Persona dialogue

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Dataset

Persona 1	Persona 2
I like to ski My wife does not like me anymore I have went to Mexico 4 times this year I hate Mexican food I like to eat cheetos	I am an artist I have four children I recently got a cat I enjoy walking for exercise I love watching Game of Thrones

[PERSON 1:] Hi
[PERSON 2:] Hello ! How are you today ?
[PERSON 1:] I am good thank you , how are you.
[PERSON 2:] Great, thanks ! My children and I were just about to watch Game of Thrones.
[PERSON 1:] Nice ! How old are your children?
[PERSON 2:] I have four that range in age from 10 to 21. You?
[PERSON 1:] I do not have children at the moment.
[PERSON 2:] That just means you get to keep all the popcorn for yourself.
[PERSON 1:] And Cheetos at the moment!
[PERSON 2:] Good choice. Do you watch Game of Thrones?
[PERSON 1:] No, I do not have much time for TV.
[PERSON 2:] I usually spend my time painting: but, I love the show.

Persona Profile

对话history

→ Response

One-turn / Multi-turns

Personalizing Dialogue Agents: I have a dog, do you have pets too? (ACL 2018)

Persona Dialogue Methods

- Ranking models

  计算相似度，从训练集语料库中检索utterance作为response

- Generative models

  (1) Per-Seq2Seq

  persona profile || dialogue history 编码器编码→隐藏状态→解码器解码

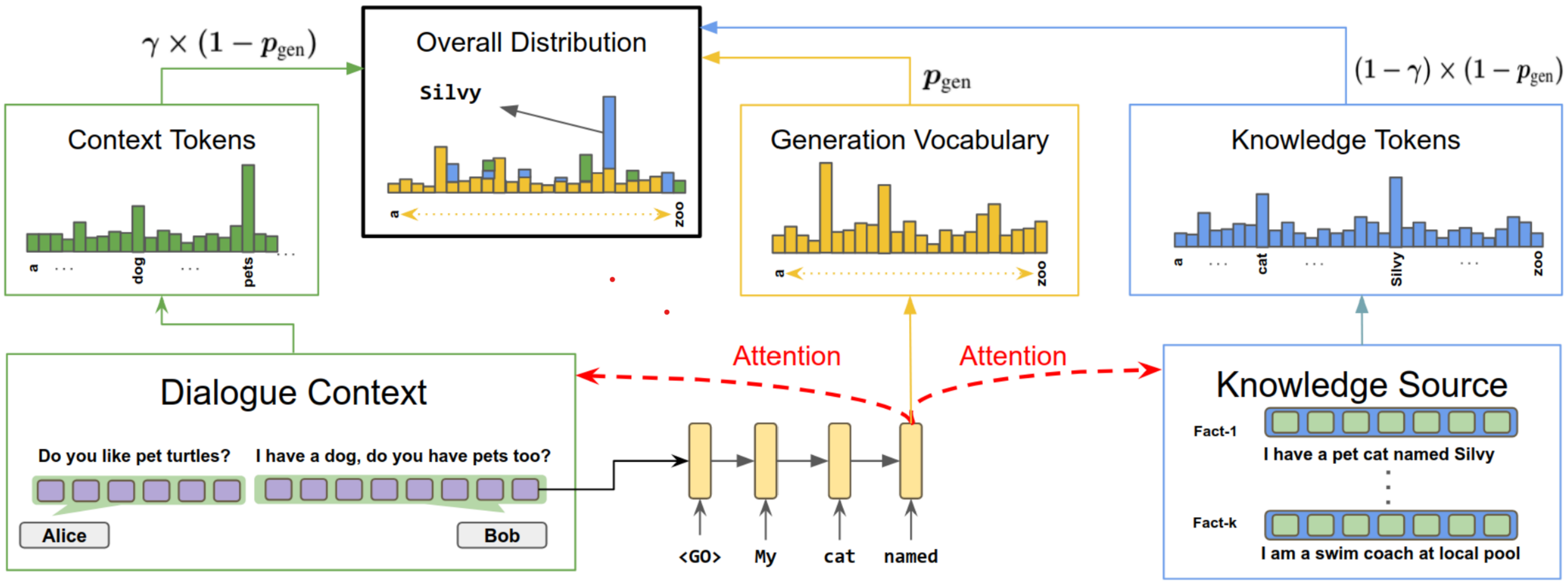
  (2) Generative Profile Memory Network（GPMN）

  history 编码

  each profile entries 编码 (衡量单词重要程度进行单词embedding的累加)

  → 解码器解码 (attends over the encoded profile entries)

DeepCopy



DeepCopy: Grounded Response Generation with Hierarchical Pointer Networks (SIGdial 2019)

