User-Centric Conversational Recommendation with Multi-Aspect User Modeling

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Introduction

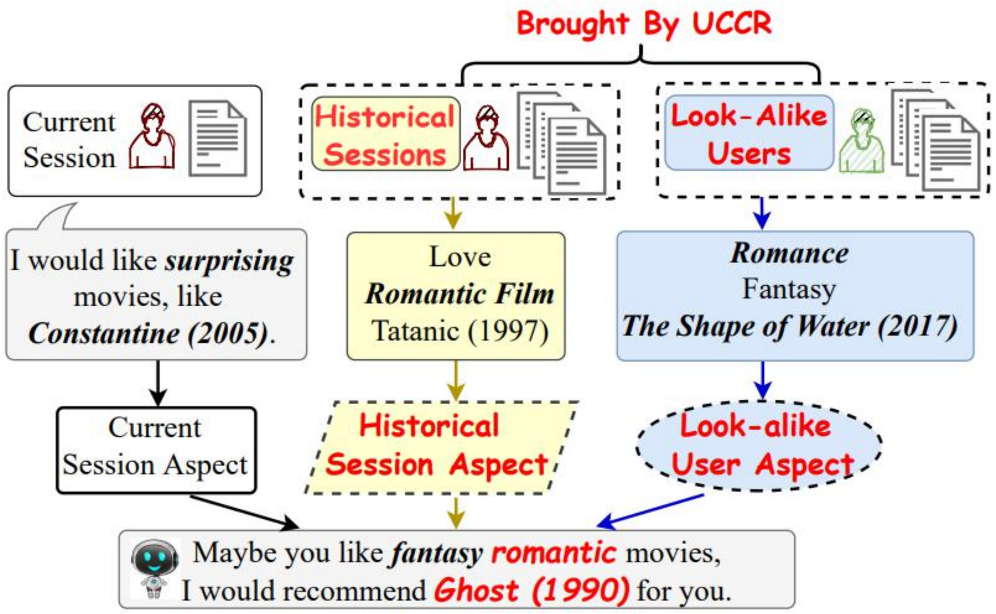


Figure 1: An example of the multi-aspect user information. UCCR introduces the historical dialogue sessions and look-alike users to CRS for user-centric preference learning.

Most of methods pay too much attention to the current dialogue session and only learn the preferences reflected by the session, ignoring the central subjects in CRS, i.e., users.

