

# Cooperative Memory Network for Personalized Task-oriented Dialogue Systems with Incomplete User Profiles

Jiahuan Pei, Pengjie Ren\*, Maarten de Rijke

University of Amsterdam, {*j.pei, m.derijke*}@uva.nl  
Shandong University\*, *renpengjie@sdu.edu.cn*

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UvA



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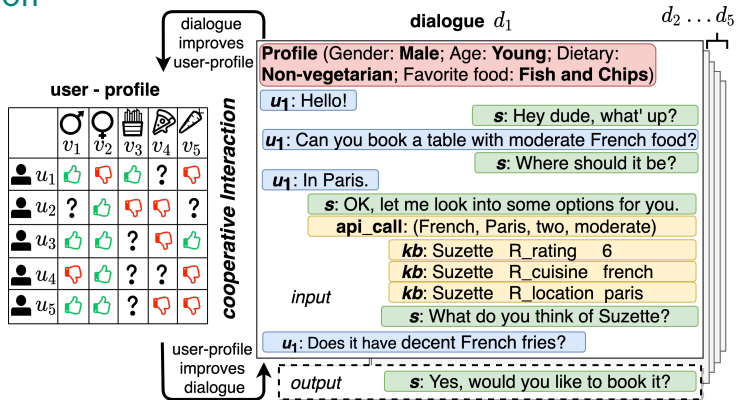
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# 1.1 Motivation



User profiles are usually *incomplete* with lots of missing values

- 1 not everyone is willing to expose their profiles due to privacy concerns; and
- 2 user profiles involve too many aspects (e.g., gender, age, tastes), which makes it impossible to collect all these information.

## 1.2 Task: Personalized TDS with incomplete user profiles

Dialogue context  $(u, D_t, X_t^u) \implies$  an appropriate response  $y_t = X_t^s$  from candidates.

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$X_t^u$  User utterance at turn  $t$ .

$X_t^s$  System response at turn  $t$ .

$D_t$  Dialogue history at turn  $t$ .

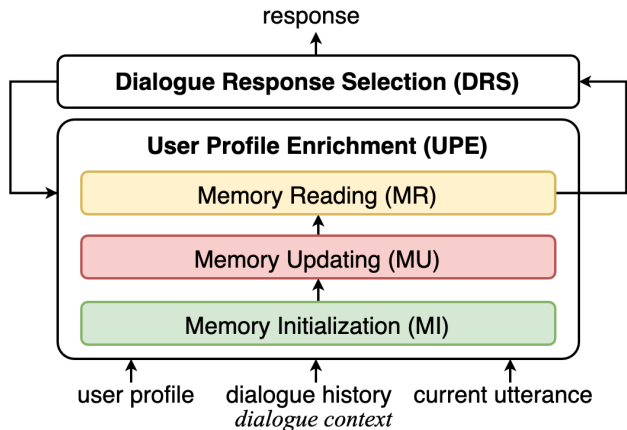
$u$  A user profile in the form of  $\{(a_i, v_i)\}_{i=1}^m$ ,  $v_i$  is a candidate value of  $i$ -th attribute  $a_i$ .

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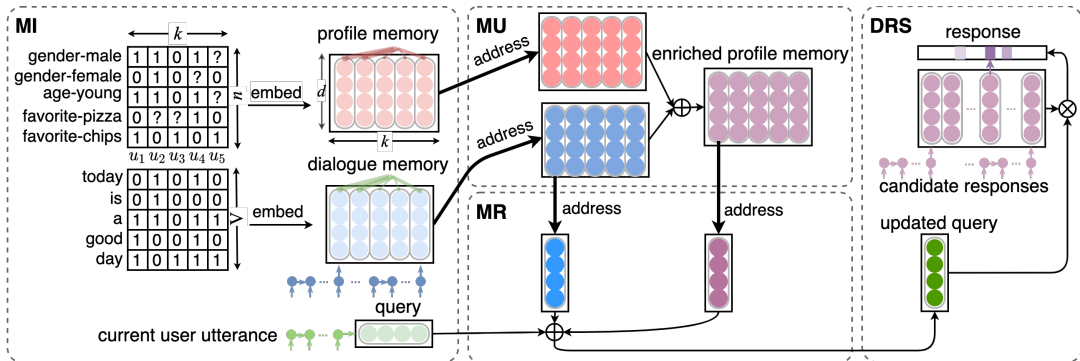
Note: it is impossible to enumerate all candidate values in a user profile!

