HERS: Modeling Influential Contexts with Heterogeneous Relations for Sparse and Cold-Start Recommendation

构建具有异构关系的影响上下文

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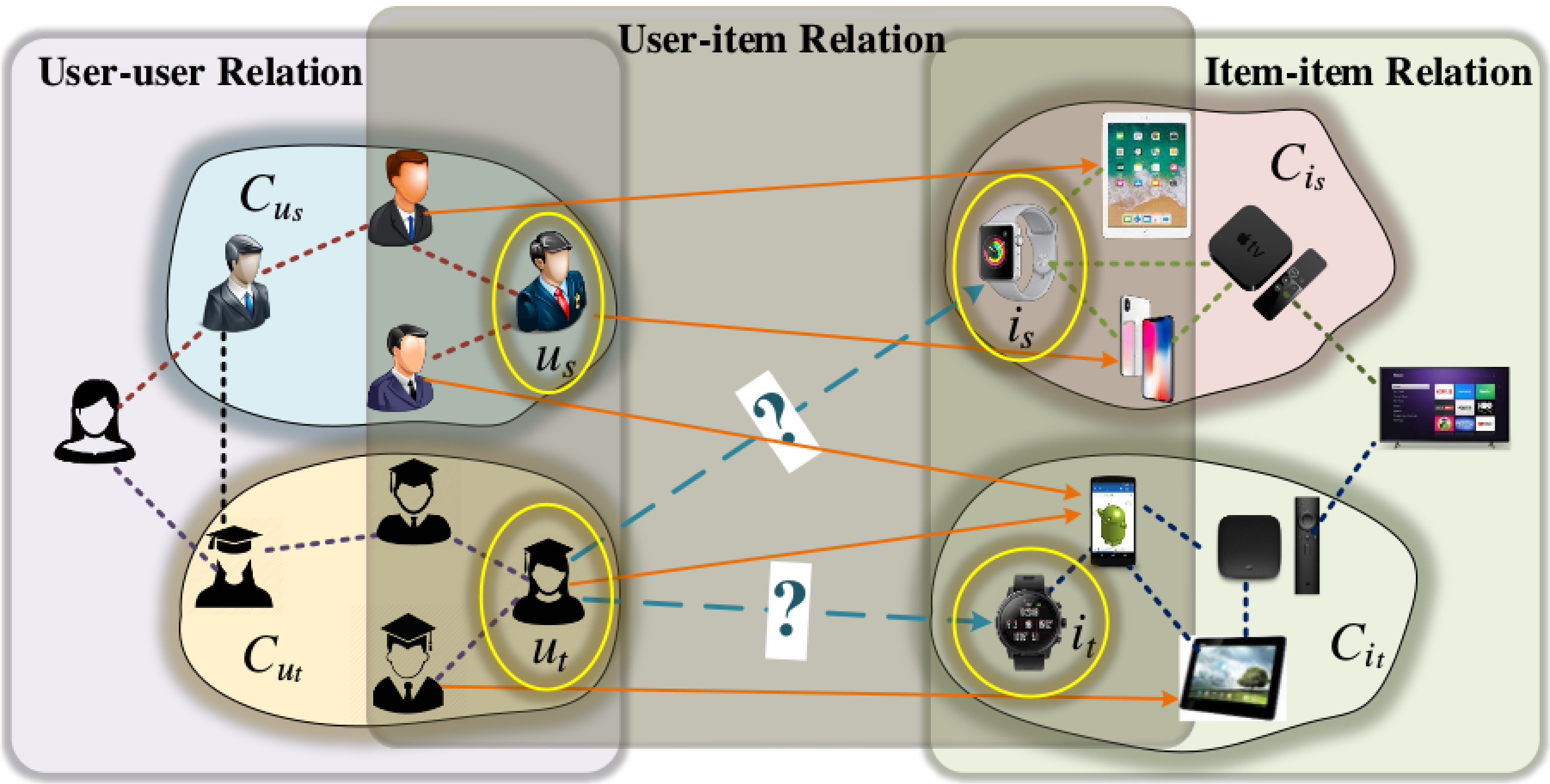
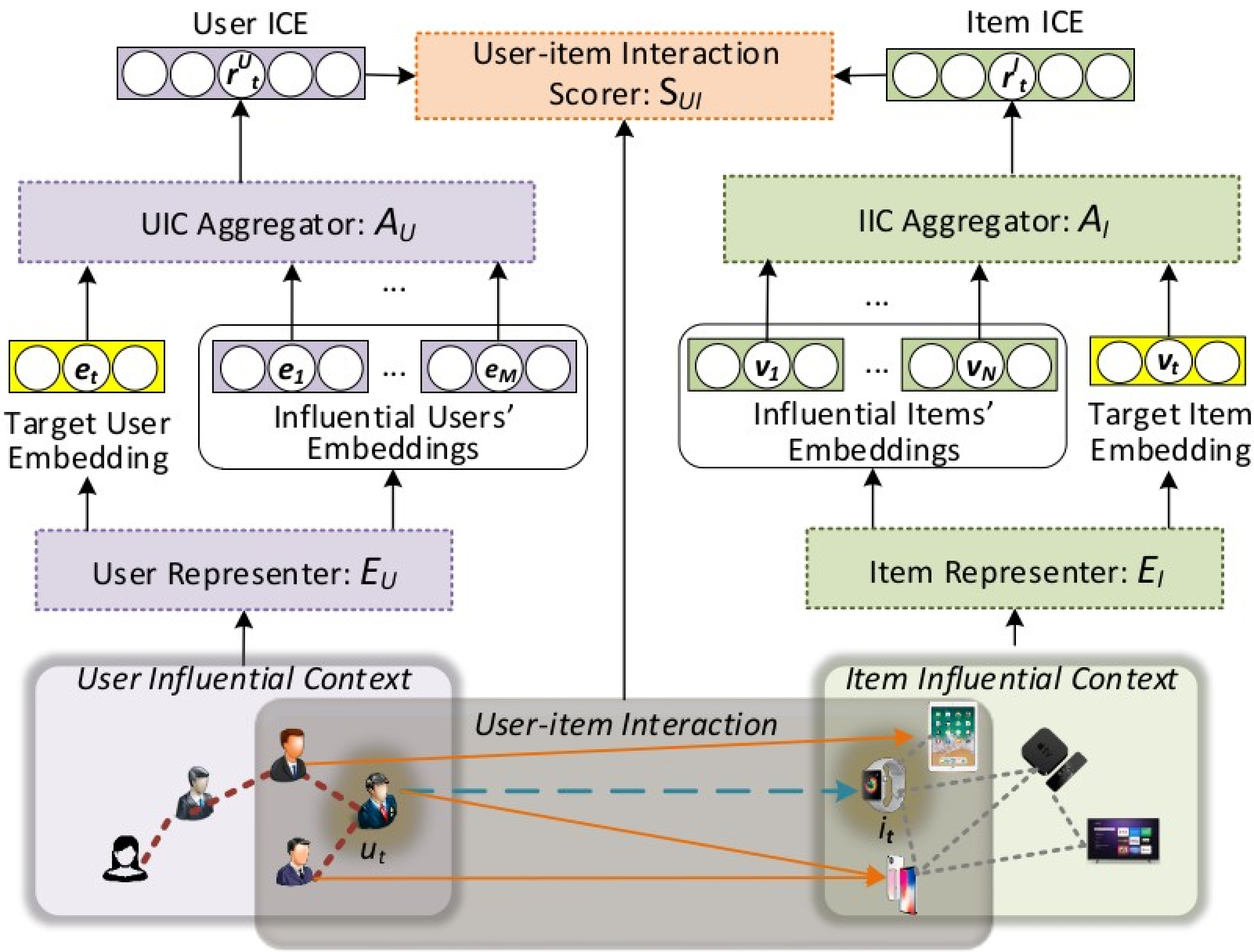
HERS