Method

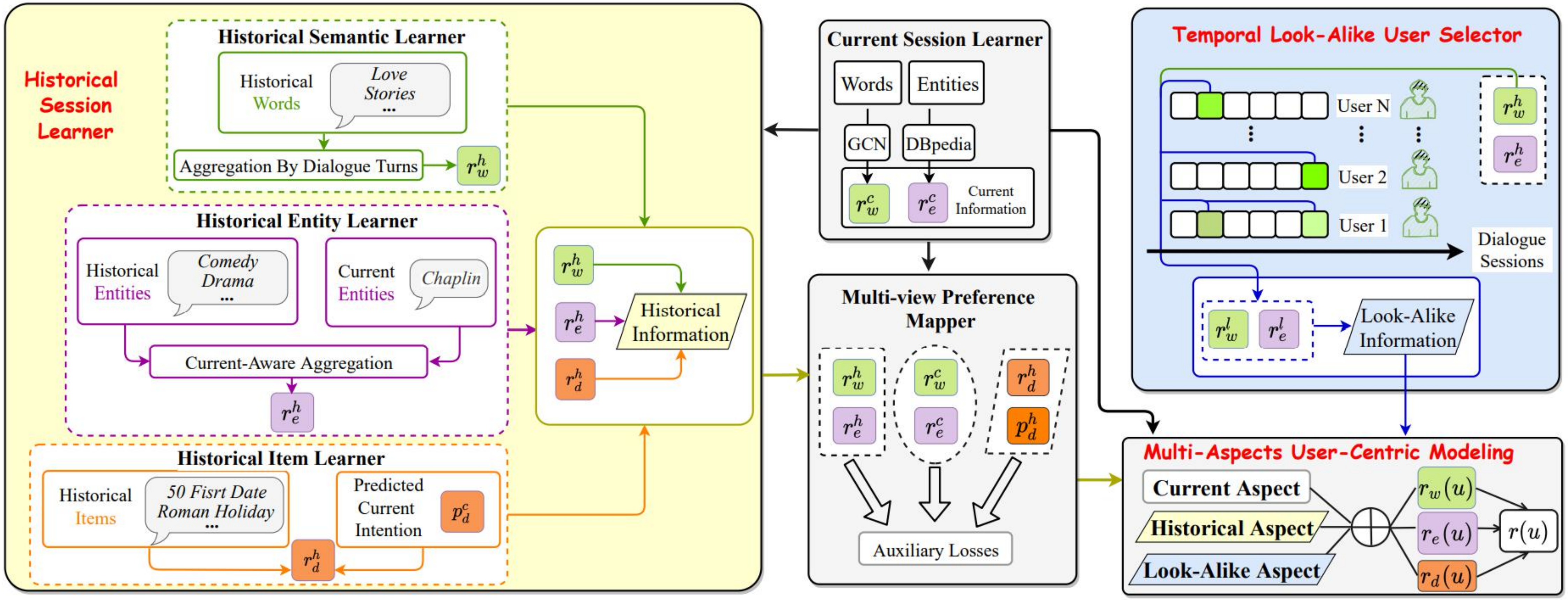
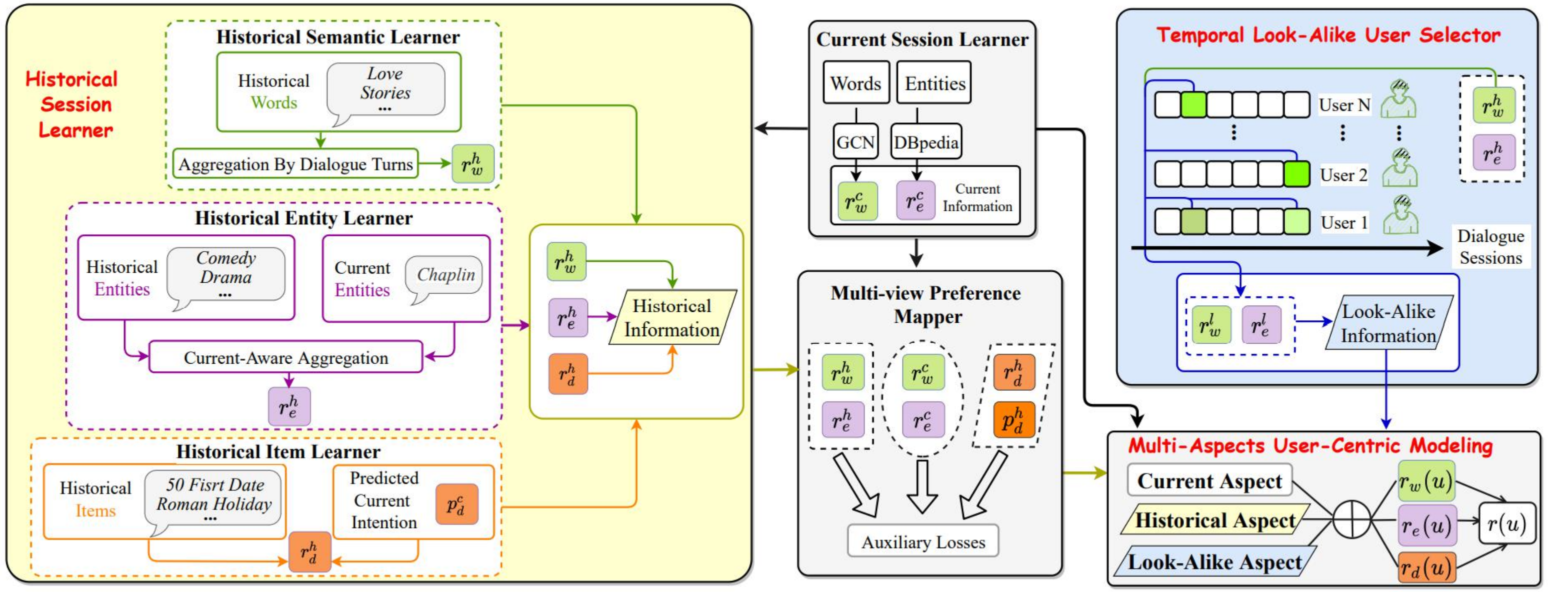


Figure 2: The overview of our model UCCR. First, the multiple views information is encoded by the historical and current session learners. Second, the multi-view preference mapper further explores the correlations between views. Next, the temporal look-alike users selector provides another aspect feature. Finally, these aspects are fused by the user-centric modeling module.

