One Chatbot Per Person

Creating Personalized Chatbots based on Implicit User Profiles

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Introduction

Personalized chatbot

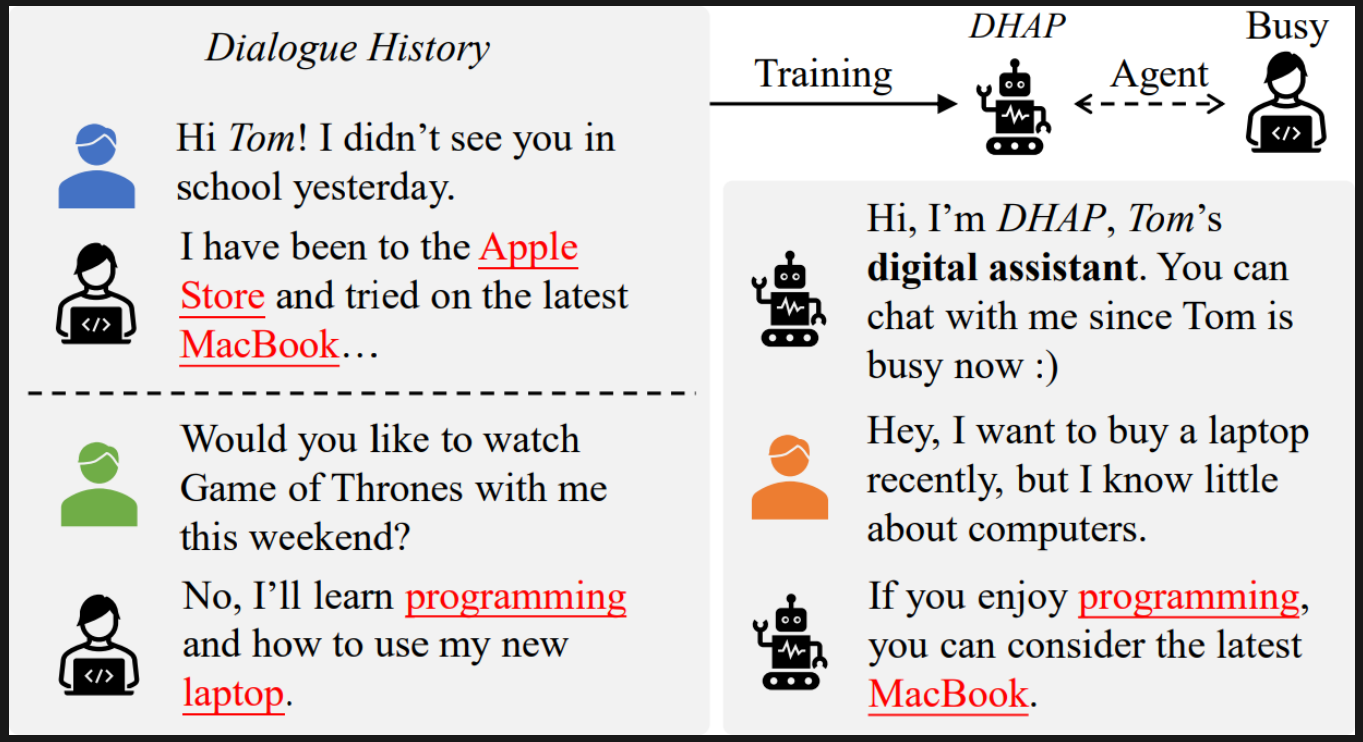
- More consistent conversation style
- Behave like a real person
- Even act as a personal assistant.

Introduction(cont.)

But

- The cost of collecting a large number of user profiles is high.
- Troublesome pre-configuration required for application.
- Existing methods cannot automatically update user information

Introduction(cont.)



