected from Tmall.com which is the largest online B2C platform in China, and it contains anonymized users' shopping logs for the six months before and on the “Double 11” day (November 11th).

Statistic of IJCAI-15 dataset for evaluation
#users: 50K
#items: 52K
avg. session length: 2.99
#training sessions: & 0.20M
#training examples: & 0.59M
#testing cases (***LAST***): 4.5K
#testing cases (***LOO***): 11.9K

Accuracy Evaluation

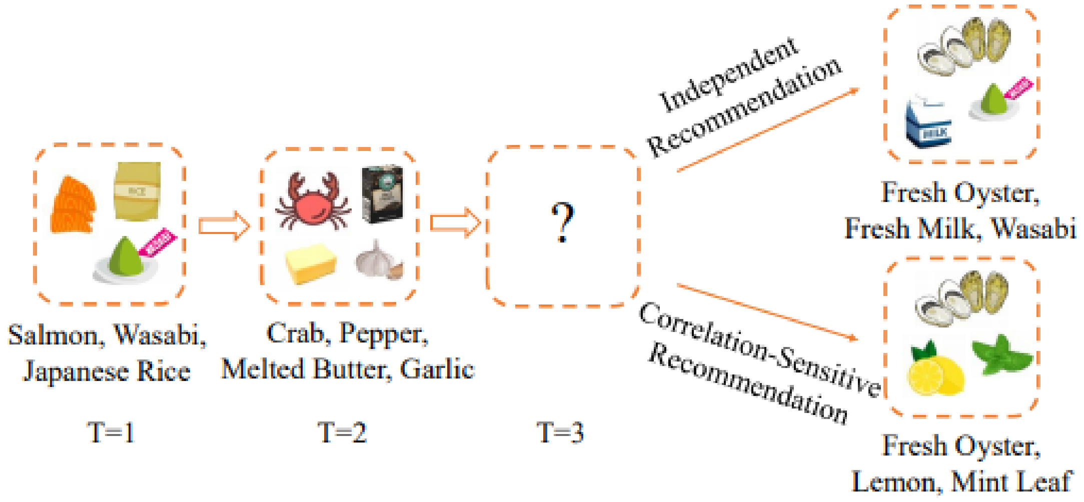
- Table 2 demonstrates the results of MRR@10, MRR@20, MRR@50 and AUC over the testing sets ***Last*** and ***LOO***.
- ***LAST*** means that the last item in each testing session is used as ground truth.
- ***LOO*** means each item in a testing session was held out in turn to serve as ground truth, i.e., leave-one-out.

Table 2: The evaluation results for MRR and AUC

Last				
Model	**MRR@10**	**MRR@20**	**MRR@50**	**AUC**
POP	0.0077	0.0086	0.0092	0.8170
KNN	0.1755	0.1773	0.1810	0.6682
FPMC	0.1482	0.1516	0.1537	0.8075
GRU4Rec	0.2601	0.2654	0.2676	0.8756
GRU4RecX	0.3943	0.3972	0.3985	0.8667
SWIWO	0.4038	0.4071	0.4084	0.9126
NCSF	**0.4318**	**0.4351**	**0.4368**	**0.9348**
LOO				
Model	**MRR@10**	**MRR@20**	**MRR@50**	**AUC**
POP	0.0089	0.0102	0.0109	0.8269
KNN	0.1643	0.1666	0.1673	0.6717
FPMC	0.1611	0.1649	0.1666	0.8211
GRU4Rec	0.2494	0.2556	0.2584	0.8890
GRU4RecX	0.4074	0.4109	0.4124	0.8756
SWIWO	0.4211	0.4242	0.4258	0.9163
NCSF	**0.4403**	**0.4440**	**0.4457**	**0.9407**