## 1.3 Research Questions

- ① How well does CoMemNN perform? Does it significantly and continuously outperform state-of-the-art methods?
- ② What are the effects of different components in CoMemNN?
- ③ Do different profile attributes contribute differently?



## 2.2 Dynamic Pipeline



## 2.3 Multiple hop CoMemNN

**Input:** turn  $t$ , user  $u_1$ , profile  $\mathbf{p}_1$ , dialogue history  $\mathbf{H}_t$ , query  $\mathbf{q}_t$ , response candidates  $\{\mathbf{r}_1, \dots, \mathbf{r}_{|Y|}\}$ , max hop  $HopN$ ,  $(k - 1)$  neighbors

**Output:** A index  $\mathbf{y}_t$  of next response; An one-hot vector  $\tilde{\mathbf{p}}_t^1$  presenting the enriched profile.

- 1  $\{u_2, \dots, u_k\} \leftarrow \text{Search}(\mathbf{p}_1, k - 1);$  ▷ MI
- 2  $\mathbf{M}_t^P \leftarrow [\mathbf{p}_1, \dots, \mathbf{p}_k];$
- 3  $\mathbf{M}_t^D \leftarrow [\mathbf{h}_t^1, \dots, \mathbf{h}_t^k]; \mathbf{h}_t^i \leftarrow (\tilde{\mathbf{q}}_t, \mathbf{H}_t^i), i \in [1, k]; \tilde{\mathbf{q}}_t \leftarrow \mathbf{q}_t;$
- 4 **while**  $hop \leq HopN$  **do**
- 5      $\tilde{\mathbf{M}}_t^D \leftarrow \mathbf{M}_t^D; \tilde{\mathbf{M}}_t^P \leftarrow \mathbf{M}_t^P;$  ▷ MU
- 6      $\mathbf{M}_t^D \leftarrow \tilde{\mathbf{M}}_t^D;$
- 7      $\mathbf{M}_t^P \leftarrow \Gamma(\tilde{\mathbf{M}}_t^P, \tilde{\mathbf{M}}_t^D);$
- 8      $\mathbf{m}_t^D \leftarrow \mathbf{M}_t^D; \tilde{\mathbf{q}}_t \leftarrow \tilde{\mathbf{q}}_t + \mathbf{m}_t^D;$  ▷ MR
- 9      $\mathbf{m}_t^P \leftarrow \mathbf{M}_t^P; \tilde{\mathbf{q}} \leftarrow \tilde{\mathbf{q}}_t + \mathbf{m}_t^P;$
- 10 **end**
- 11  $\tilde{\mathbf{y}}_t \leftarrow \text{Softmax}(\tilde{\mathbf{q}}_t^T \mathbf{r}_1 + \mathbf{b}_1, \dots, \tilde{\mathbf{q}}_t^T \mathbf{r}_{|Y|} + \mathbf{b}_{|Y|});$  ▷ DRS
- 12  $\mathbf{y}_t \leftarrow \text{Argmax}_j(\tilde{\mathbf{y}}_t);$
- 13  $\tilde{\mathbf{p}}_t^1 \leftarrow \text{PiecewiseArgmax}(\mathbf{m}_t^P)$



- Cross entropy loss of Dialogue Response Selection (DRS)

$$\mathcal{L}_{\text{drs}}(\theta) = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^{|Y|} \mathbf{y}_j \log \hat{\mathbf{y}}_j \quad (1)$$

- Loss of User Profile Enrichment (UPE)

$$\mathcal{L}_{\text{UPE}}(\theta) = -\frac{1}{N_2} \sum_{i=1}^{N_2} (p_i - \tilde{p}_i), \quad (2)$$

- In total,

$$\mathcal{L}(\theta) = \lambda \mathcal{L}_{\text{drs}}(\theta) + (1 - \lambda) \mathcal{L}_{\text{crp}}(\theta) \quad (3)$$

- Personalized bAbI dialog dataset.
  - ▶ Four user profile attributes (gender, age, dietary preference, favorite food)
  - ▶ Statistics: a large version with 12,000 dialogues and a small version with 1,000 dialogues for train/dev/test, respectively. Vocabulary size is 14, 819 and candidate response size is 43, 863.
- Simulation of the incomplete profile with various degrees. Randomly discard some values in a user profile with probabilities of [0%, 10%, 30%, 50%, 70%, 90%, 100%].