Method



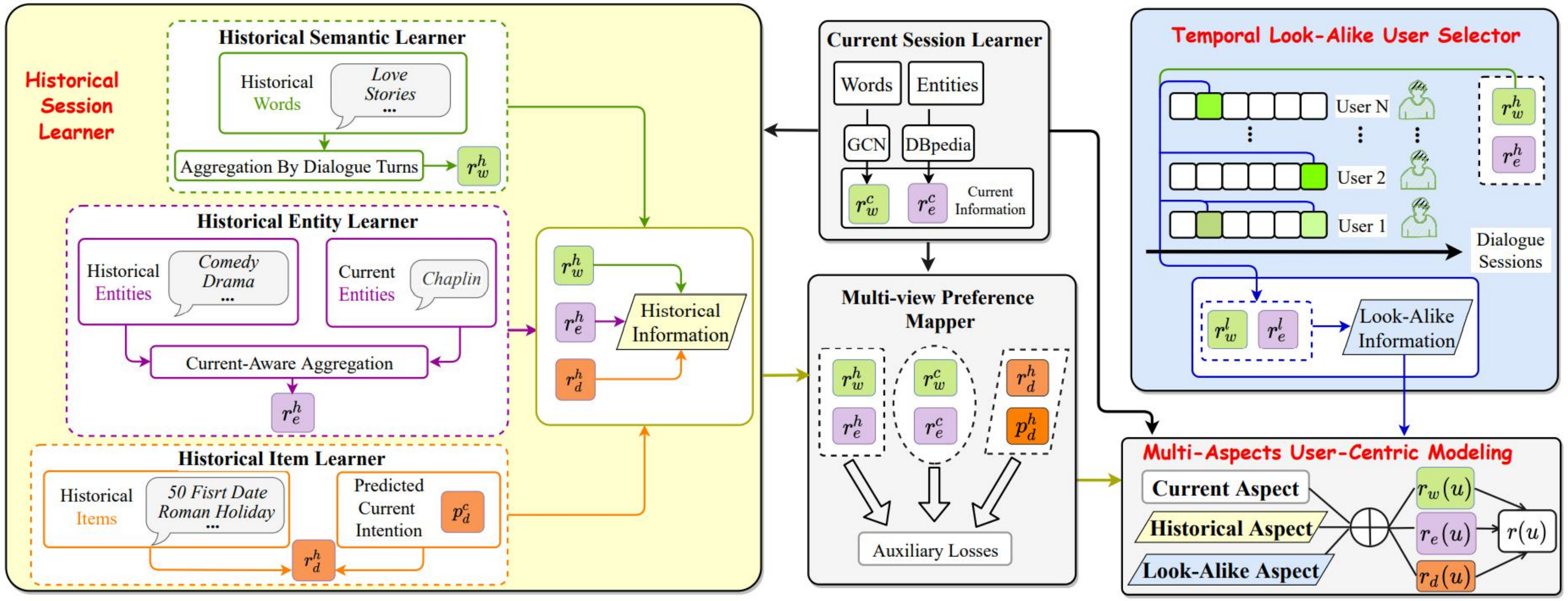
Notions of our UCCR. In real-world CRS, a user may have multiple dialogue sessions with the system. We organize user dialogue sessions in chronological order. For a user u from $\mathcal{U}$ having T dialogue sessions, we have the following definitions:

Definition 1: Current Dialogue Session. We regard the T-th session as the current dialogue session that we should recommend for. In the current (dialogue) session, when recommending items at a certain turn, all t user mentioned entities $C_e = \{e_1^T, ..., e_t^T\}$ of the current session before this turn are viewed as the *current entities*. For words, the definition of *current words* C_w is the same as C_e.

Definition 2: Historical Dialogue Sessions. We call all previous sessions before the current session as historical dialogue sessions. It also includes the *historical entities* $\mathcal{H}_e = \{\mathcal{H}_e^1, \cdots, \mathcal{H}_e^{T-1}\}$ and *historical words* $\mathcal{H}_w$ extracted from all $T-1$ sessions. Besides, the previous recommended items in historical sessions are viewed as *historical preferred items* $\mathcal{H}_d$. Precisely, $\mathcal{H}_e^j = \{e_1^j, ...e_{t_j}^j\}$ includes all t_j user mentioned entities of the j-th historical dialogue session, and similar as $\mathcal{H}_w$ and $\mathcal{H}_d$. We should double clarify that our proposed historical dialogue session is completely different from the dialog/conversation history used in [2, 18, 39], for their "historical" information locates in the historical sentences (turns) of the current dialogue session. To the best of our knowledge, we are the first to highlight the significance of historical dialogue sessions in generative CRS.

Definition 3 (Look-alike Users). The look-alike users refer to similar users. The user similarity can be calculated from multiple perspectives, such as user profiles and historical behaviors. In UCCR, we rely on the historical words, entities, and items for look-alike users learning. In light of user-CF, the look-alike users may have similar tastes, thus could enhance the user representations, which is especially effective when users only have sparse information learned from the current or historical dialogue sessions.