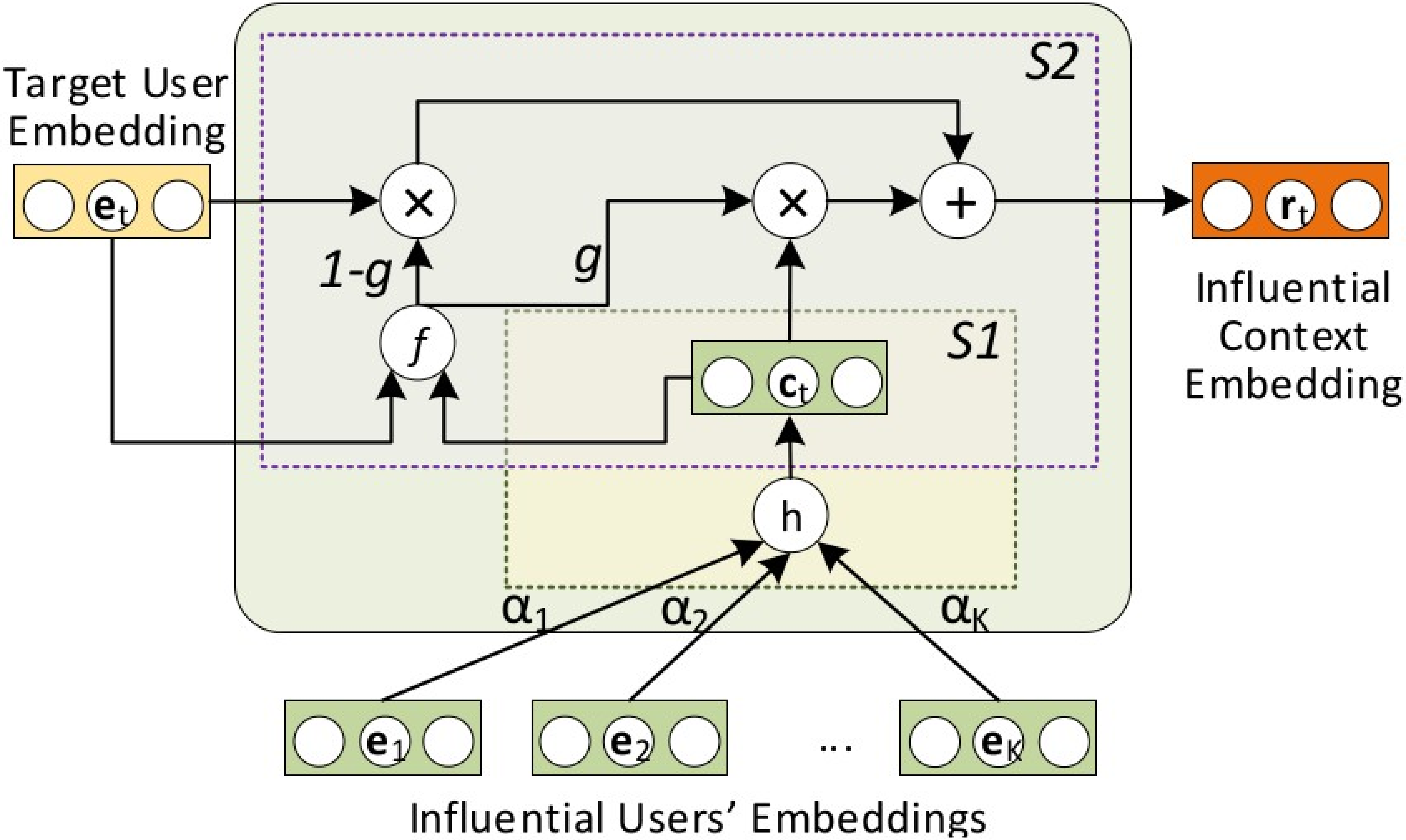
- Heterogeneous relations-Embedded Recommender System(HERS)



The architecture of HERS



Influential-Context Aggregation Unit (ICAU)