Persona-CVAE

- Prior network

根据history和profile，推测潜在变量z（先验）

$p_\theta(z|x,p)$

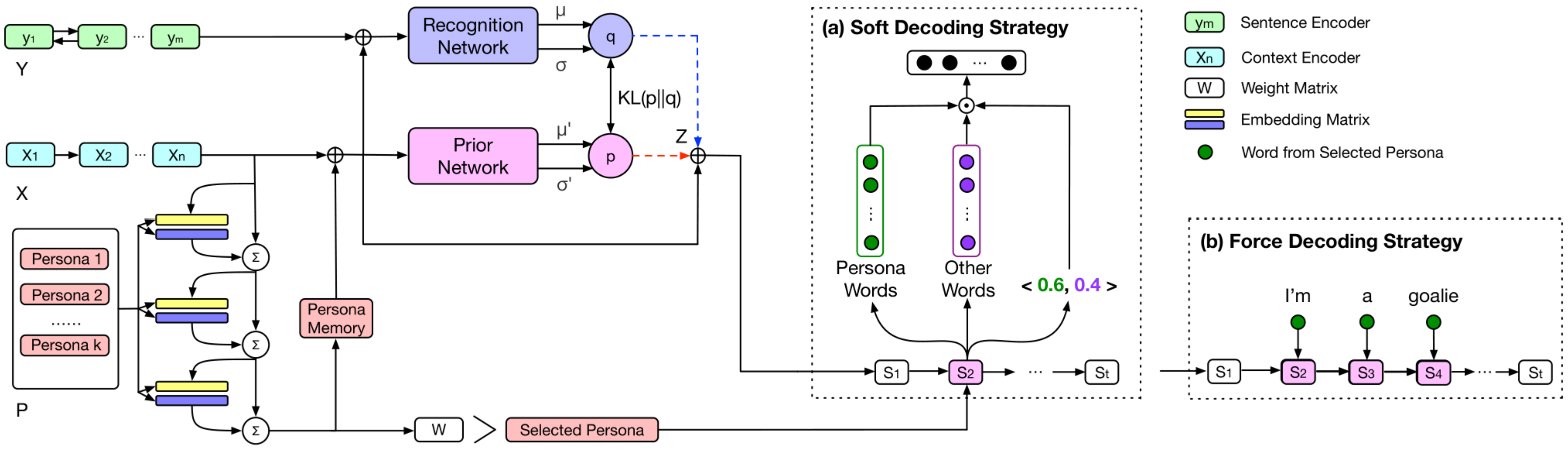
- Recognition network

根据history、profile和response，推测潜在变量（后验）

$q_\varphi(z|x,y,p)$

缩小二者的KL散度

Persona-CVAE



Persona Memory

对Persona texts进行编码，并选择出一条最合适的persona

$$prob_i = \textbf{softmax}(h^{\mathrm{T}}_{context} m_i)$$

$$o = \sum_i prob_i c_i$$

$$u^k = u^{k-1} + o^{k-1}$$

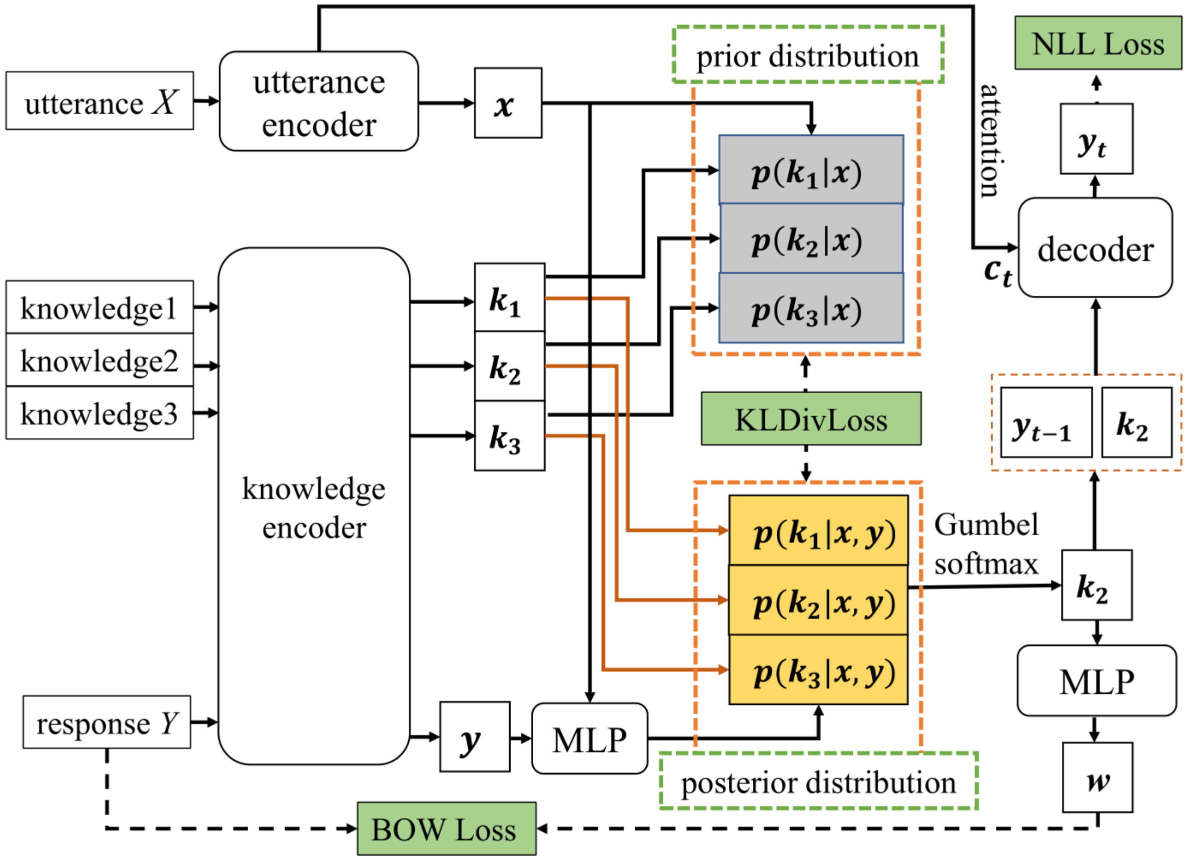
$$\alpha_i = \textbf{softmax}(\mathbf{W_p}[u^3, z]) = \textbf{MLP}([u^3, z])$$

Dialogue history和persona profile，进行多跳的attention

Results

Methods	N = 1			N = 5			N = 10		
	Dtinct-1	**Dtinct-2**	**P. Cover**	**Dtinct-1**	**Dtinct-2**	**P. Cover**	**Dtinct-1**	**Dtinct-2**	**P. Cover**
Seq2Seq	.0125	.0464	.0026	.0031	.0142	.0057	.0018	.0089	.0071
CVAE	.0366	.2080	.0021	.0090	.0875	.0029	.0050	.0663	.0048
Per.-Seq2Seq	.0159	.0745	.0091	.0036	.0213	.0217	.0021	.0139	.0193
GPMN	.0179	.0738	.0080	.0045	.0195	.0184	.0027	.0103	.0178
Oracle. Copy	.0203	.0830	**.0181**	.0050	.0276	.0273	.0031	.0189	.0247
Per.-CVAE	**.0383**⋆	**.2088**	.0167	**.0120**⋆	**.1037**⋆	**.0410**⋆	**.0075**⋆	**.0779**⋆	**.0395**⋆

PostKS



$$p(\mathbf{k} = \mathbf{k}_i|\mathbf{x}) = \frac{\exp(\mathbf{k}_i \cdot \mathbf{x})}{\sum_{j=1}^{N} \exp(\mathbf{k}_j \cdot \mathbf{x})}$$

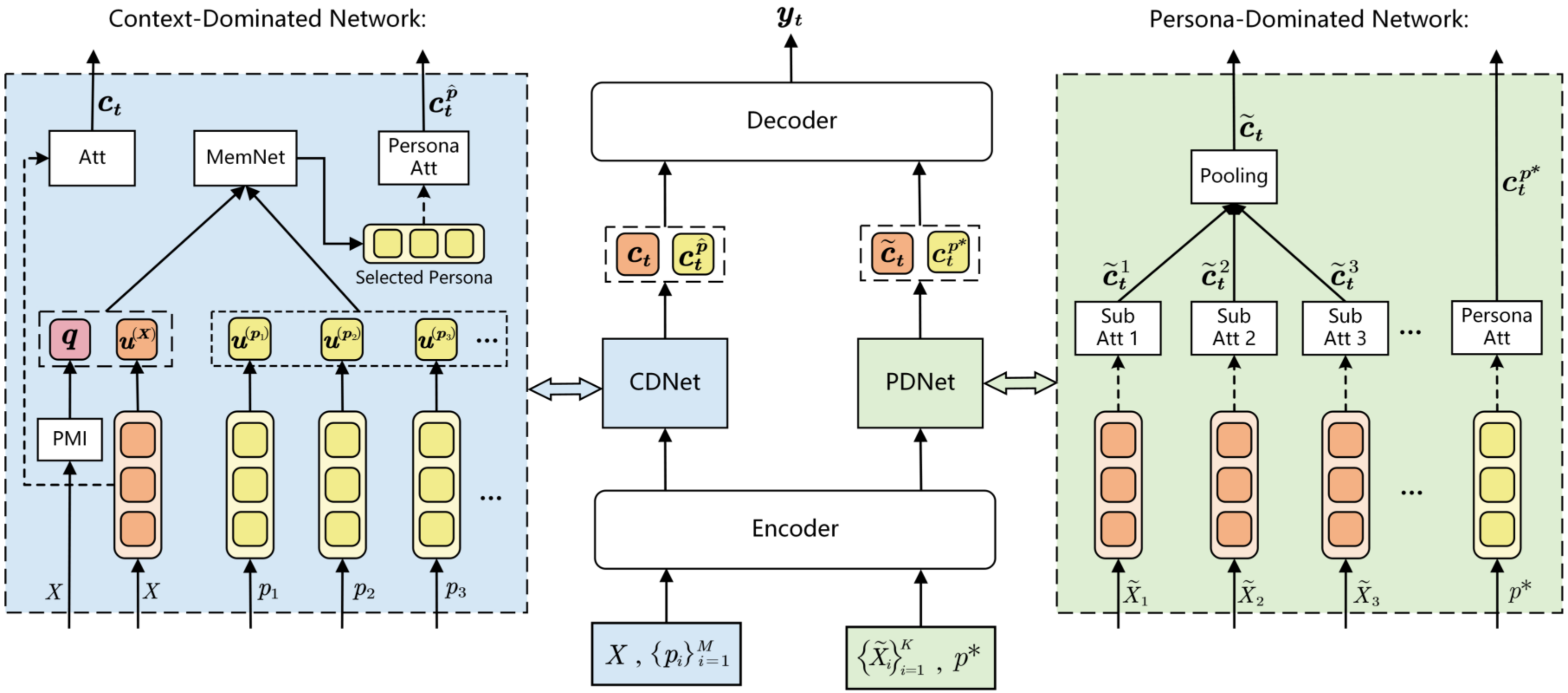
$$p(\mathbf{k} = \mathbf{k}_i|\mathbf{x}, \mathbf{y}) = \frac{\exp(\mathbf{k}_i \cdot \mathsf{MLP}([\mathbf{x}; \mathbf{y}]))}{\sum_{j=1}^{N} \exp(\mathbf{k}_j \cdot \mathsf{MLP}([\mathbf{x}; \mathbf{y}]))}$$