Method



Current Session Learner

$$C_e = \{e_1^T, ..., e_t^T\}$$

$$v_e^{l+1} = \sigma\Big(\sum_{r\in\mathcal{R}} \sum_{e'\in\mathcal{N}_e^r} \frac{1}{Z_{e,r}} W_r^l v_{e'}^l + W^l v_e^l\Big), \quad (1)$$

$$r_e^c = \text{R-GCN}(C_e) = \mathcal{F}(\mu_e (V_e)^{\mathrm{T}}),$$
$$\mu_e = \text{Softmax}(b_e \text{Tanh}(W_e V_e)), \quad (2)$$

$$C_w = \{w_1^T, ..., w_t^T\}$$

$$r_w^c = \text{GCN}(C_w)$$

Historical Session Learner

$$r_e^h = \text{Agg}(r_e^c, h_e^1, ..., h_e^{T-1}) = \sum_{j=1}^{T-1} \varphi(h_e^j, r_e^c)\, h_e^j,$$
$$\varphi(h_e^j, r_e^c) = \text{Softmax}(h_e^j W_s r_e^c \,/\, \lambda_e), \quad (3)$$

$$h_w^j = \mathcal{F}\Big(\sum_{m=1}^{t} s(w_m^j)\, v_{w_m^j}\Big), \quad (4)$$

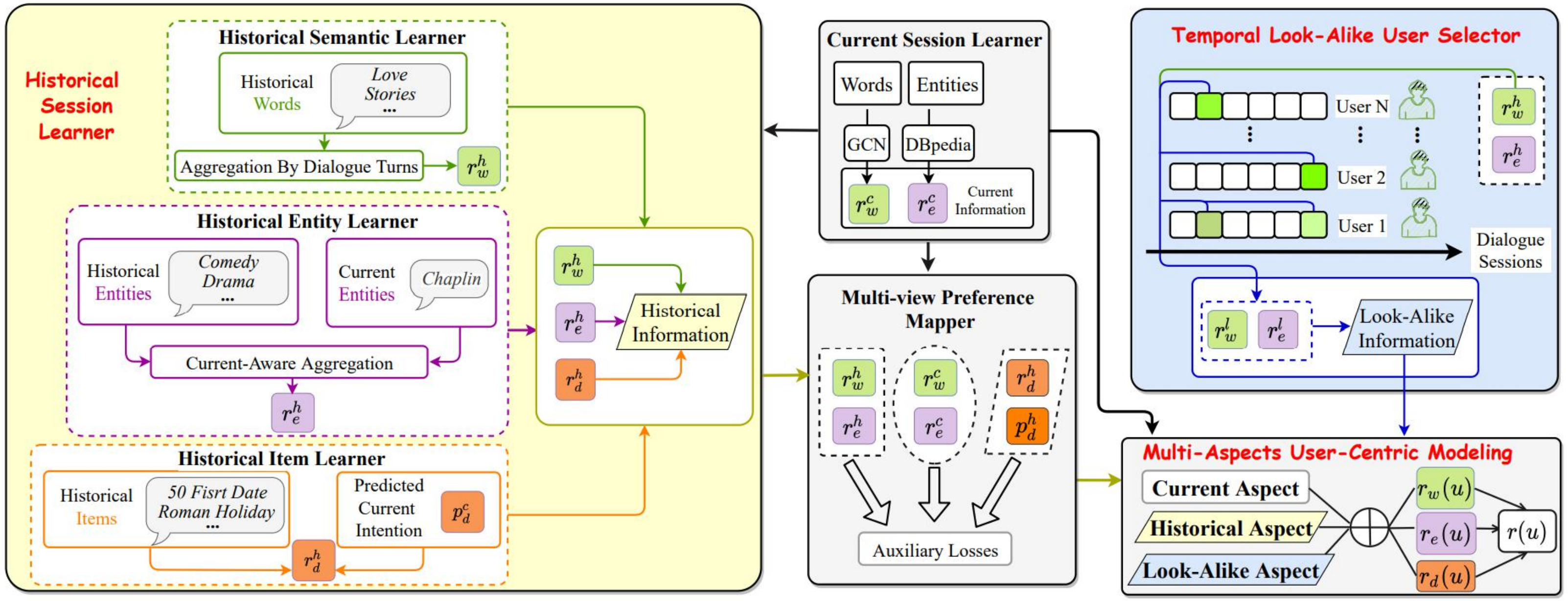
$$s(w_m^j) = \text{Softmax}(1, 2, ..., t)[m]$$

$$r_w^h = \textstyle\sum_{j=1}^{T-1} s(h_w^j)\, h_w^j$$

$$\mathcal{H}_d^j = \{d_1^j, ...d_t^j\}$$
$$h_d^j = \text{R-GCN}(\mathcal{H}_d^j)$$

$$p_d^c = g(r_w^c, r_e^c) = \tau \cdot r_w^c + (1-\tau)\cdot r_e^c,$$
$$\tau = \sigma(W_g \text{Concat}(r_w^c, r_e^c)), \quad (5)$$
$$r_d^h = \text{Agg}(p_d^c, h_d^1, ..., h_d^{T-1})$$

Method



where $\delta(x) = \max(0, x - \delta_w)$ is a clip function to avoid too much noise, and δ_w is the threshold. $\boldsymbol{r}_w^l(u,u')$ is viewed as the contribution of u' on user u's current word modeling, and $\boldsymbol{r}_w^l(u,u')$ equals 0 when $\mathrm{sim}(\boldsymbol{r}_w^h(u), \boldsymbol{r}_w^h(u'_k))$ is smaller than δ_w for all time points. For the entity view, the formalization of $\boldsymbol{r}_e^l(u,u')$ is the same as Eq. (7). $l_w(u,u')$ and $l_e(u,u')$ will be used as look-alike user supplements for u.