Learn user profiles from historical data

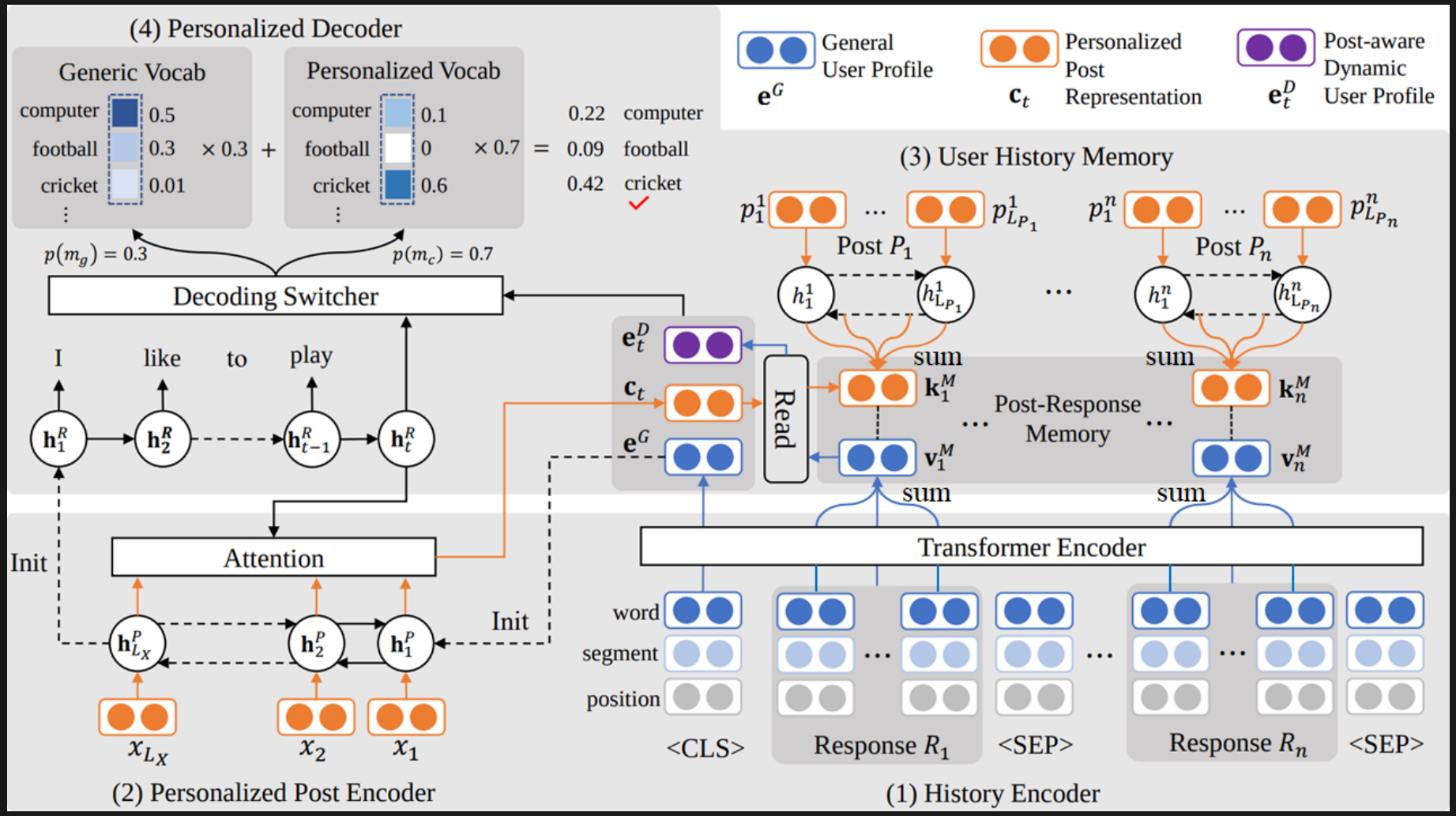
Introduction(cont.)