Learning to Select Knowledge for Response Generation in Dialog Systems (IJCAI 2019)

Results

Dataset	Model	Automatic Evaluation			Human Evaluation
		BLEU-1/2/3	Distinct-1/2	Knowledge R/P/F1	
Persona-chat	Seq2Seq	0.182/0.093/0.055	0.026/0.074	0.0042/0.0172/0.0066	0.70
	MemNet(hard)	0.186/0.097/0.058	0.037/0.099	0.0115/0.0430/0.0175	0.79
	MemNet(soft)	0.177/0.091/0.055	0.035/0.096	0.0146/0.0567/0.0223	0.81
	PostKS(concat)	0.182/0.096/0.057	**0.048**/0.126	0.0365/0.1486/0.0567	0.92
	PostKS(fusion)	**0.190/0.098/0.059**	0.046/**0.134**	**0.0574/0.2137/0.0870**	**0.97**

PEDNet



PMI: 提取和Persona Profile高度相关的单词

PEDNet: A Persona Enhanced Dual Alternating Learning Network for Conversational Response Generation (Coling 2020)

Results

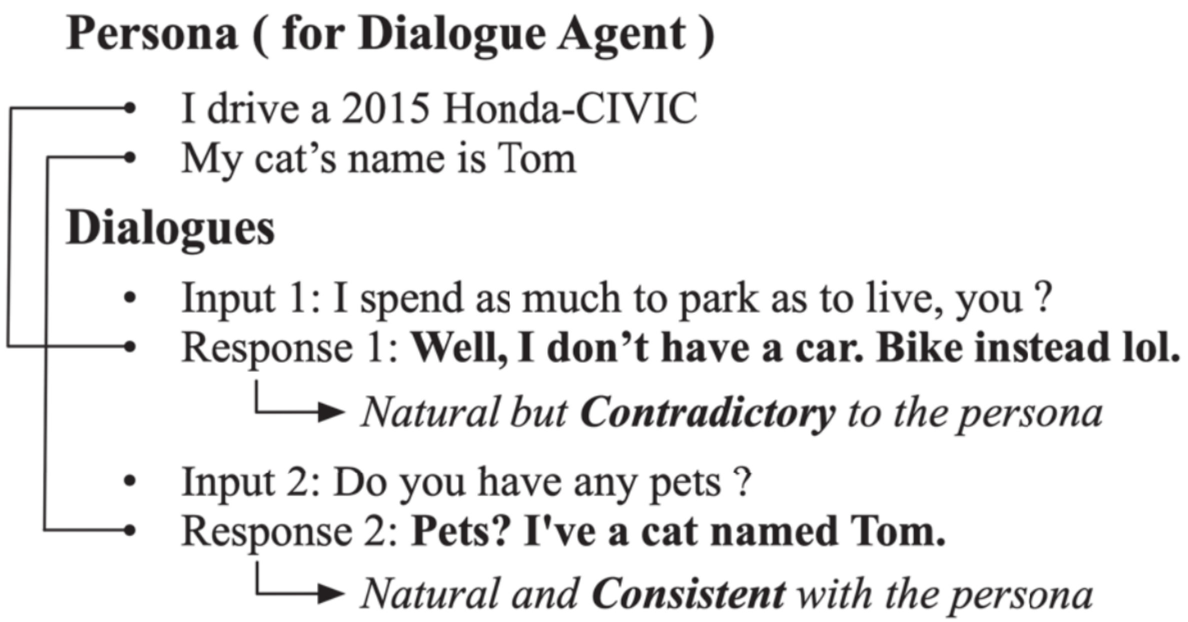
Model	Distinct-1/2	P-R/P/F1	P-Cover
Seq2Seq	0.018/0.064	0.048/0.030/0.037	0.016
GPMN	0.028/0.160	0.082/0.048/0.060	0.034
PostKS	0.031/0.174	0.111/0.068/0.084	0.037
PEDNet ($K = 1$)	0.031/0.165	0.128/0.077/0.096	0.040
PEDNet ($K = 5$)	0.031/0.175	0.136/0.082/0.102	0.044
PEDNet ($K = 10$)	**0.032/0.177**	0.141/0.086/0.107	0.044
PEDNet ($K = 15$)	0.031/0.173	**0.143/0.088/0.109**	**0.045**
PEDNet ($K = 20$)	0.030/0.164	0.133/0.082/0.101	0.041

Consistency

之前的工作重点：产生丰富多样、具有Persona信息的Response

后来又提出了一致性问题：虽然生成的句子和Persona相关联，但内容缺乏一致性

The model will learn to **minimize the overall loss of every decoded word**, but this may lead to **the neglect of the key personas**: change of one **persona-related word** may not significantly affect the overall loss, but could turn a good response into a totally **inconsistent** one.