Multi-View Preference Mapper

$$\mathcal{L}_a(\boldsymbol{v}_1,\boldsymbol{v}_2) = \sum_{u\in\mathcal{B}} (1-\mathrm{sim}(\boldsymbol{v}_1^u,\boldsymbol{v}_2^u))^2 + \lambda_a \sum_{u,u'\in\mathcal{B}} (\mathrm{sim}(\boldsymbol{v}_1^u,\boldsymbol{v}_2^{u'}))^2, \quad (6)$$

Specifically, we have three alignment tasks: (1) $\boldsymbol{v}_1 = \boldsymbol{r}_w^c$, $\boldsymbol{v}_2 = \boldsymbol{r}_e^c$; (2) $\boldsymbol{v}_1 = \boldsymbol{r}_w^h$, $\boldsymbol{v}_2 = \boldsymbol{r}_e^h$; (3) $\boldsymbol{v}_1 = \boldsymbol{r}_d^h$, $\boldsymbol{v}_2 = \boldsymbol{p}_d^h$, $\boldsymbol{p}_d^h$ is the combination of historical words and entities (refers to Eq. (5)).

Temporal Look-Alike User Selector

$$\boldsymbol{r}_w^l(u,u') = \sum_{k=1}^{K} \delta(\mathrm{sim}(\boldsymbol{r}_w^h(u), \boldsymbol{r}_w^h(u'_k)))\, \boldsymbol{r}_w^c(u'_k), \quad (7)$$

Multi-Aspect User-Centric Modeling

$$\boldsymbol{r}_e(u) = \boldsymbol{r}_e^c(u) + \alpha_h \boldsymbol{r}_e^h(u) + \alpha_s \sum_{u'\in\mathcal{U}} \boldsymbol{r}_e^l(u,u'), \quad (8)$$

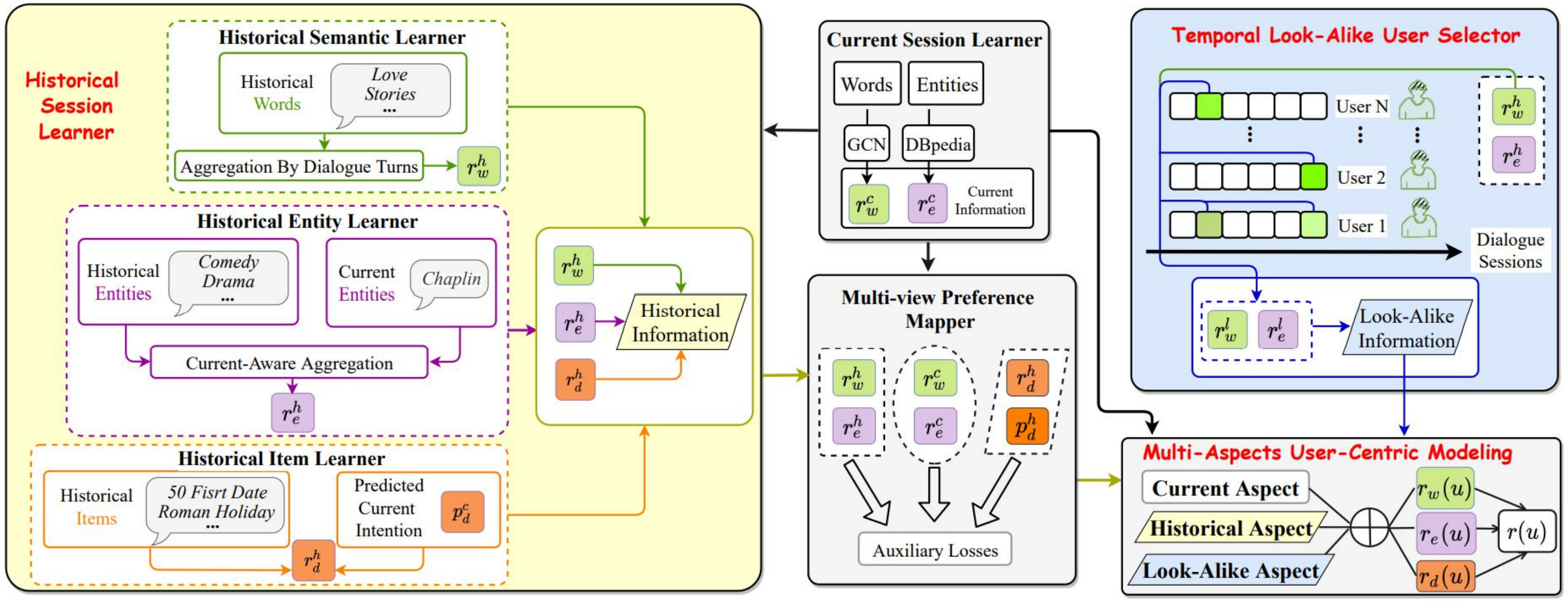
$$\alpha_h = \mathcal{G}(\mathrm{Concat}(\boldsymbol{r}_e^c(u), \boldsymbol{r}_e^h(u))) \,/\, \tau_e, \quad (9)$$