### Performance:

- *Response Selection Accuracy (RSA)*: the fraction of correct responses out of all candidate responses.
- *Profile Enrichment Accuracy (PEA)*: we define this metric as the fraction of correct profile values out of all discarded profile values.

**Stability:** Given a list of evaluation values  $[z_1, \dots, z_{N+1}]$ , either RSA or PEA,  $\sigma$  is computed as follows:

$$\sigma(\mathbf{z}) = \sqrt{\frac{1}{N} \sum_{i=1}^N (z_i - \bar{\mathbf{z}})^2}, \quad (4)$$
$$\mathbf{z} = [z_2 - z_1, \dots, z_{N+1} - z_N],$$

where  $\bar{\mathbf{z}}$  is the mean of the values in performance difference list  $\mathbf{z}$ .

## 4.1 Results without discarding user profiles

	Small Set (%)	Large Set (%)
MemNN	77.74	85.10
Split MemNN	78.10	87.28
Retrieval MemNN	83.94	87.33
Personalized MemNN	88.07	95.33
SOTAMemNN	87.91	97.49
CoMemNN	<b>91.13*</b>	<b>98.13*</b>

- **MemNN**. Profile as the first user utterance + standard MemNN model.
- **Split MemNN**. Profile MemNN + dialogue MemNN.
- **Retrieval MemNN**. Encoder-encoder MemNN + Response Candidates Retrieval.
- **Personalized MemNN**. MemNN (current user profile, current dialogue history, dialogue history of all users with the same gender and age, user bias towards different KB entries).
- **NPMemNN**. Our implementation. Dialogue history from nearest  $(k - 1)$  neighbors.

## 4.2 Results with different profile discard ratios

Discard Ratio	0%	10%	30%	50%	70%	90%	100%
NPMemNN	87.91	86.11	86.56	85.79	83.93	84.08	<b>84.83</b>
CoMemNN	<b>91.13*</b>	<b>89.90*</b>	<b>88.69*</b>	<b>87.80*</b>	<b>86.35*</b>	<b>84.83*</b>	82.85
Small Set/Diff.	3.22	3.79	2.13	2.01	2.42	0.75	-1.98
NPMemNN	97.49	97.01	96.05	95.52	95.40	90.96	90.50
CoMemNN	<b>98.13*</b>	<b>97.94*</b>	<b>97.68*</b>	<b>97.53*</b>	<b>96.98*</b>	<b>96.63*</b>	<b>92.73*</b>
Large Set/Diff.	0.64	0.93	1.63	2.01	1.58	5.67	2.23

- CoMemNN significantly outperforms NPMemNN on both datasets.
- CoMemNN steadily decreases with the increase of the profile discard ratio.
- Model stability: NPMemNN has higher deviations; CoMemNN is more stable.

## 5.1 Ablation study on Profile Enrichment Accuracy (PEA)

	10%	30%	50%	70%	90%	100%
CoMemNN	99.99	99.93	99.82	99.83	99.38	98.98
-PEL	85.71 (↓14.28)	87.85 (↓12.08)	91.34 (↓8.48)	89.19 (↓10.64)	90.04 (↓9.34)	90.60 (↓8.38)
-NP	99.87 (↓0.12)	99.85 (↓0.08)	99.24 (↓0.58)	99.15 (↓0.68)	99.13 (↓0.25)	98.86 (↓0.12)
-NP-CP	98.89 (↓1.10)	99.09 (↓0.84)	99.16 (↓0.66)	99.20 (↓0.63)	99.14 (↓0.23)	98.92 (↓0.06)
-ND	99.72 (↓0.26)	99.87 (↓0.06)	99.80 (↓0.02)	99.46 (↓0.37)	98.72 (↓0.66)	97.23 (↓1.75)
-ND-CD	99.99 (  0.00)	99.86 (↓0.07)	99.68 (↓0.14)	99.69 (↓0.14)	99.19 (↓0.19)	34.78 (↓64.2)
-ND-NP	99.09 (↓0.90)	98.98 (↓0.95)	97.95 (↓1.87)	97.69 (↓2.14)	97.06 (↓2.32)	97.23 (↓1.75)

- PEL: Profile Enrichment Loss.
- Input of UPE: Neighbor Profile (NP); Neighbor Profile (NP); Neighbor Dialogue (ND); Current Dialogue (CD).