Next-basket recommendation

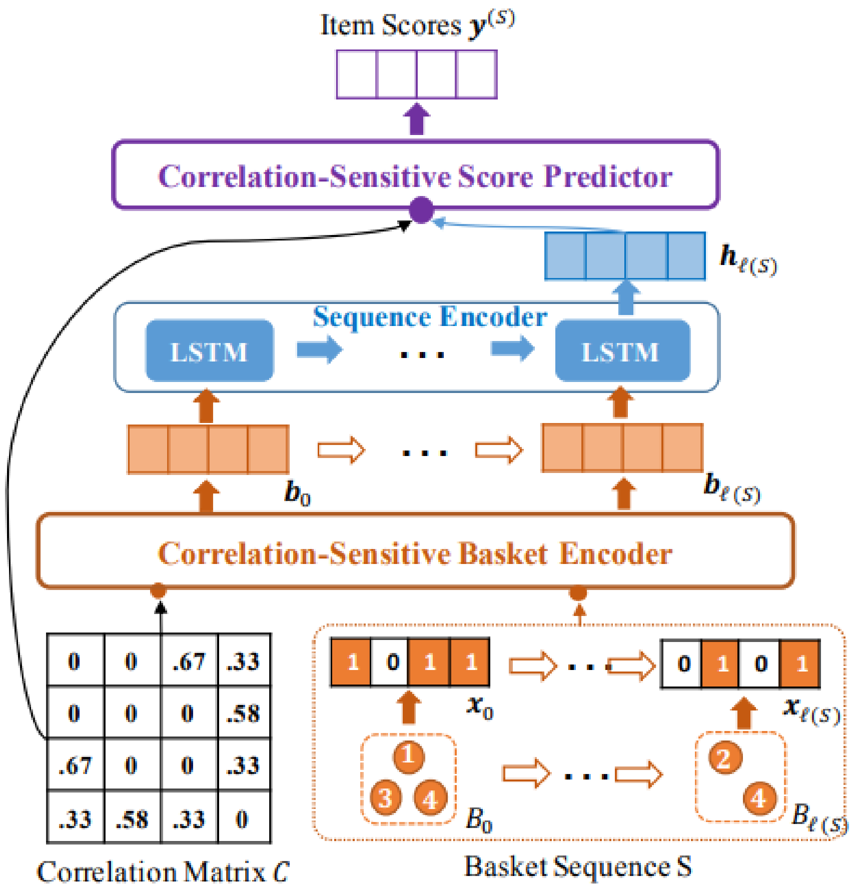
- Given a user's historical purchased baskets, next-basket prediction aims at predicting the next basket of items for the user:



An example of next-basket prediction

Le, Duc-Trong, Lauw, Hady W and Fang, Yuan, Correlation-Sensitive Next-Basket Recommendation, *In Proceedings of the International Joint Conference on Artificial Intelligence*, 2019

Architecture of the framework Beacon



Basket Sequence COrrelation Networks (Beacon)

- *Correlation-Sensitive Basket Encoder*

$$\boldsymbol{z}_t = \boldsymbol{x}_t * \boldsymbol{\omega} + \boldsymbol{x}_t \boldsymbol{C}$$

where $\boldsymbol{C}$ is correlation matrix based on the Laplacian matrix

$$\boldsymbol{C} = \boldsymbol{D}^{-\frac{1}{2}} \boldsymbol{F} \boldsymbol{D}^{-\frac{1}{2}}$$

- *Correlation-Sensitive Score Predictor*

$$\boldsymbol{s}^{(S)} = \sigma\left(\boldsymbol{h}_{l(S)} \boldsymbol{W}\right)$$

$$\boldsymbol{y}^{(S)} = \alpha\left(\boldsymbol{s}^{(S)} * \boldsymbol{\omega} + \boldsymbol{s}^{(S)} \boldsymbol{C}\right) + (1-\alpha)\boldsymbol{s}^{(S)}$$

Le, Duc-Trong, Lauw, Hady W and Fang, Yuan, Correlation-Sensitive Next-Basket Recommendation, *In Proceedings of the International Joint Conference on Artificial Intelligence*, 2019