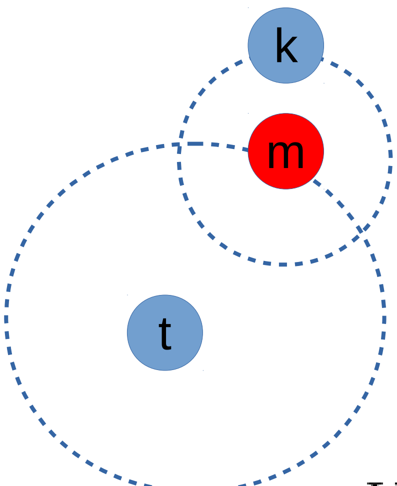
$$\{\alpha_1, \cdots \alpha_K\} = a(\mathbf{e}_1, \cdots \mathbf{e}_K)$$

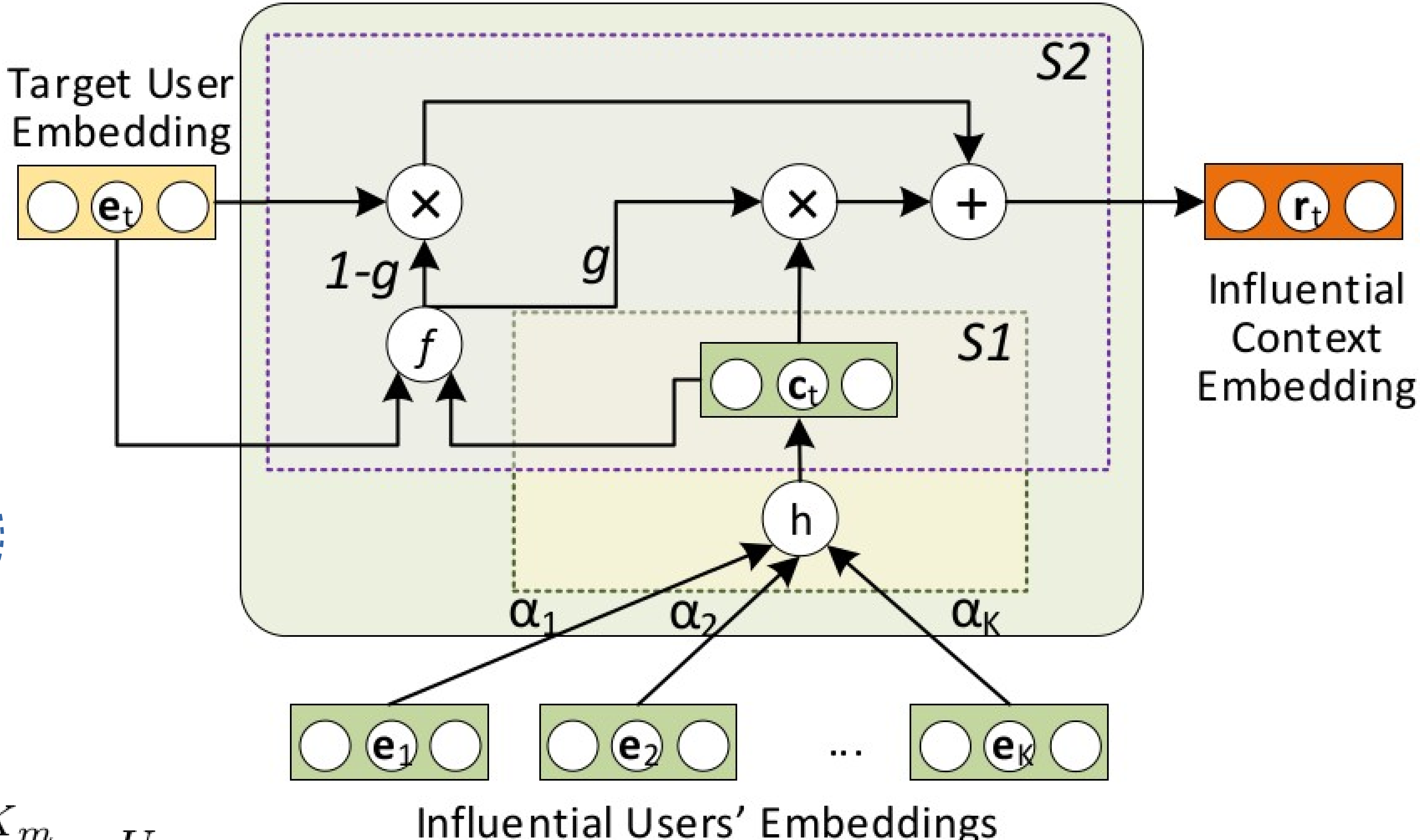
$$\mathbf{c}_t = h(\mathbf{e}_1, \cdots \mathbf{e}_K | \alpha_1, \cdots \alpha_K)$$