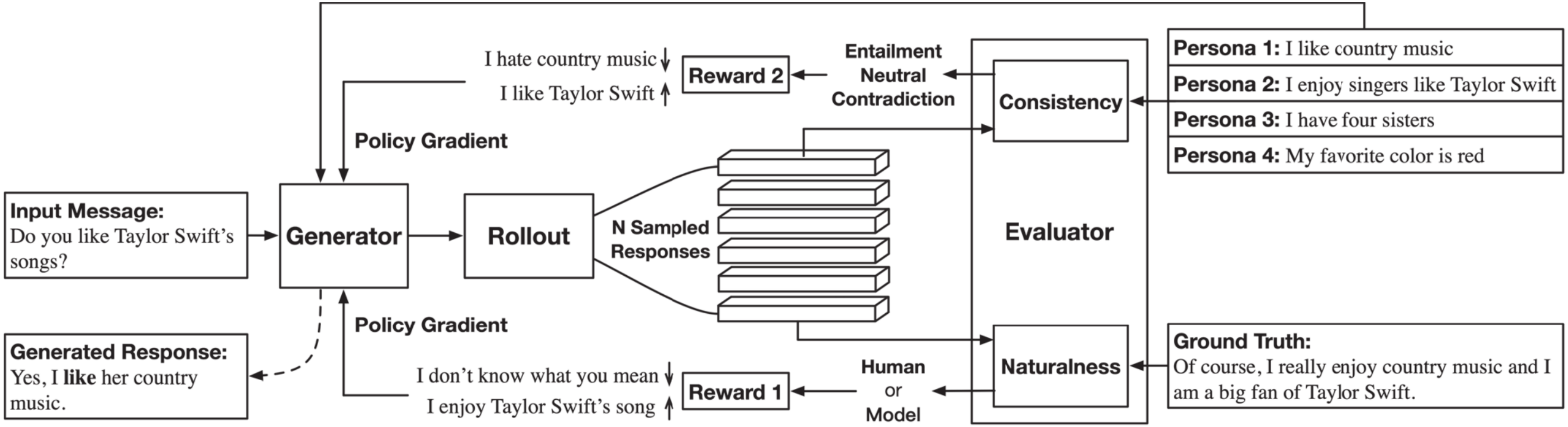
RCDG

- 采用了NLI，判断Persona和Response是否一致
（比如，fine tune Bert on the DNLI dataset，再用Bert判断一致性）
3分类（entail, neutral, contradiction）

- 判断Response是否Naturalness
2分类（Human like / Generator like）

强化学习，上面两个评估得到**Reward1, Reward2**

RCDG

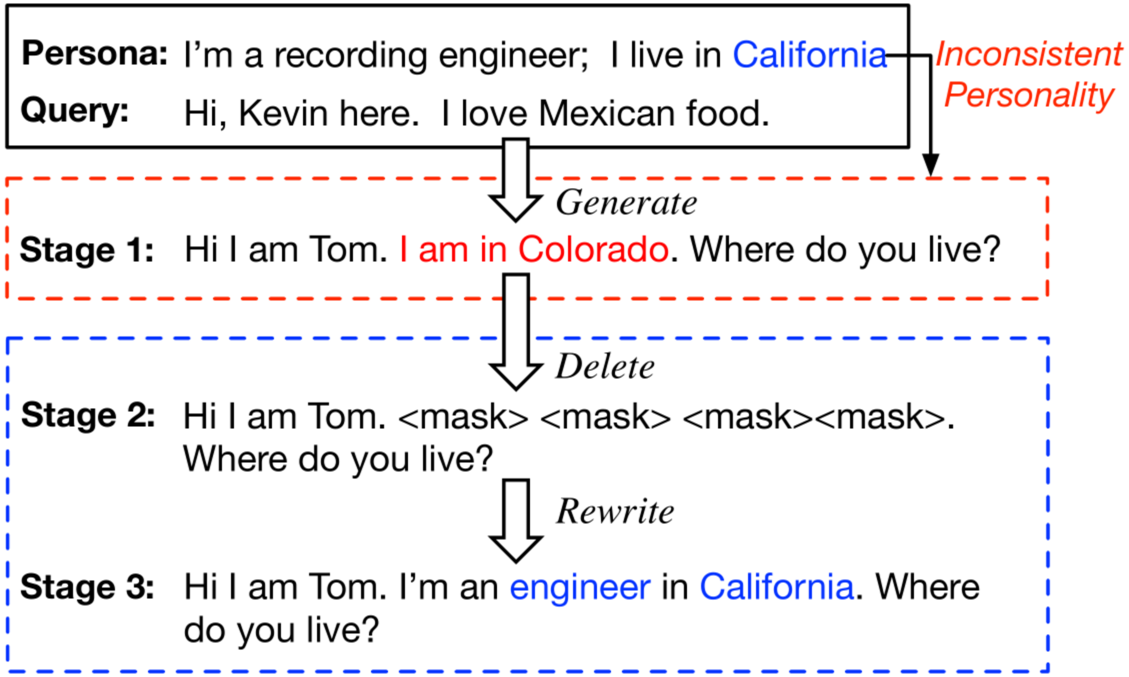


I hate country music
I like Taylor Swift
Reward 2
Entailment
Neutral
Contradiction
Persona 1: I like country music
Persona 2: I enjoy singers like Taylor Swift
Persona 3: I have four sisters
Persona 4: My favorite color is red
Consistency
Policy Gradient
Input Message:
Do you like Taylor Swift's songs?
Generator
Rollout
N Sampled Responses
Evaluator
Policy Gradient
Generated Response:
Yes, I **like** her country music.
I don't know what you mean
I enjoy Taylor Swift's song
Reward 1
Human
or
Model
Naturalness
Ground Truth:
Of course, I really enjoy country music and I am a big fan of Taylor Swift.

RCDG

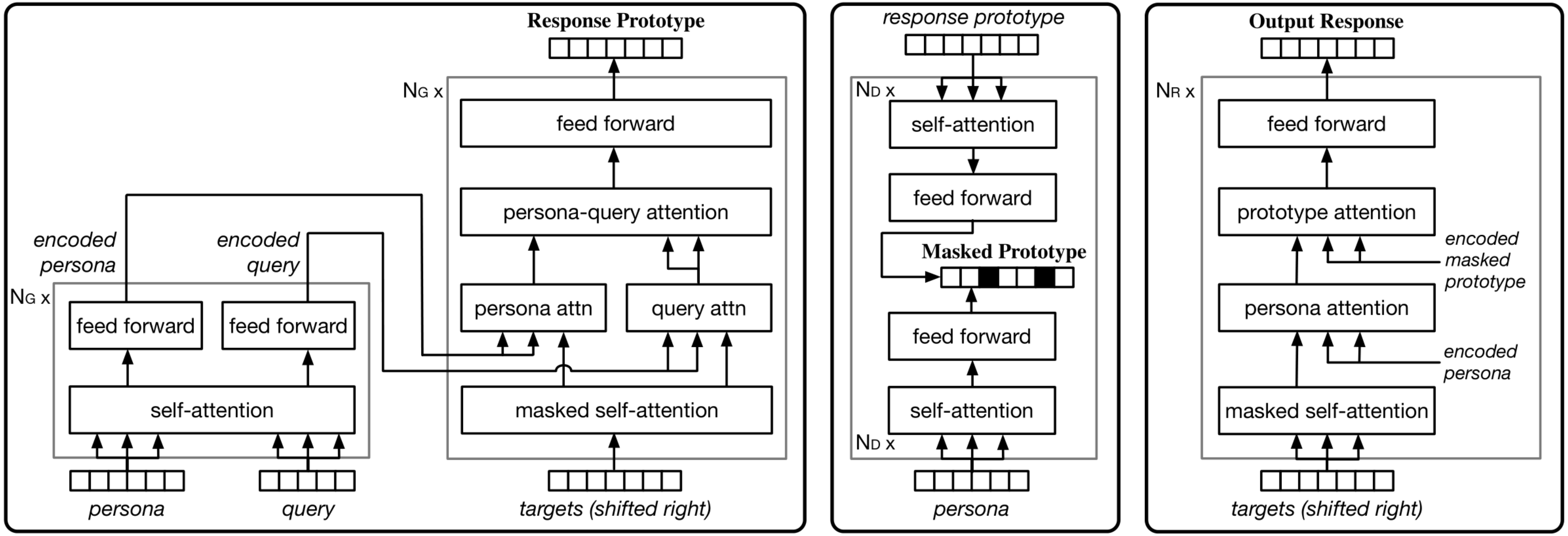
Model	Entail.(%)	Contr.(%)
Human	48.00	1.16*
S2SA	8.37	12.94
GPMN	12.98	11.53
Per-S2S	13.27	12.19
REGS	14.08	10.83
Transformer	14.20	9.00
DeepCopy	14.62	12.17
RCDG_{base}	18.71 (28.0%)	5.93 (34.1%)
RCDG_{bert}	**19.07** (30.4%)	**5.56** (38.2%)