$$\boldsymbol{r}_w(u) = \boldsymbol{r}_w^c(u) + \beta_h \boldsymbol{r}_w^h(u) + \beta_s \sum_{u'\in\mathcal{U}} \boldsymbol{r}_w^l(u,u'), \quad (10)$$

$$\boldsymbol{r}_d(u) = \gamma_h \boldsymbol{r}_d^h(u), \qquad \gamma_h = \delta(\mathrm{sim}(\boldsymbol{p}_d^h, \boldsymbol{p}_d^c)), \quad (11)$$

$$\boldsymbol{r}(u) = g(\boldsymbol{r}_w(u), \boldsymbol{r}_e(u)) + \boldsymbol{r}_d(u), \quad (12)$$

Method



Optimization

$$p_{rec}(u, d_i) = \text{Softmax}(\boldsymbol{r}(\boldsymbol{u})^\top \cdot \boldsymbol{d}_i), \quad (13)$$

$$\mathcal{L}_{rec} = -\sum_{u \in \mathcal{U}} \sum_{i=1}^{N_u} \log p_{rec}(u, d_i) + \lambda_{CL} \sum_{(v_1, v_2)} \mathcal{L}_a(v_1, v_2), \quad (14)$$

$$p_{dial}(y_t | y_1, ..., y_{t-1}) = \text{Softmax}(W^G \boldsymbol{q} + \mathcal{M}(\boldsymbol{r}(u))[y_t], \quad (15)$$

$$\mathcal{L}_{dial} = -\sum_{u \in \mathcal{U}} \sum_{t=2}^{N_t} \log(p_{dial}(y_t | y_1, ..., y_{t-1})). \quad (16)$$

Experiments

Table 1: The recommendation results. The marker * indicates that the improvement is statistically significant compared with the best baseline (t-test with p-value < 0.05).

Dataset	TG-ReDial						ReDial					
Method	HR@10	HR@50	MRR@10	MRR@50	NDCG@10	NDCG@50	HR@10	HR@50	MRR@10	MRR@50	NDCG@10	NDCG@50
SASRec	0.0048	0.0170	0.0011	0.0016	0.0019	0.0046	0.0418	0.1598	0.0385	0.0407	0.0473	0.0712
Text CNN	0.0052	0.0188	0.0015	0.0022	0.0029	0.0058	0.0733	0.1810	0.0438	0.0482	0.0576	0.0808
Bert	0.0098	0.0356	0.0027	0.0040	0.0051	0.0101	0.1499	0.2937	0.0683	0.0761	0.0813	0.1167
ReDial	0.0102	0.0370	0.0028	0.0041	0.0053	0.0107	0.1733	0.3359	0.0779	0.0841	0.0969	0.1351
KBRD	0.0141	0.0481	0.0045	0.0063	0.0072	0.0143	0.1827	0.3688	0.0784	0.0855	0.1004	0.1428
TG-ReDial	0.0168	0.0513	0.0061	0.0080	0.0088	0.0161	0.1893	0.3801	0.0801	0.0883	0.1032	0.1477
KGSF	0.0175	0.0543	0.0073	0.0088	0.0096	0.0175	0.2006	0.4034	0.0837	0.0932	0.1110	0.1556
KECRS	0.0113	0.0394	0.0033	0.0042	0.0057	0.0111	0.1772	0.3423	0.0780	0.0851	0.0983	0.1391
RevCore	0.0191	0.0581	0.0077	0.0093	0.0105	0.0189	0.2058	0.4088	0.0850	0.0946	0.1132	0.1583
UCCR w/o En	0.0167	0.0506	0.0071	0.0085	0.0092	0.0165	0.1976	0.3885	0.0812	0.0908	0.1084	0.1502
UCCR w/o Wo	0.0207	0.0592	0.0080	0.0095	0.0114	0.0196	0.2106	0.4196	0.0865	0.0959	0.1168	0.1613
UCCR w/o It	0.0211	0.0626	0.0082	0.0098	0.0116	0.0201	0.2146	0.4193	0.0865	0.0966	0.1173	0.1619
UCCR	**0.0232***	**0.0664***	**0.0088***	**0.0107***	**0.0122***	**0.0214***	**0.2161***	**0.4258***	**0.0883***	**0.0981***	**0.1182***	**0.1642***