$$g = f(\mathbf{c}_t, \mathbf{e}_t)$$

$$\mathbf{r}_t = g\mathbf{c}_t + (1 - g)\mathbf{e}_t$$

Specifically



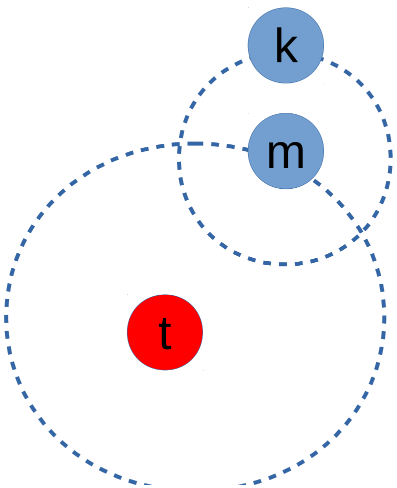


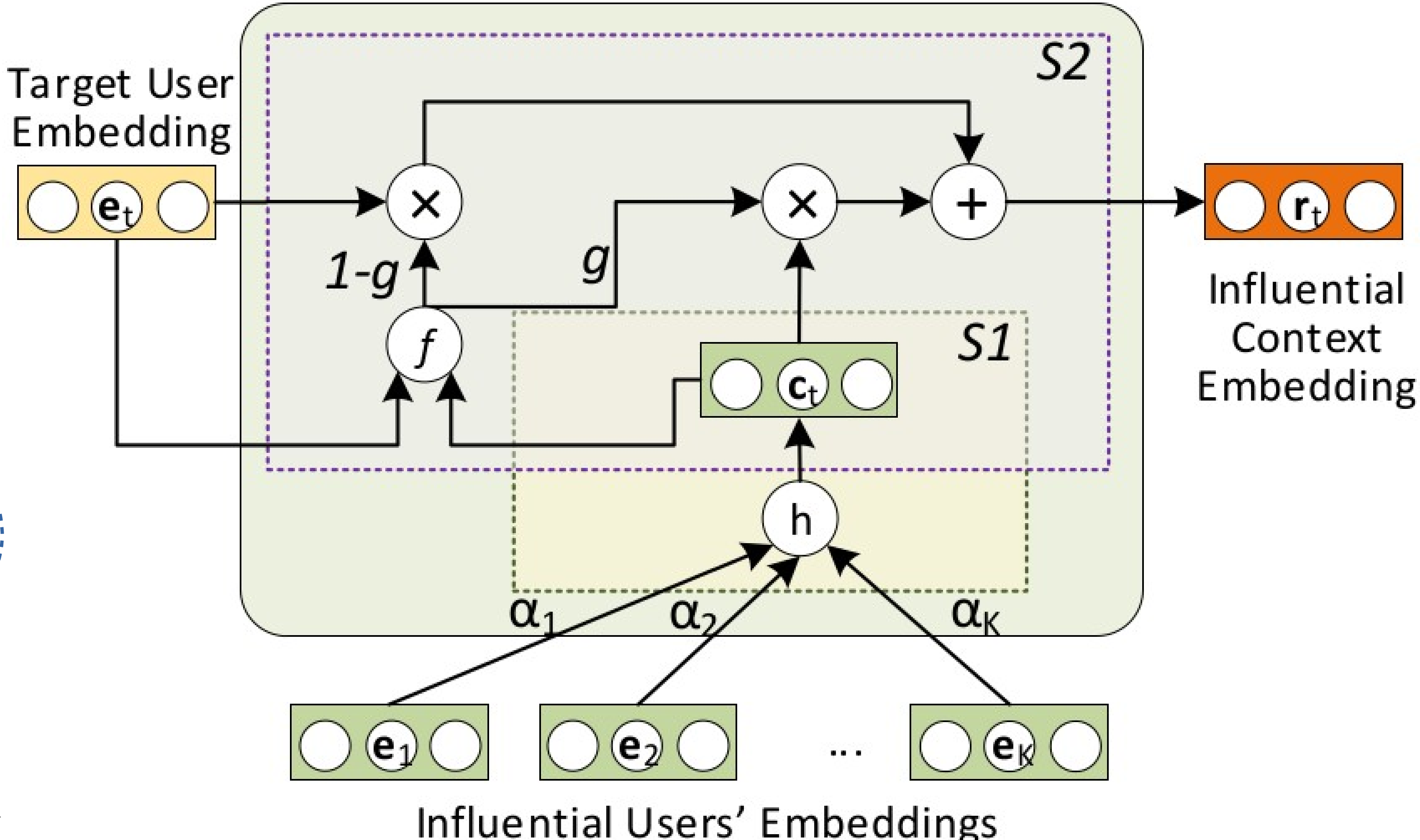
$$\mathbf{c}_{t,m} = \sum_{k=1}^{K_m} \alpha^{U}_{t,m,k} \mathbf{e}_{t,m,k} \qquad \boxed{\text{S1}}$$