Performance comparison

Dataset	Model	L	H	F1@K (%) @5	@10	HLU
TaFeng	*POP*	-	-	4.66	4.02	6.64
	MC	-	-	4.11	3.61	5.78
	MCN	8	-	4.56	4.02	6.34
	DREAM	8	-	5.85	4.90	6.96
	BSEQ	32	16	4.48	4.04	6.34
	triple2vec	64	-	4.66	3.88	4.85
	Beacon	8	64	**6.36**†	**5.26**†	**7.83**†
Delicious	*POP*	-	-	3.88	4.04	6.05
	MC	-	-	4.27	4.59	6.52
	MCN	32	-	4.20	4.59	6.50
	DREAM	32	-	3.13	3.47	4.93
	BSEQ	64	32	3.86	3.97	5.95
	triple2vec	32	-	3.76	4.04	5.16
	Beacon	64	64	**4.93**†	**5.47**†	**7.76**†
Foursquare	*POP*	-	-	2.73	2.90	4.84
	MC	-	-	3.58	3.43	5.53
	MCN	64	-	3.09	2.89	5.08
	DREAM	64	-	2.84	3.00	4.98
	BSEQ	64	32	2.80	2.89	4.82
	triple2vec	64	-	2.73	2.90	4.53
	Beacon	64	64	**3.61**	**3.59**†	**6.32**†

Multi-temporal domain recommender systems

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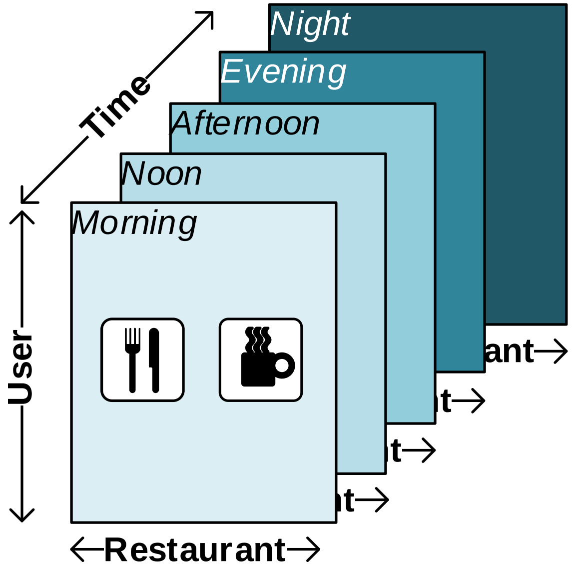
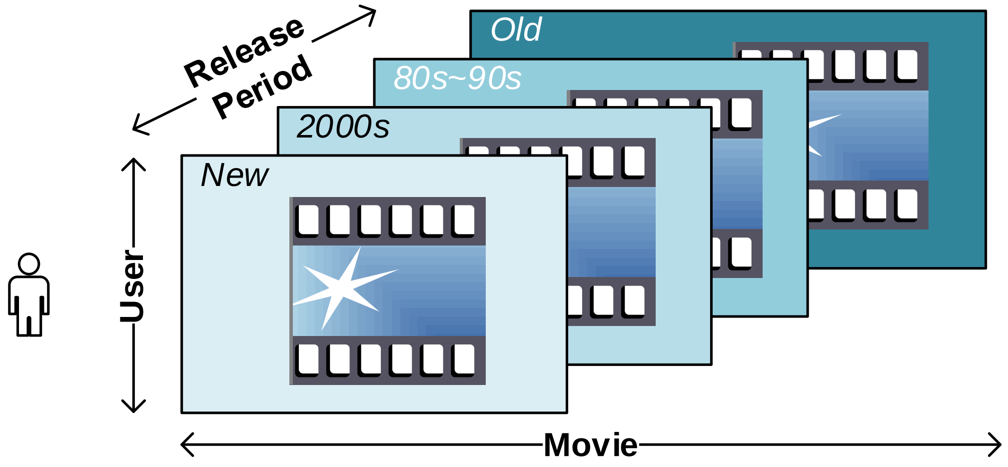
3-order interaction for time-aware recommendation