Experiments

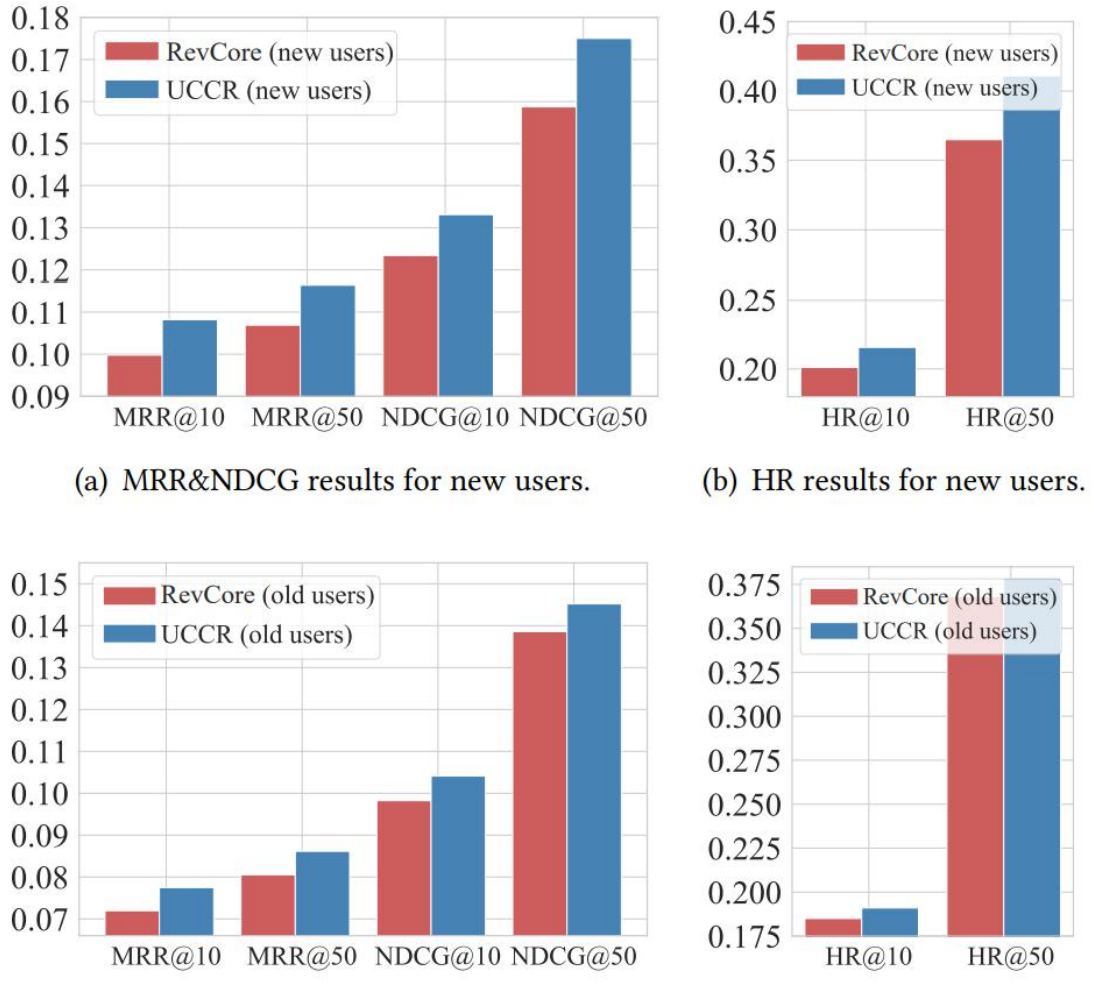
Table 2: Results on dialogue generation. Flu. and Inf. stand for Fluency and Informativeness, respectively. The marker * indicates that the improvement is statistically significant compared with the best baseline (t-test with p-value< 0.05).