$$\mathbf{r}_{t,m} = g_{t,m}\mathbf{c}_{t,m} + (1 - g_{t,m})\mathbf{e}_{t,m} \qquad \boxed{\text{S2}}$$

$$g_{t,m} = \sigma\left(isr_{\theta}\left(\mathbf{W}^{(3)} \tanh\left(\mathbf{W}^{(4)}\mathbf{c}_{t,m} + \mathbf{W}^{(5)}\mathbf{e}_{t,m}\right)\right)\right)$$

Specifically





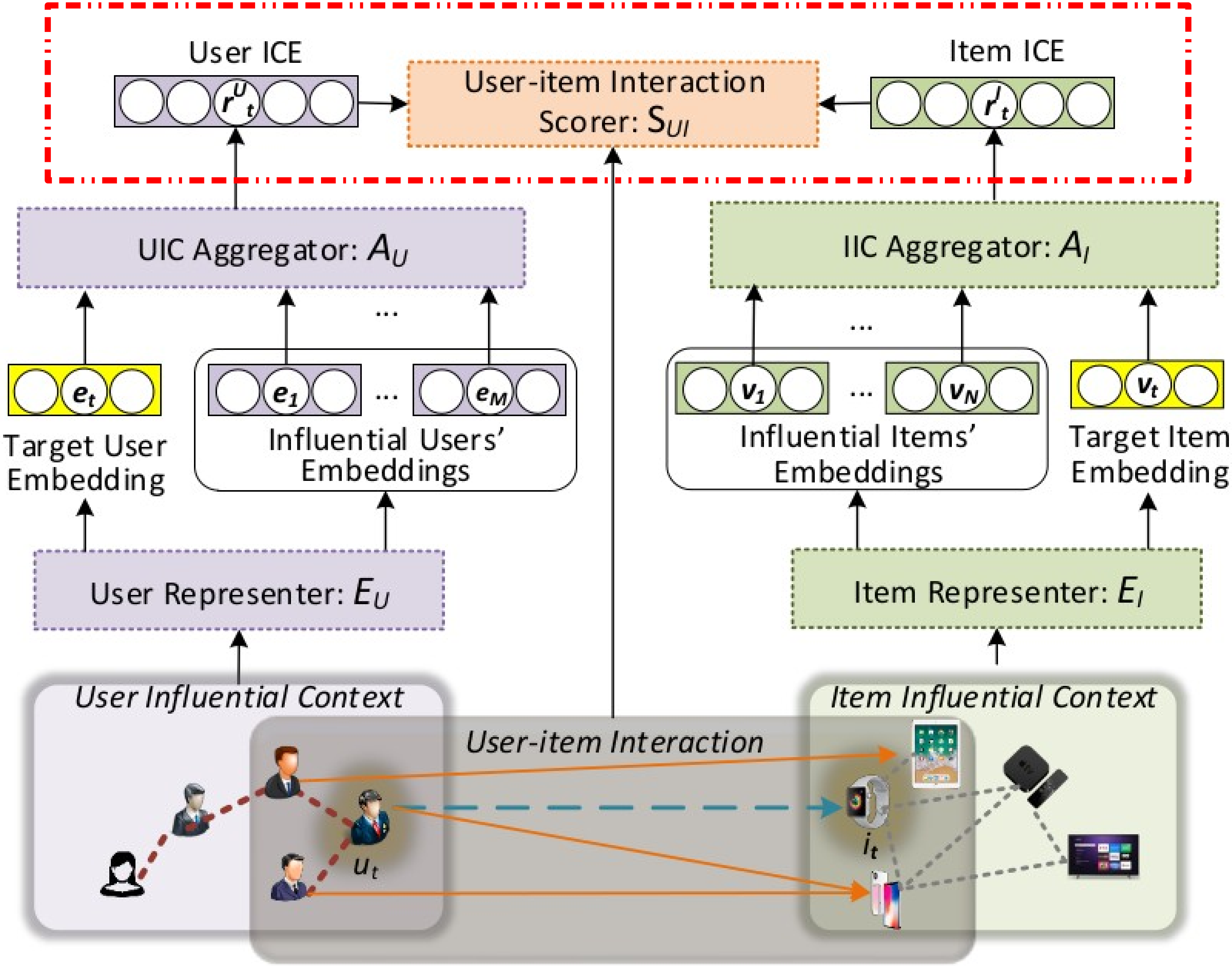
$$\mathbf{c}_t^U = \sum_{m=1}^{M} \alpha_{t,m}^U \mathbf{r}_{t,m}$$

S1

$$\mathbf{r}_t^U = g_t^U \mathbf{c}_t^U + (1 - g_t^U)\mathbf{e}_t$$

S2

The architecture of HERS



User-item Interaction Score

$$S_{\langle u_t, i_t \rangle} = \mathbf{r}_t^{U\top} \mathbf{r}_t^{I}$$

$$\mathcal{L} = \frac{1}{|\mathcal{B}|} \sum_{\langle u_t, i_p, i_n \rangle \in \mathcal{B}} L_{\langle u_t, i_p \rangle \succeq \langle u_t, i_n \rangle}$$

Data Preparation

Table 1: Statistics of the datasets: Delicious and Lastfm

	Property	User-user	Item-item	User-Item
Delicous	#Entity	1,892	17,632	1,892+17,632
	#Link	25,434	199,827	104,799
	#Link/#Entity	13.44	22.66	5.37
	Sparsity	0.0071	0.0006	0.0031
Lastfm	#Entity	1,867	69,226	1,867+69,226
	#Link	15,328	682,314	92,834
	#Link/#Entity	8.24	15.75	3.03
	Sparsity	0.0044	0.0001	0.0007

- The item-item relationships are built on the common tags between items.
- The friendships between users are used as the user-user relation.

user relationships from the social domain. The Neural Factorization Machine (NFM) extends FM with neural networks by adding multiple hidden layers to learn non-linear interactions. CoupledCF (Zhang et al. 2018) learns explicit and implicit user-item couplings in recommendation for deep collaborative filtering. However, all these methods only model pairwise interactions instead of all influences in the influential contexts. Moreover, they cannot tell the strengths of influence from each user or item.

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The End

Thank You