- Rating with context
  - $R(u,i,c) = 5$





Hu, L., Cao, L., Cao, J., Gu, Z., Xu, G., & Yang, D. (2016). Learning Informative Priors from Heterogeneous Domains to Improve Recommendation in Cold-Start User Domains. *ACM Transactions on Information Systems (TOIS)*, *35*(2), 13.

Fast context-aware recommendations with factorization machines

- The idea behind FMs is to model interactions between features using factorized parameters. The FM model has the ability to the estimate all interactions between features even with extreme sparse data.

- FM models all interactions between pairs of variables with the target (2nd-order), including nested ones (1st-order), by using factorized interaction parameters

$$\hat{y}(\mathbf{x}) := \boxed{w_0 + \sum_{i=1}^{n} w_i\, x_i} + \boxed{\sum_{i=1}^{n} \sum_{j=i+1}^{n} \hat{w}_{i,j}\, x_i\, x_j}$$

where $\widehat{w}_{i,j}$ are the factorized interaction parameters between pairs:

$$\hat{w}_{i,j} := \langle \mathbf{v}_i, \mathbf{v}_j \rangle = \sum_{f=1}^{k} v_{i,f} \cdot v_{j,f}$$

Rendle, S., Gantner, Z., Freudenthaler, C., and Schmidt-Thieme, L. Fast context-aware recommendations with factorization machines. In *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*, 635-644, 2011.

Representing context data as features

Recommender Data

(A,TI,H,{C},5)
(A,NH,S,{},3)
(A,SW,N,{B,C},1)
(B,SW,N,{A,C},4)
(B,ST,H,{},5)
(C,TI,S,{A},1)
(C,SW,H,{A,B},5)

→

Feature vector x | **Target y**

	User			Movie				Mood			Watched with			Target y	
	A	B	C	TI	NH	SW	ST	S	N	H	A	B	C		
$\mathbf{x}^{(1)}$	1	0	0	1	0	0	0	0	0	1	0	0	1	5	$y^{(1)}$
$\mathbf{x}^{(2)}$	1	0	0	0	1	0	0	1	0	0	0	0	0	3	$y^{(2)}$
$\mathbf{x}^{(3)}$	1	0	0	0	0	1	0	0	1	0	0	0.5	0.5	1	$y^{(2)}$
$\mathbf{x}^{(4)}$	0	1	0	0	0	1	0	0	1	0	0.5	0	0.5	4	$y^{(3)}$
$\mathbf{x}^{(5)}$	0	1	0	0	0	0	1	0	0	1	0	0	0	5	$y^{(4)}$
$\mathbf{x}^{(6)}$	0	0	1	1	0	0	0	1	0	0	1	0	0	1	$y^{(5)}$
$\mathbf{x}^{(7)}$	0	0	1	0	0	1	0	0	0	1	0.5	0.5	0	5	$y^{(6)}$