GDR (Generate-Delete-Rewrite)



Generate, Delete and Rewrite: A Three-Stage Framework for Improving Persona Consistency of Dialogue Generation (ACL 2020)

GDR (Generate-Delete-Rewrite)



(1) Generate (2) Delete (3) Rewrite

Results

Model	Const.	Fluc.	Relv.	Info.	PPL	Dist-1.	Dist-2.	Ent_{diin}	Ent_{bert}
S2SA	15.9%	3.17	2.84	2.63	34.8	1.92	4.86	9.80%	1.83%
GPMN	34.8%	3.78	3.57	$3.76^{\dagger}$	34.1	1.89	7.53	14.5%	7.36%
Per-S2S	35.3%	3.43	3.22	3.32	36.1	2.01	7.31	13.5%	6.15%
DeepCopy	36.0%	3.26	3.08	2.87	41.2	2.35	8.93	16.7%	8.81%
Transformer	38.8%	3.46	$3.65^{\dagger}$	3.54	27.9	3.12	15.8	14.2%	9.52%
Per-CVAE	42.7%	3.53	2.97	3.66	-*	**3.83**†	20.9	17.2%	7.36%
GDR (ours)	**49.2%**	**3.86**	**3.68**	**3.77**	**16.7**	3.66	**22.7**	**21.5%**	**13.0%**

TransferTransfo + RL

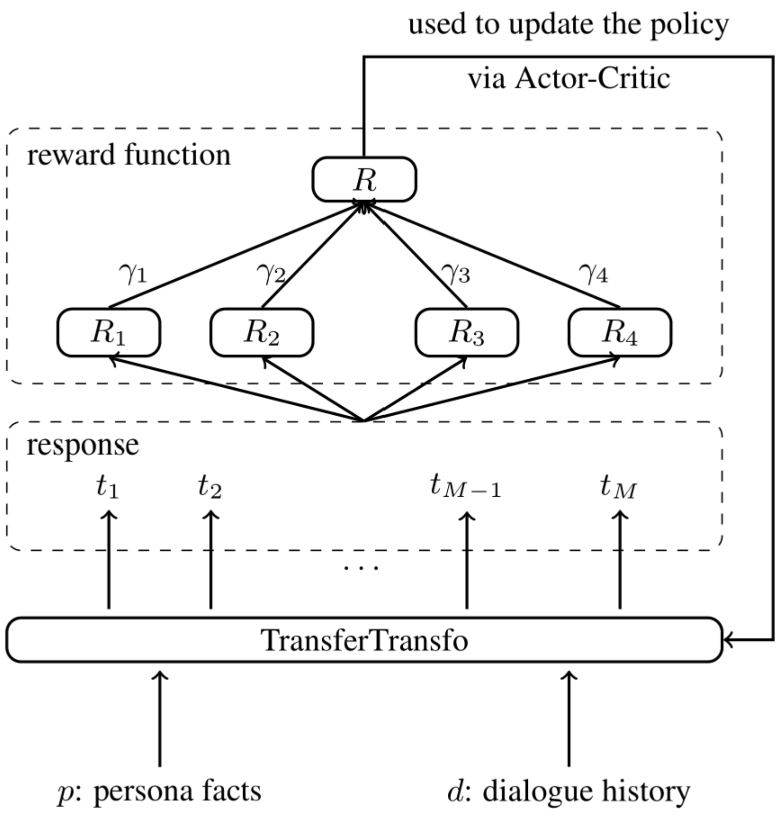


Figure 1: An abstract view of our RL approach.

R1: factual consistency with the persona facts

$$h^{\texttt{[cls]}}, - = \texttt{BERT}(\texttt{[cls]}\, f_i\, \texttt{[SEP]}\, r)\ ,$$
$$[s_e, s_c, s_n] = \texttt{MLP}(h^{\texttt{[cls]}})\ ,$$
$$[\mathcal{P}_e^{\mathrm{NLI}}, \mathcal{P}_c^{\mathrm{NLI}}, \mathcal{P}_n^{\mathrm{NLI}}] = \texttt{Softmax}([s_e, s_c, s_n])$$

R2: topical coherence with the former utterance

Response与U(t-1)的余弦相似度

R3、R4: fluency

(1) Negative Log-Likelihood (NLL) Loss

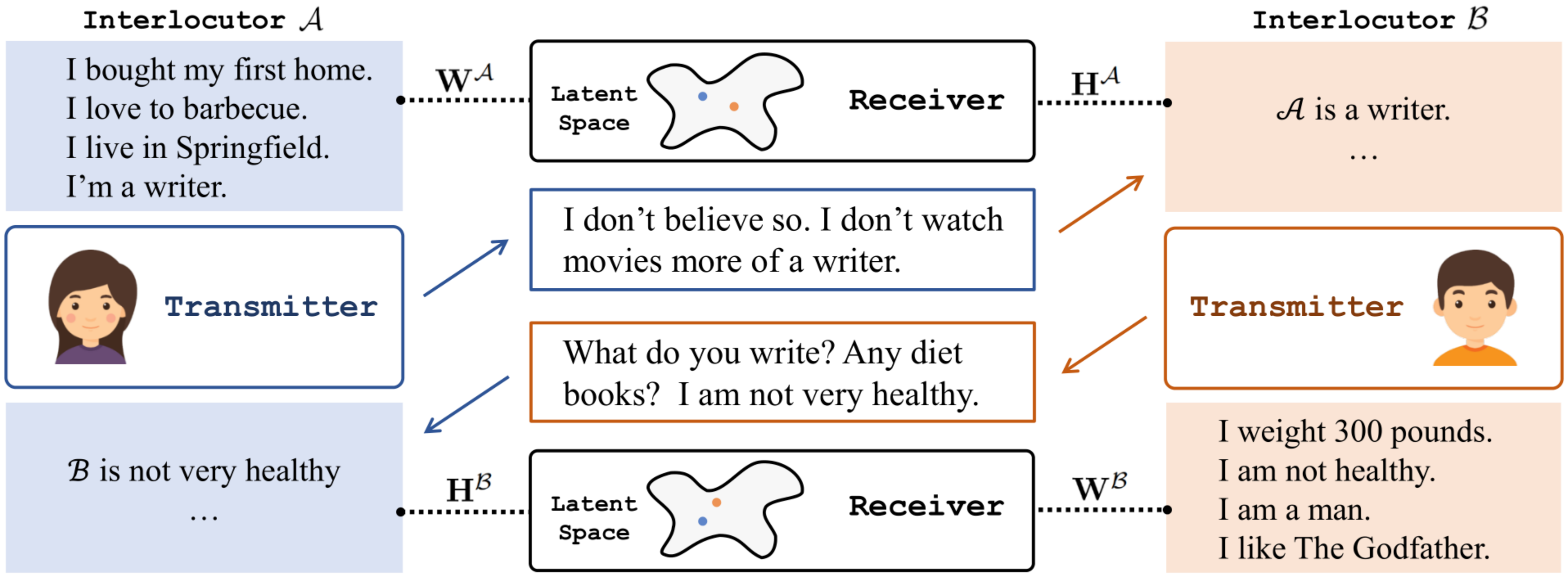
(2) 尽量减少Response中的重复token

Results

Method	PPL	F1	BLEU	PC
TransferTransfo-SL	21.31	17.06	0.065	09.32
TransferTransfo-RL	22.64	**17.78**	**0.067**	**13.06**