	User Profiles	Historical Data
包含用戶資訊	包含	包含
收集難易度	難	簡單
擴充難易度	難	簡單
噪音	低	高

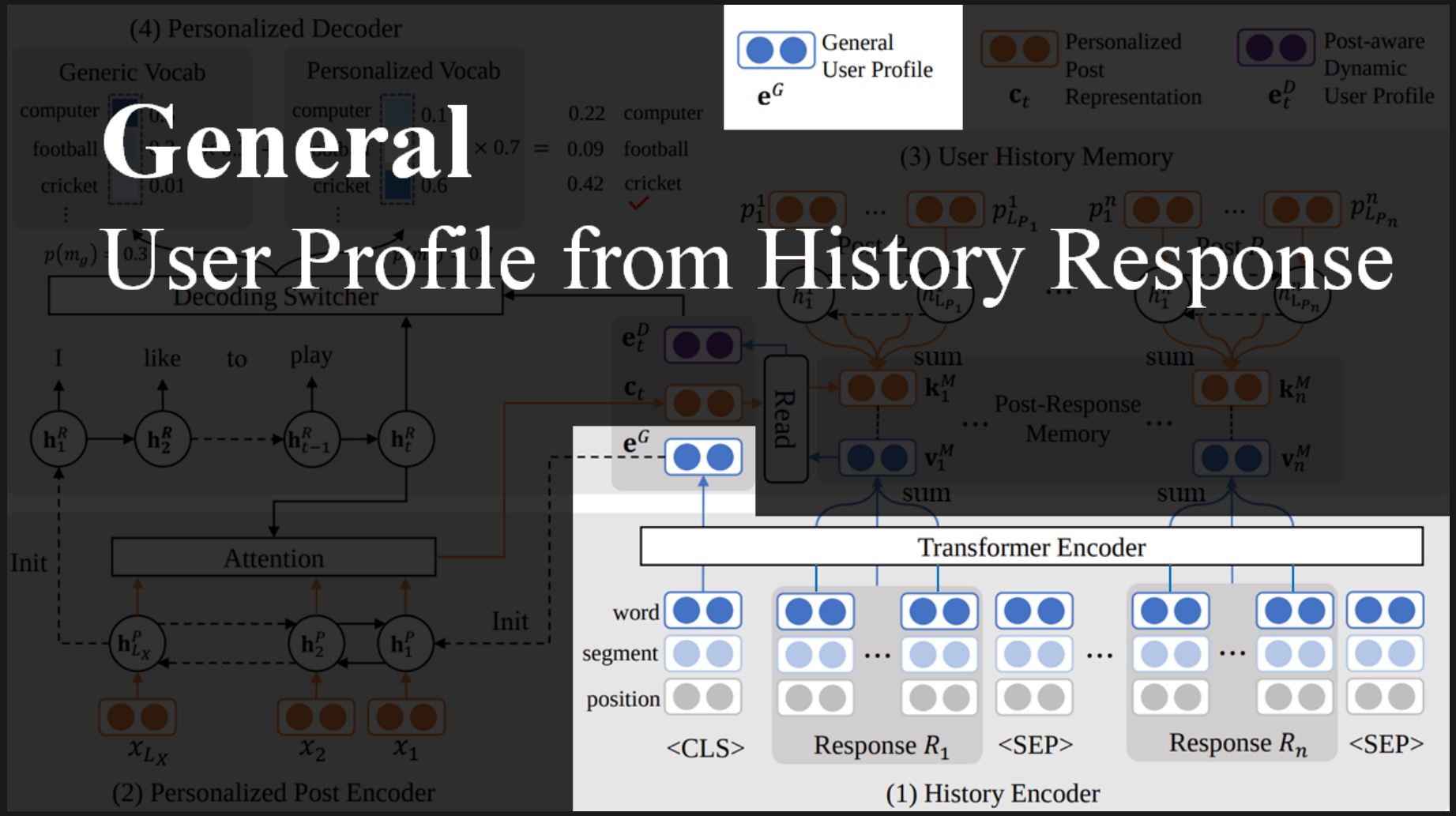
DHAP

user ***D***ialogue ***H***istory ***A***utomatically and generating ***P***ersonalized responses

DHAP(cont.)


(4) Personalized Decoder
Generic Vocab
computer 0.5
football 0.3
cricket 0.01
× 0.3 +
Personalized Vocab
computer 0.1
football 0
cricket 0.6
× 0.7 =
0.22 computer
0.09 football
0.42 cricket
$p(m_g) = 0.3$
$p(m_c) = 0.7$
Decoding Switcher
I like to play
Attention
Init
Init
x_{L_X} x_2 x_1
(2) Personalized Post Encoder
General User Profile
$\mathbf{e}^G$
Personalized Post Representation
$\mathbf{c}_t$
Post-aware Dynamic User Profile
$\mathbf{e}_t^D$
(3) User History Memory
Post P_1
Post P_n
sum
Read
Post-Response Memory
Transformer Encoder
word
segment
position
<CLS>
Response R_1
<SEP>
Response R_n
<SEP>
(1) History Encoder