## 5.2 Ablation study on Response Selection Accuracy (RSA)

	0%	10%	30%	50%	70%	90%	100%
CoMemNN	91.13	89.90	88.69	87.80	86.35	84.83	82.85
-PEL	90.84 (↓0.29)	90.29 (↑0.39)	89.07 (↑0.38)	87.18 (↓0.62)	85.42 (↓0.93)	80.54 (↓4.29)	81.23 (↓1.62)
-PEL-UPE	87.91 (↓3.22)	86.11 (↓3.79)	86.56 (↓2.13)	85.79 (↓2.01)	83.93 (↓2.42)	84.08 (↓0.75)	<u>84.83</u> (↑1.98)
-NP	91.06 (↓0.07)	<u>91.23</u> (↑1.33)	89.17 (↑0.48)	85.26 (↓2.54)	83.30 (↓3.05)	82.10 (↓2.73)	82.83 (↓0.02)
-NP-CP	86.60 (↓4.53)	86.10 (↓3.80)	84.56 (↓4.13)	83.53 (↓4.27)	82.48 (↓3.87)	81.95 (↓2.88)	81.35 (↓1.50)
-ND	90.91 (↓0.22)	87.33 (↓2.57)	89.06 (↑0.37)	87.49 (↓0.31)	86.59 (↑0.24)	85.38 (↑0.55)	<u>85.41</u> (↑2.56)
-ND-CD	87.70 (↓3.43)	90.44 (↑0.54)	85.79 (↓2.90)	84.90 (↓2.90)	83.56 (↓2.79)	82.57 (↓2.26)	<u>85.38</u> (↑2.53)
-ND-NP	90.04 (↓1.09)	91.08 (↑1.18)	89.23 (↑0.54)	87.38 (↓0.42)	85.76 (↓0.59)	85.46 (↑0.63)	<u>85.41</u> (↑2.56)

- PEL: Profile Enrichment Loss.
- UPE: User Profile Enrichment module.
- Input of UPE: Neighbor Profile (NP); Neighbor Profile (NP); Neighbor Dialogue (ND); Current Dialogue (CD).

## 5.3 Effect of different profile attributes

<b>Discard</b>	none	gender	age	dietary	favorite	all
gender	/	93.05	91.94	88.86	91.95	/
age	/	/	92.26	89.37	91.04	/
dietary	/	/	/	86.74	86.42	/
favorite	/	/	/	/	90.25	/
<b>Remain</b>	<u>82.85</u>	87.46	87.93	90.57	87.37	<b>91.13</b>
RSA (Diff.)						
CoMemNN /wo neighbors	<b>90.34</b>					
CoMemNN /wo neighbors-gender	88.25 (↓2.09)					
CoMemNN /wo neighbors-age	85.62 (↓4.72)					
CoMemNN /wo neighbors-gender-age	83.73 (↓6.61)					

- Each attribute works well in isolation.
- Different types of attributes depend on each other differently.



- **Contribution:**

- ▶ A novel, practical task, i.e., personalized Task-oriented Dialogue System (TDS) with incomplete user profiles.
- ▶ A CoMemNN model with cooperative interactive modules, which can enrich user profiles gradually as dialogues go on, and to promote response selection based on enriched profiles simultaneously.
- ▶ Extensive experiments to demonstrate that CoMemNN significantly outperforms SOTA methods especially in incomplete user profile settings.

- **Limitation:** CoMemNN is tested only available personalized TDS dataset PbAbl.

- **Future work:** Experiment on more datasets and explore whether we can further improve the performance by leveraging non-personalized TDS datasets.

# Thanks for your attention!