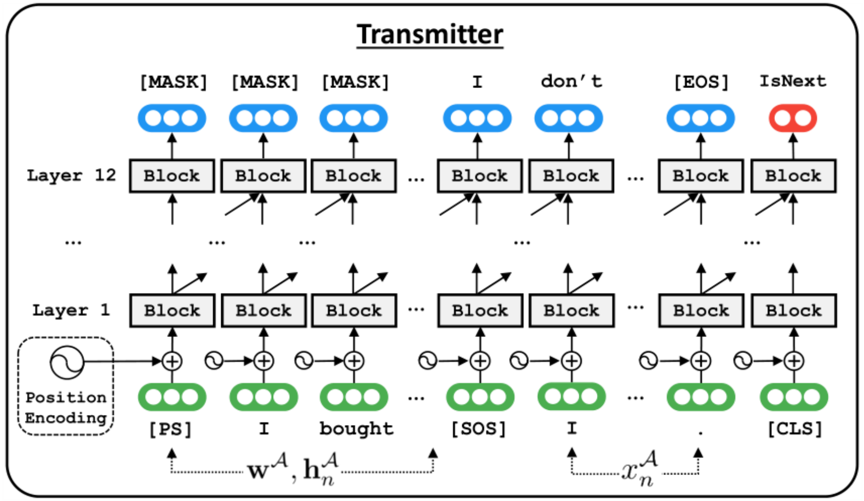
	Consistent	Contradicting	Neutral
Automatic Evaluation			
TransferTransfo-SL	11.14	01.82	87.04
TransferTransfo-RL	**14.81**	**01.75**	**83.43**
Δ	3.41 $\uparrow$	0.07 $\downarrow$	3.61 $\downarrow$
Human Evaluation			
TransferTransfo-SL	43.71	17.71	38.58
TransferTransfo-RL	**52.71**	**14.00**	**33.29**
Δ	9.00 $\uparrow$	3.71 $\downarrow$	5.29 $\downarrow$

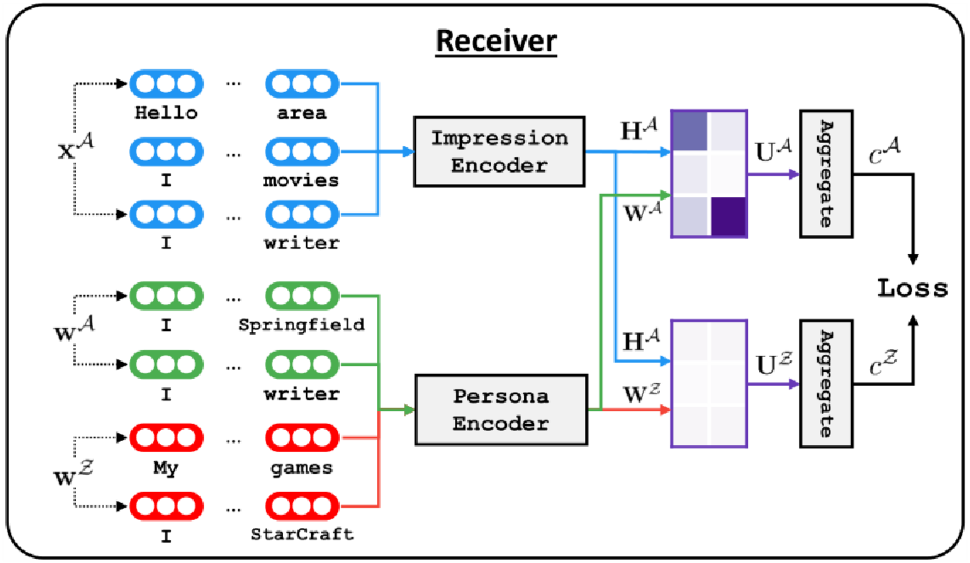
P2 Bot



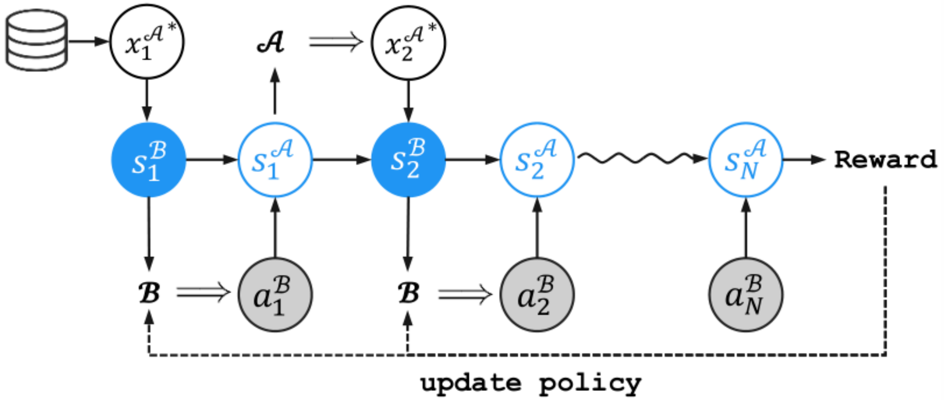
You Impress Me: Dialogue Generation via Mutual Persona Perception (ACL 2020)

P2 Bot





强化学习



RS.1 Language Style

RS.2 Discourse Coherence

RS.3 Mutual Persona Perception

P2 Bot

Category	Model	Original			Revised		
		Hits@1(%)↑	ppl↓	F1(%)↑	Hits@1(%)↑	ppl↓	F1(%)↑
Retrieval	KV Profile Memory	54.8	-	14.25	38.1	-	13.65
	Dually Interactive Matching	78.8	-	-	**70.7**	-	-
Generative	Generative Profile Memory	10.2	35.01	16.29	9.9	34.94	15.71
	Language Model	-	50.67	16.30	-	51.61	13.59
	SEQ2SEQ-ATTN	12.5	35.07	16.82	9.8	39.54	15.52
Pretrain Fintune	Lost In Conversation	17.3	-	17.79	16.2	-	16.83
	Transfertransfo	**82.1**	17.51	19.09	-	-	-
	$\mathcal{P}^2$ BOT (Our)	81.9 [0.1]	**15.12** [0.16]	**19.77** [0.08]	68.6 [0.2]	**18.89** [0.11]	**19.08** [0.07]