DHAP(cont.)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User Profile from History Response
General User Profile
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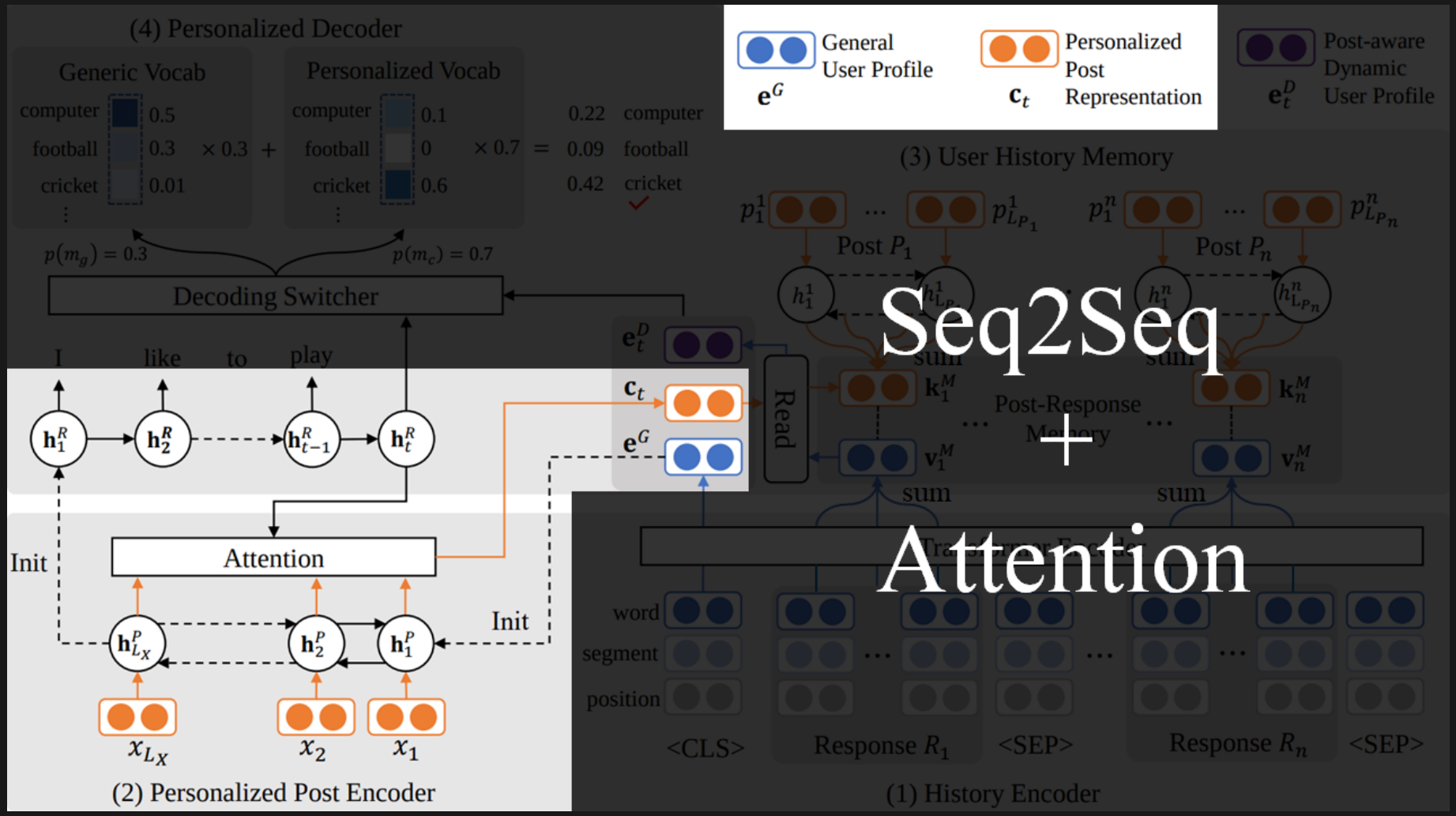
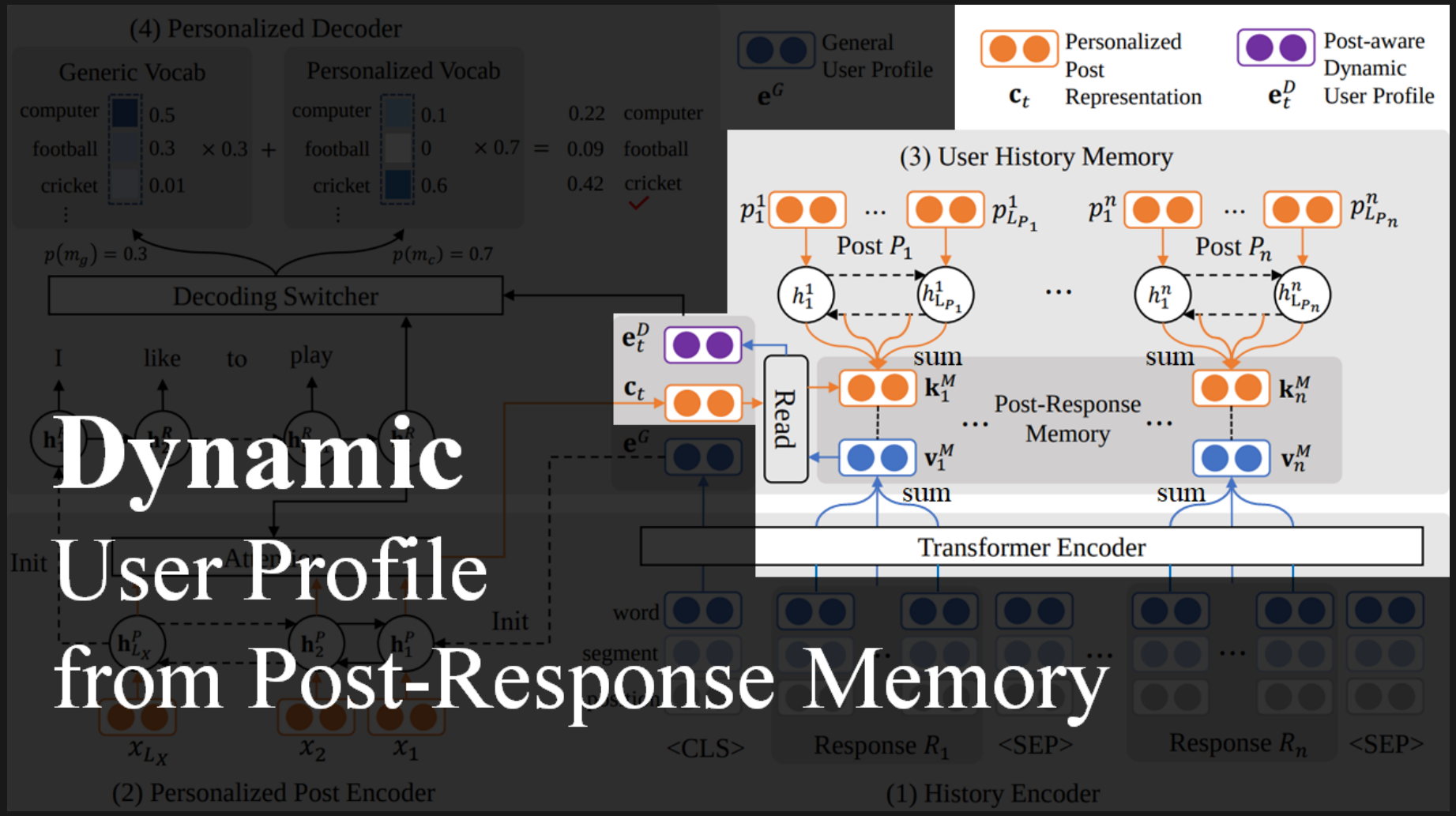