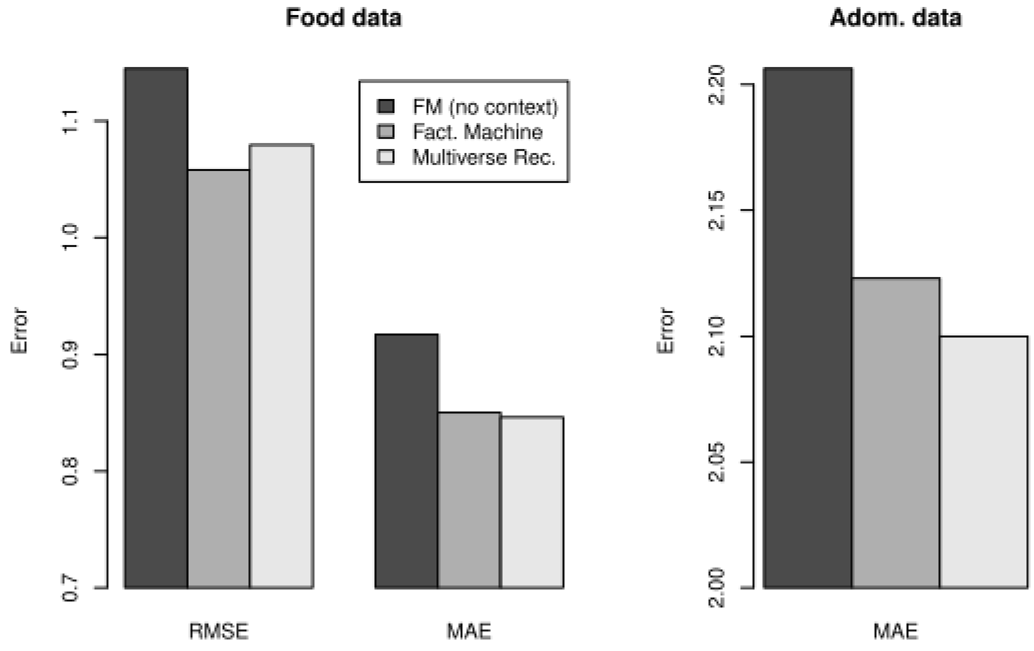
Here in the feature vector x, the first three values indicate the user, the next four ones the movie, the next three ones the mood and the last three ones the other users a movie has been watched with.

Datasets

- Adom dataset
  - 1524 rating events (1 to 15 stars) for movies with five context variables about companion, the weekday and other time information

- Food dataset
  - 6360 ratings (1 to 5 stars) by 212 users for 20 menu items with two context variables:
    - One context variable indicates whether the user is hungry or not.
    - The other one indicates how hungry the user is.

With/without context



The context-aware methods Multiverse Recommendation and context-aware Factorization Machine benefit from incorporating the context-information into the rating prediction.

Context-aware recommendations with neural architectural factorization machines

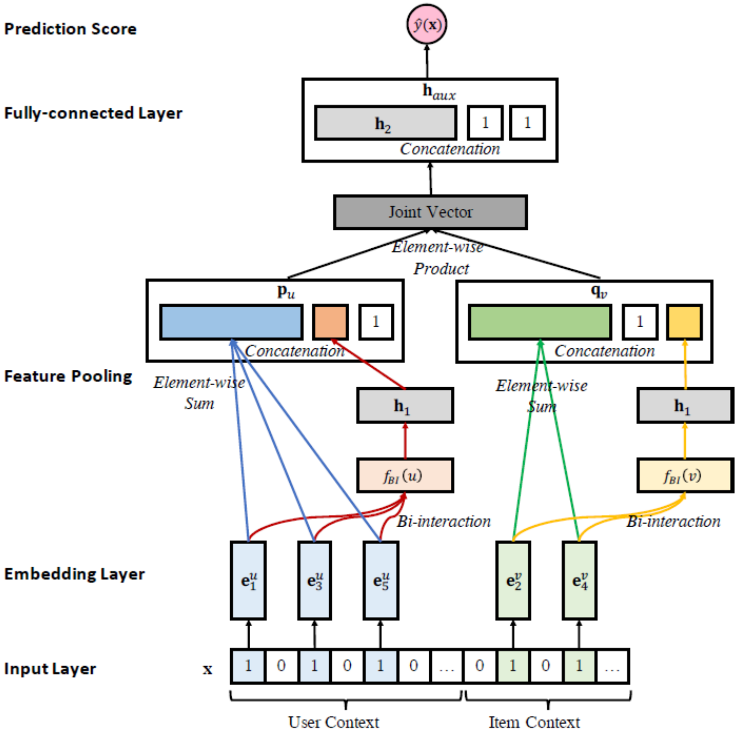


Figure 1: Illustration of our ENSFM framework, showing how to represent FM in a matrix factorization manner (for clarity purpose, the first-order linear regression part is not shown in the figure, which can be trivially incorporated).