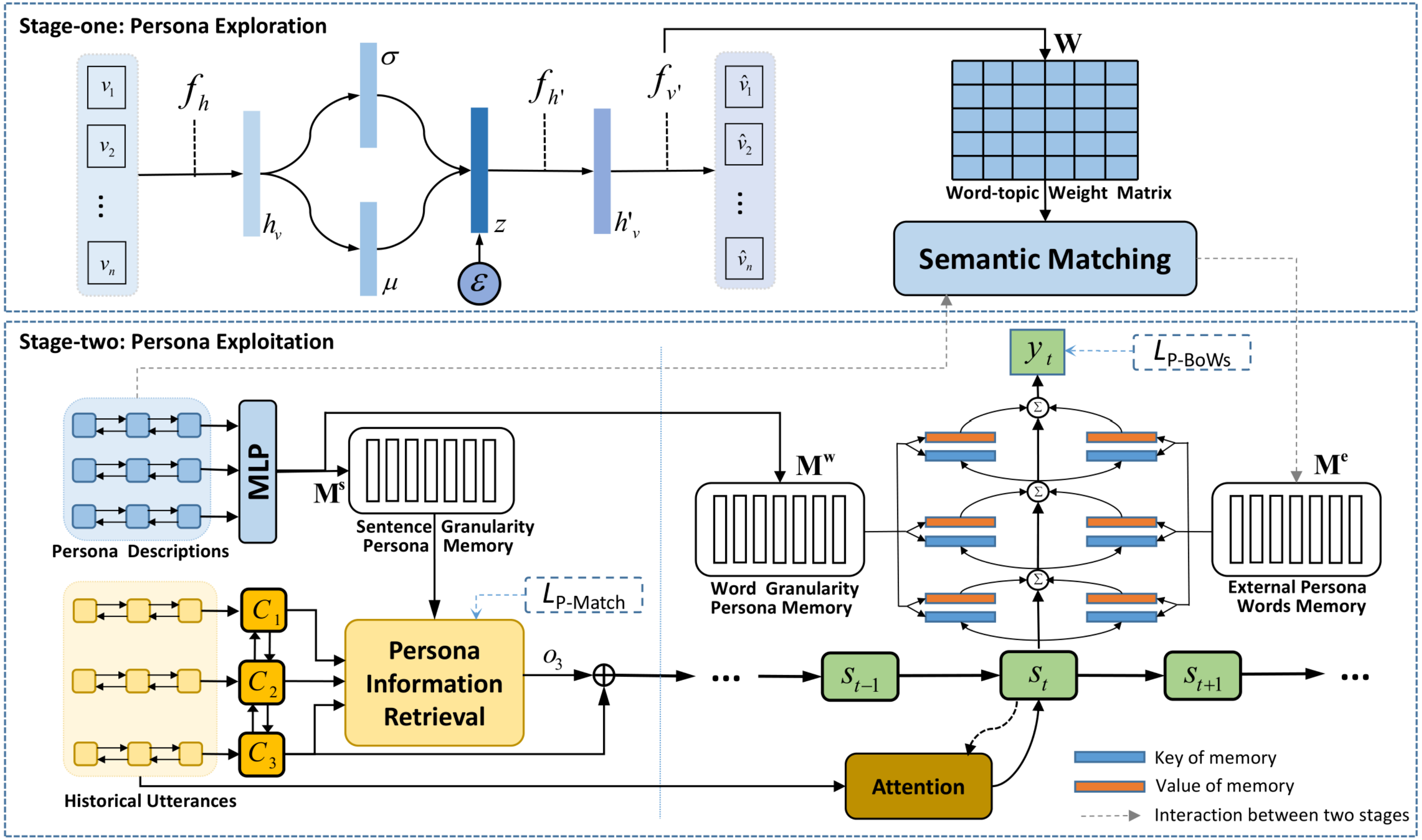
Variant	Hits@1(%)↑	F1(%)↑	BLEU(%)↑
$\mathcal{P}^2$ BOT-S	68.7	18.14	0.56
- Persona	65.5	17.77 (- 2.0%)	0.57 (+ 1.8%)
- Next	17.6	18.11 (- 0.1%)	0.55 (- 1.8%)
+ RS.1	68.4	18.32 (+0.9%)	0.60 (+ 7.1%)
↪ + RS.2	68.6	18.41 (+1.5%)	0.61 (+ 8.9%)
↪ + RS.3	68.6	19.08 (+5.2%)	0.75 (+33.9%)

PEE

预先定义的Persona信息比较简短，内容词汇有限，不能很好的被利用

=> 提出给Persona进行topical expansion，促进后面的decoder解码

PEE



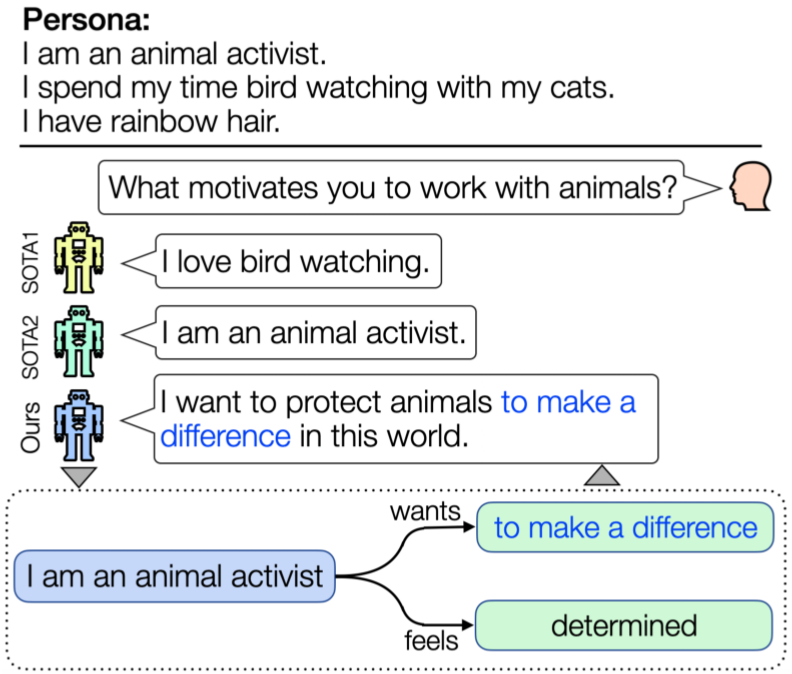
Stage-one: Persona Exploration
W
Word-topic Weight Matrix
Semantic Matching
Stage-two: Persona Exploitation
MLP
Persona Descriptions
Sentence Granularity Persona Memory
Word Granularity Persona Memory
External Persona Words Memory
Persona Information Retrieval
Historical Utterances
Attention
Key of memory
Value of memory
Interaction between two stages