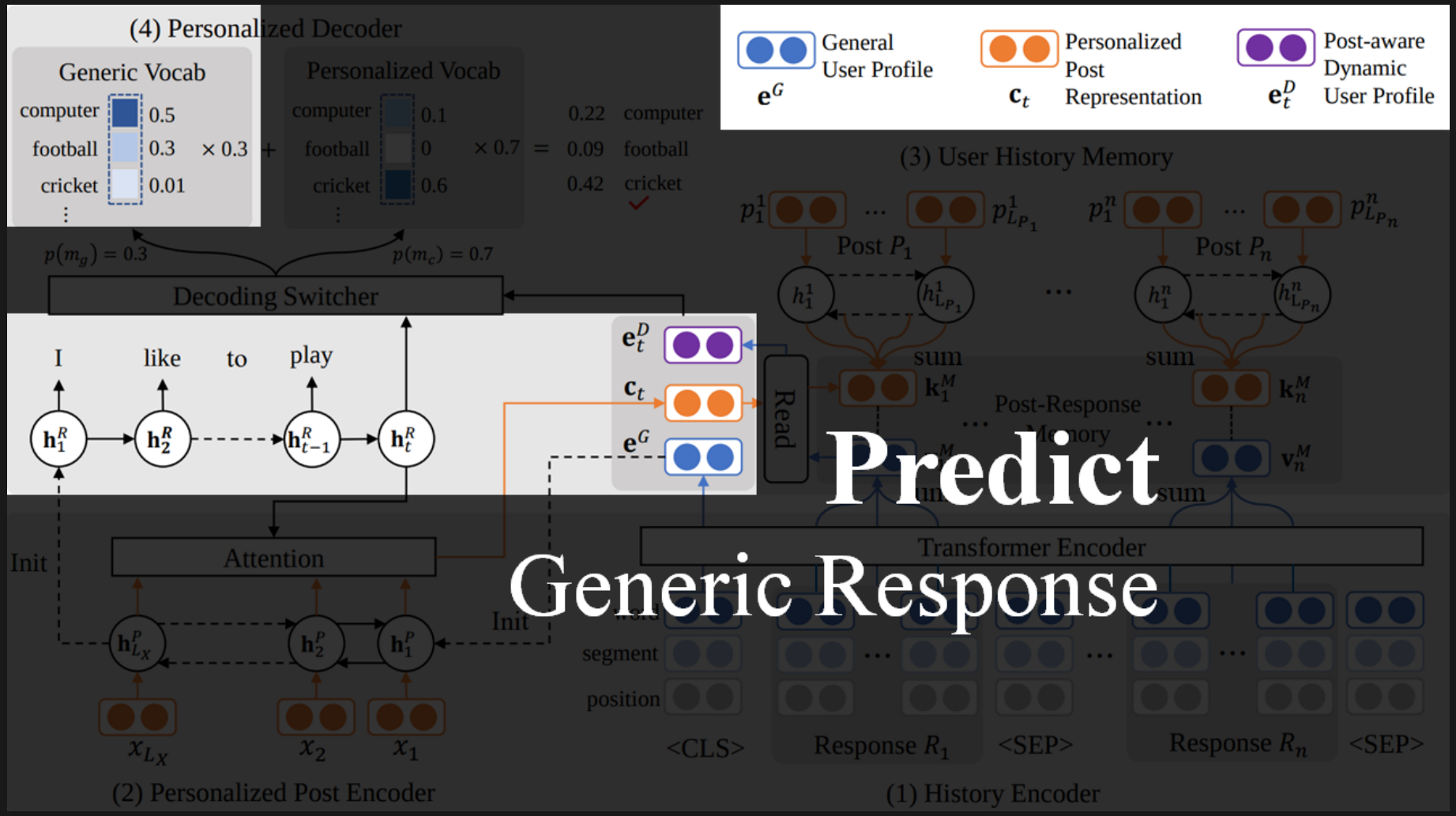
Seq2Seq + Attention

DHAP(cont.)