Dataset	TG-ReDial								ReDial							
Method	Bleu-2	Bleu-3	Dist-2	Dist-3	Dist-4	PPL	Flu.	Inf.	Bleu-2	Bleu-3	Dist-2	Dist-3	Dist-4	PPL	Flu.	Inf.
ReDial	0.0409	0.0102	0.2672	0.5288	0.8012	55.71	0.71	0.75	0.0217	0.0078	0.0689	0.2697	0.4638	56.21	0.73	0.91
KBRD	0.0423	0.0119	0.3482	0.6911	0.9972	53.08	0.83	0.88	0.0238	0.0088	0.0712	0.2883	0.4893	54.89	0.82	1.00
KGSF	0.0461	0.0135	0.4447	1.0450	1.5792	51.27	1.01	1.09	0.0249	0.0091	0.0756	0.3024	0.5177	54.75	0.95	1.14
KECRS	0.0332	0.0078	0.1893	0.3799	0.6531	58.97	0.63	0.64	0.0133	0.0051	0.0473	0.1532	0.3188	59.35	0.59	0.71
RevCore	0.0467	0.0136	0.4513	1.0932	1.6631	51.03	1.06	1.11	0.0252	0.0098	0.0769	0.3065	0.5283	54.43	0.98	1.15
UCCR w/o En	0.0465	0.0138	0.4349	1.0289	1.5543	51.33	1.02	1.08	0.0245	0.0089	0.0729	0.3001	0.5082	54.95	0.96	1.12
UCCR w/o Wo	0.0478	0.0141	0.5093	1.2239	1.8583	50.68	1.07	1.14	0.0253	0.0097	0.0801	0.3195	0.5493	54.01	1.00	1.18
UCCR w/o It	0.0481	0.0142	0.5217	1.2589	1.9122	50.34	1.08	1.16	0.0255	0.0103	0.0815	0.3255	0.5561	53.56	1.03	1.18
UCCR	**0.0494***	**0.0145***	**0.5365***	**1.2783***	**1.9376***	**50.21***	**1.13***	**1.18***	**0.0257***	**0.0106***	**0.0818***	**0.3289***	**0.5635***	**53.24***	**1.06***	**1.22***

Experiments

Table 3: Results of cold-start scenarios on ReDial with different number of user's current entities.

#Entity	Method	H@10	H@50	M@10	M@50	N@10	N@50
0	RevCore	10.23	26.31	0.0317	0.0409	0.0483	0.0799
	UCCR	**11.61**	**28.36**	**0.0384**	**0.0471**	**0.0574**	**0.0906**
1	RevCore	23.88	41.76	0.1094	0.1186	0.1377	0.1764
	UCCR	**24.69**	**43.93**	**0.1153**	**0.1231**	**0.1409**	**0.1830**
2	RevCore	22.65	41.92	0.0939	0.1045	0.1271	0.1693
	UCCR	**23.44**	**42.12**	**0.0996**	**0.1084**	**0.1313**	**0.1725**
3	RevCore	23.15	44.69	0.0859	0.0967	0.1202	0.1684
	UCCR	**23.41**	**44.95**	**0.0886**	**0.0987**	**0.1214**	**0.1703**
≥ 6	RevCore	18.63	40.77	0.0789	0.0898	0.1048	0.1562
	UCCR	**19.28**	**41.64**	**0.0829**	**0.0942**	**0.1116**	**0.1617**



(a) MRR&NDCG results for new users.

(b) HR results for new users.

(c) MRR&NDCG results for old users.

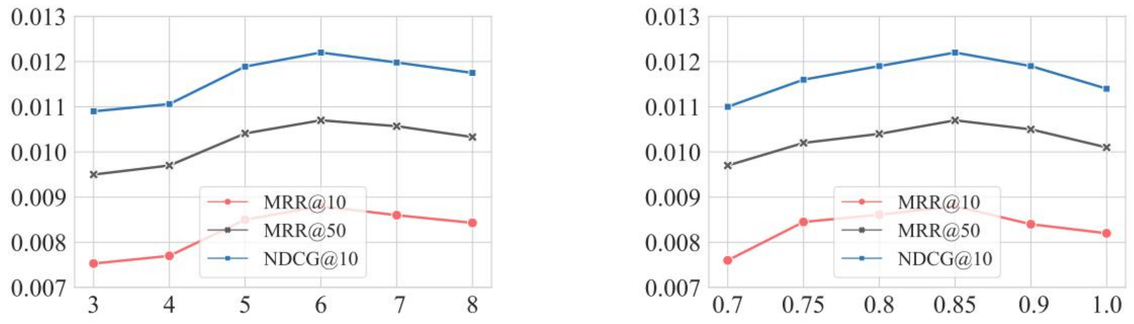
(d) HR results for old users.

Figure 3: The results for cold-start historical sessions scenario.

Experiments

Table 4: Ablation study for three aspects.

	H@10	H@50	M@10	M@50	N@10	N@50
UCCR w/o En	1.67	5.06	0.0071	0.0085	0.0092	0.0165
+ Current	1.95	6.12	0.0076	0.0093	0.0103	0.0192
+ Historical	2.14	6.33	0.0082	0.0101	0.0114	0.0204
+ Look-alike	2.32	6.64	0.0088	0.0107	0.0122	0.0214



(a) τ_e for historical aspect.

(b) δ_e for look-alike aspect.

Figure 4: Hyper-parameters sensitive analysis for historical entities and look-alike users on TG-Redial.