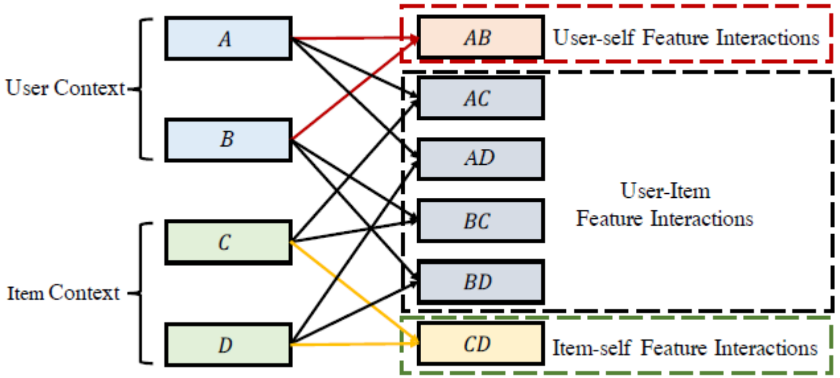


Figure 2: An example of feature interactions, which can be divided into three groups: user-self, item-self, and user-item. User-self feature interactions are independent of item features, while item-self interactions are also independent of user features.

Chen C, Zhang M, Ma W, Liu Y, Ma S. Efficient non-sampling factorization machines for optimal context-aware recommendation. In Proceedings of The Web Conference 2020.

Datasets

Table 2: Statistical details of the datasets.

Dataset	#User	#Item	#Feature	#Instance	#Field
Frappe	957	4,082	5,382	96,203	10
Last.fm	1,000	20,301	37,358	214,574	4
Movielens	6,040	3,706	10,021	1,000,209	6

Frappe: Frappe is a context-aware app discovery tool. It contains 96,203 app usage logs of different user contexts. Each log contains 10 contextual feature fields including *user ID, item ID, daytime and some other information*.

Chen C, Zhang M, Ma W, Liu Y, Ma S. Efficient non-sampling factorization machines for optimal context-aware recommendation. In Proceedings of The Web Conference 2020.

Performance comparison

Table 3: Performance of different models on three datasets. ** denotes the statistical significance for $p < 0.01$, compared to the best baseline. "RI" indicate the average relative improvements of our ENSFM over the corresponding baseline.

Frappe[1]	HR@5	HR@10	HR@20	NDCG@5	NDCG@10	NDCG@20	RI
PopRank	0.2539	0.3493	0.4136	0.1595	0.1898	0.2060	+143.3%
FM (*Rendle et al., 2010*)	0.4204	0.5486	0.6590	0.3054	0.3469	0.3750	+39.86%
DeepFM (*Guo et al., 2017*)	0.4632	0.6035	0.7322	0.3308	0.3765	0.4092	+27.77%
NFM (*He et al., 2017*)	0.4798	0.6197	0.7382	0.3469	0.3924	0.4225	+23.64%
ONCF (*He et al., 2018*)	0.5359	0.6531	0.7691	0.3940	0.4320	0.4614	+13.24%
CFM (*Xin et al., 2019*)	0.5462	0.6720	0.7774	0.4153	0.4560	0.4859	+9.15%
ENMF (*Chen et al., 2019*)	0.5682	0.6833	0.7749	0.4314	0.4642	0.4914	+6.95%
ENSFM	**0.6094****	**0.7118****	**0.7889****	**0.4771****	**0.5105****	**0.5301****	–

Chen C, Zhang M, Ma W, Liu Y, Ma S. Efficient non-sampling factorization machines for optimal context-aware recommendation. In Proceedings of The Web Conference 2020.

Next chapter

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