Dynamic User Profile from Post-Response Memory

DHAP(cont.)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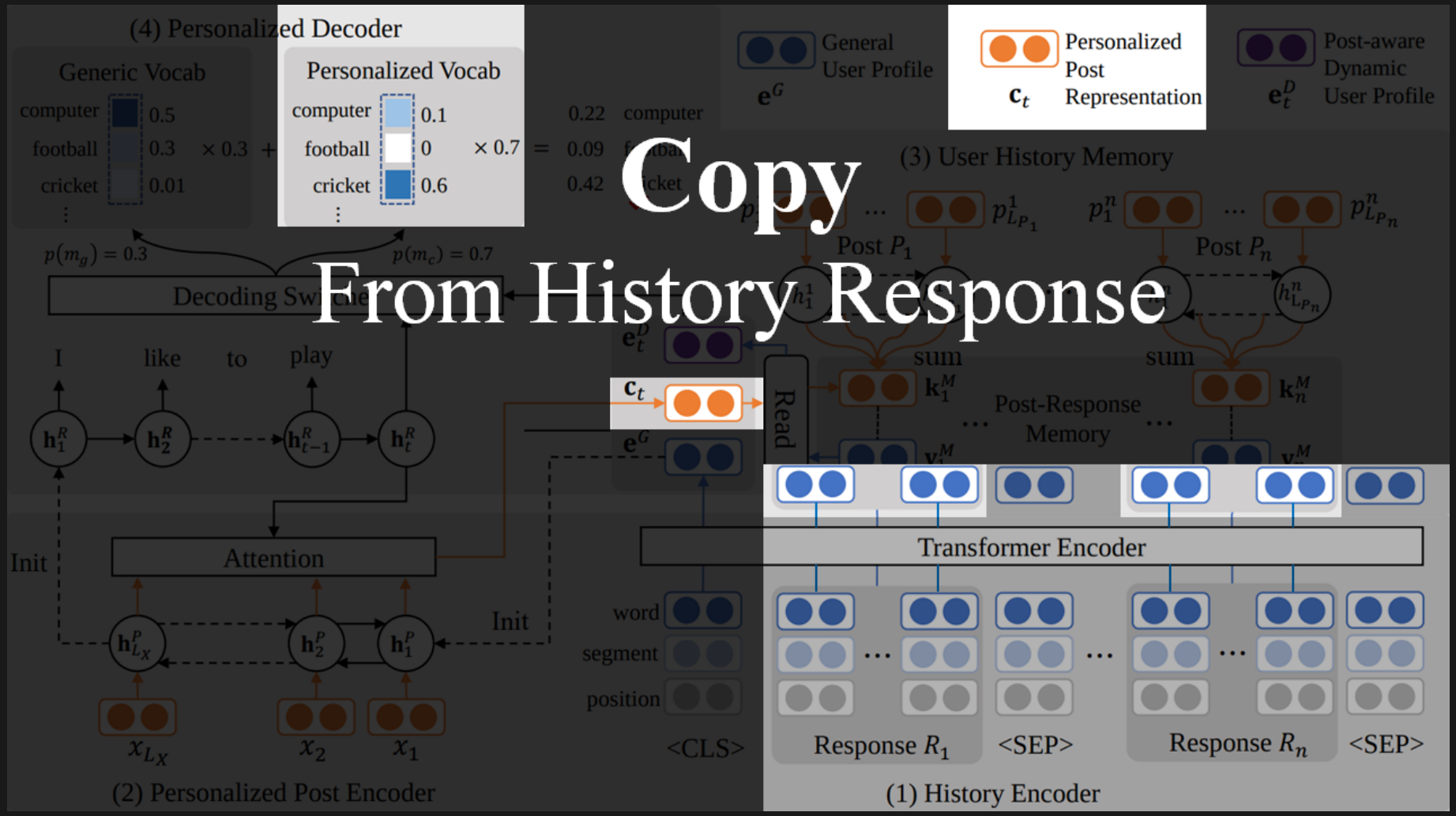
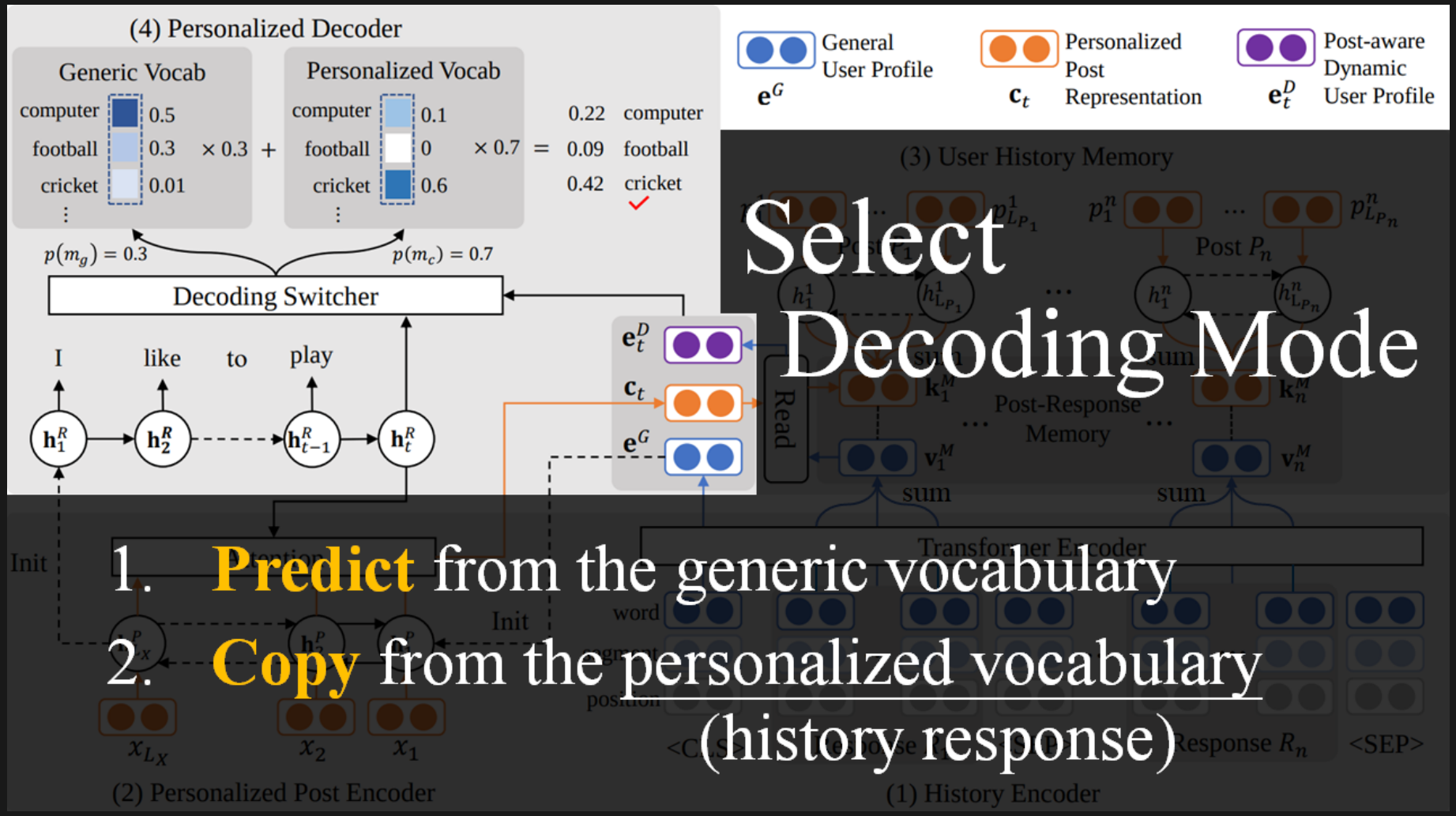
<SEP>
Response R_n
<SEP>
(1) History Encoder
Predict
Generic Response

DHAP(cont.)



Copy From History Response

DHAP(cont.)



Select Decoding Mode

1. **Predict** from the generic vocabulary
2. **Copy** from the personalized vocabulary (history response)

DHAP(cont.)

Personalized Vocab

Calculate $attnWeight(c_t, E^R)$

E^R is the "word" embedding after the historical response sentence passes Transformer.

DHAP(cont.)

Personalized Vocab(cont.)

Attention Weights

A	A	B	C	D	C	A
0.1	0.08	0.2	0.15	0.22	0.13	0.12

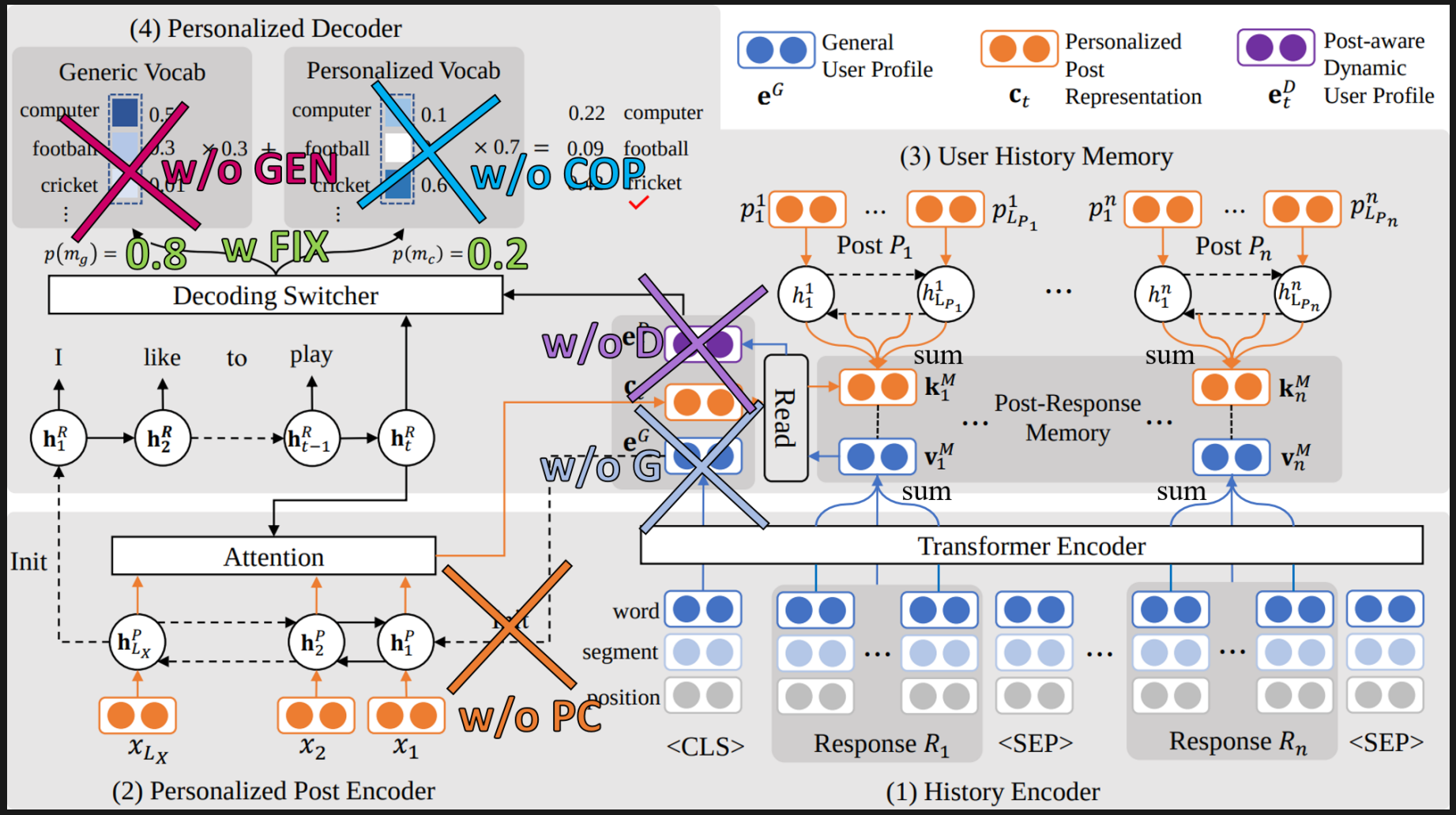
Sum the weights of the same word

A	B	C	D
0.3	0.2	0.28	0.22

Human Evaluation

Model	Readability	Informativeness	Personalization
(1) Seq2SeqWA	2.10†	1.85†	0.19†
(1) MMI	2.06†	1.88†	0.23†
(2) Speaker	<u>2.14</u>†	1.93†	0.25†
(2) PersonaWAE	2.07†	1.99†	0.36†
(3) GPMN	2.12†	1.92†	0.35†
(3) PerCVAE	2.04†	<u>2.01</u>†	0.39†
(4) VHRED-P	2.09†	1.96†	<u>0.47</u>†
(4) ReCoSa-P	2.12†	1.93†	0.44†
(4) DHAP (ours)	**2.26**	**2.09**	**0.56**
Ground-truth	2.69	2.35	0.84

Ablation Study



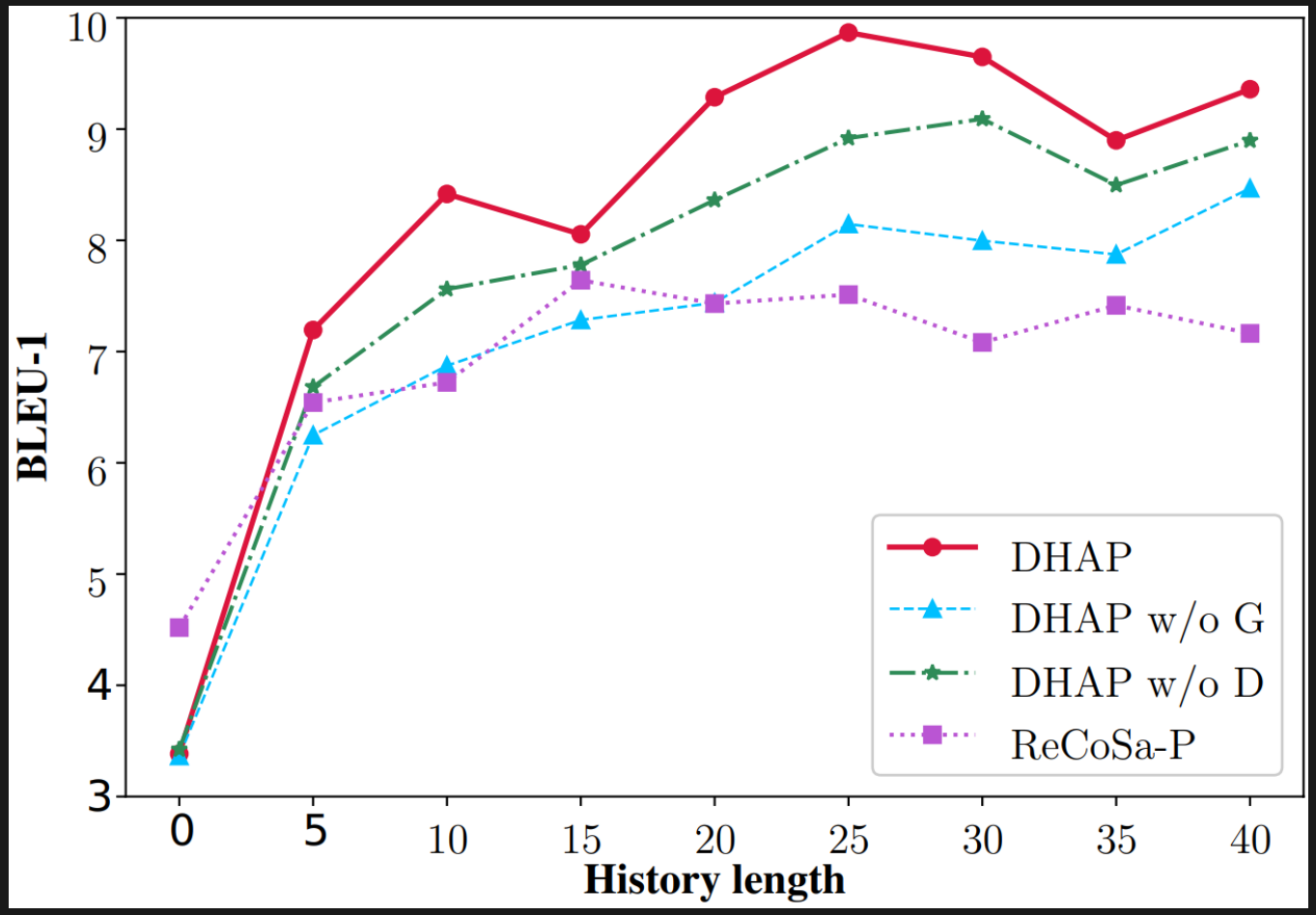
Ablation Study(cont.)

Model	Word Overlap			Diversity	
	BLEU-1	BLEU-2	ROUGE-L	Dist-1	Dist-2
DHAP	**9.324**	**0.894**	**14.122**	**15.175**	**58.806**
w/o G	7.726†	0.801†	11.815†	12.176†	49.808†
w/o D	8.503†	0.855†	12.610†	13.699†	54.623†
w/o PC	8.830	0.868†	13.981	14.457	56.263†
w/o GEN	4.982†	0.328†	9.571†	9.051†	32.566†
w/o COP	8.347†	0.837†	12.585†	13.487†	52.087†
w FIX	8.549†	0.855†	12.871†	13.904†	54.539†

Ablation Study(cont.)

Model	Embedding Similarity			Personalization	
	Average	Extrema	Greedy	P-F1(%)	P-Cover
DHAP	**0.523**	**0.747**	**0.313**	7.013	0.144
w/o G	0.495†	0.707†	0.294†	6.179†	0.107†
w/o D	0.499†	0.713†	0.303†	6.286†	0.109†
w/o PC	0.503†	0.728†	0.301†	6.884	0.120†
w/o GEN	0.478†	0.571†	0.276†	**9.331**	**0.165**
w/o COP	0.499†	0.717†	0.298†	6.234†	0.110†
w FIX	0.496†	0.716†	0.301†	6.326†	0.113†

Ablation Study(cont.)



Conclusion

- Use historical conversations to replace the predefined User Profile.
  - There is no need to prepare expensive User Profile as training data.
  - The ability to dynamically expand has been obtained.
- Too much historical data will introduce noise and degrade performance.

Thanks for your attention.