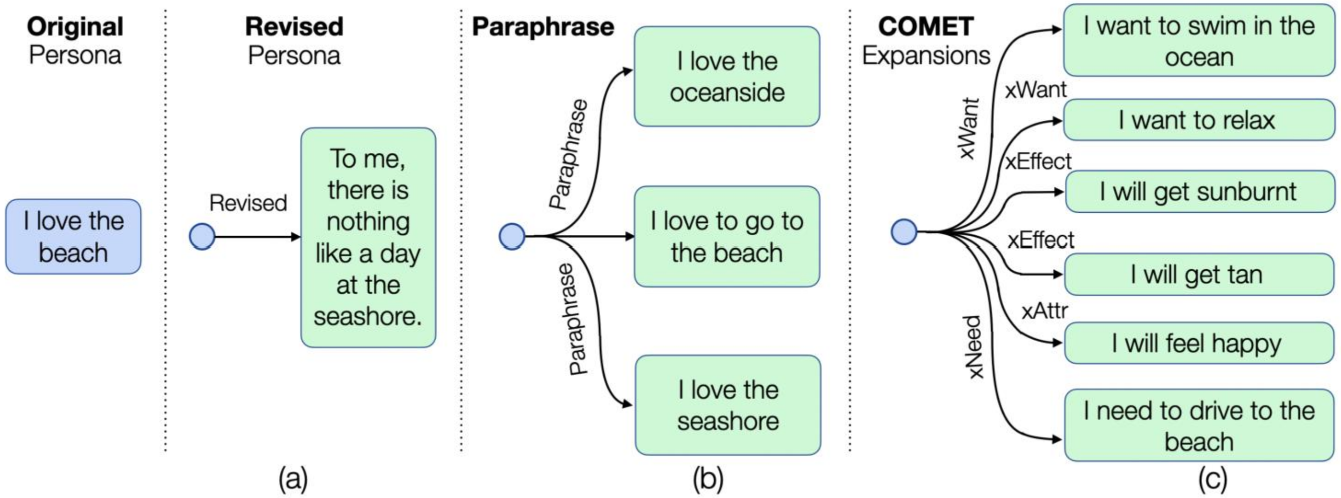
PEE

Table 2. Automatic evaluation results. The best results are bold.

Model	BLEU1	BLEU2	BLEU3	BLEU4	F1	Average	Extrema	Greedy
Seq2Seq	20.1381	9.9395	5.2887	2.9840	17.7972	0.8551	0.4980	0.6751
HRED	19.0920	9.5668	5.0191	2.7779	17.9184	0.8531	0.4882	0.6714
Profile Memory	20.8713	9.8526	4.9942	2.6852	17.1553	0.8675	0.4835	0.6752
Per.-CVAE	17.2315	7.2602	3.2081	1.4541	14.6121	0.8458	0.4688	0.6516
PED	21.4611	10.6992	5.7845	3.3344	**18.4759**	0.8593	0.4993	0.6838
PED+PE	21.8970	10.9987	5.9965	3.5334	18.4140	0.8643	0.4999	0.6856
PED+PE+P-BoWs	21.9768	11.0710	6.0154	**3.5574**	18.2781	0.8626	0.4986	0.6822
PED+PE+P-Match	22.4668	11.2560	5.9846	3.3031	18.2615	0.8592	0.4940	0.6803
PEE	**23.1926**	**11.5166**	**6.1248**	3.4977	18.4130	**0.8691**	**0.5010**	**0.6906**

COMPAC

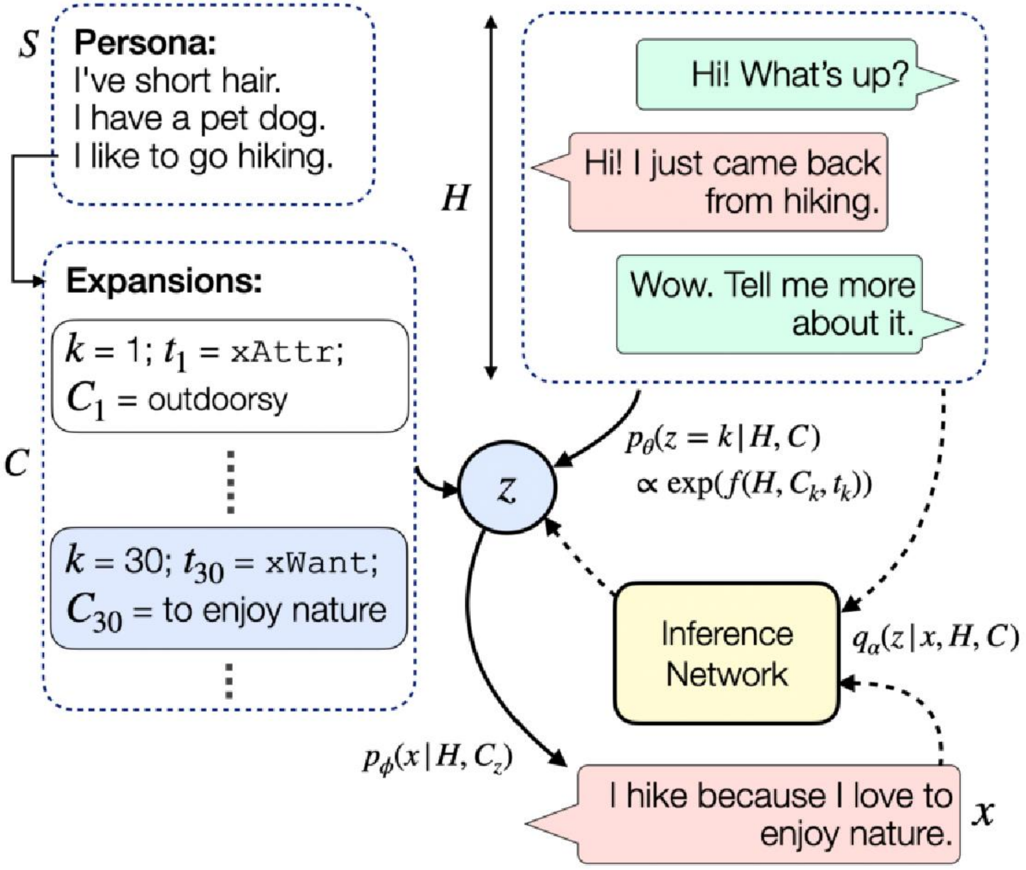




通过常识库扩展Persona信息，丰富

Like hiking? You probably enjoy nature: Persona-grounded Dialog with Commonsense Expansions (EMNLP 2020)

COMPAC



扩充之后，本文的COMPAC模块，用来选择最适合的Persona句子

COMPAC

System	PPL	BLEU-1	BLEU-2	D-1	D-2
Original					
Per-CVAE (2019b)	48.37	0.19	0.11	0.03	0.21
LIC + KS (2019)	30.50	0.18	0.07	0.07	0.24
GPT2 (2019)	21.46	1.42	0.78	0.05	0.11
COMPAC-original	19.56	3.24	1.31	0.15	0.25
Paraphrased					
GPT2-revised	21.01	1.54	0.97	0.13	0.25
GPT2-paraphrase	21.57	1.61	0.86	0.16	0.35
COMPAC-revised	18.12	3.52	0.99	0.48	0.65
COMPAC-paraphrase	17.09	3.83	**1.87**	0.56	0.85
COMET					
GPT2-COMET	21.12	1.62	0.81	0.21	0.39
COMPAC	**16.21**	**4.12**	1.82	**0.87**	**1.07**

System	Persona Entailment		Human
	Prior	Inference Network	eval.
Original			
COMPAC-original	25.5	79.3	–
Paraphrased			
COMPAC-revised	20.6	78.9	40.6
COMPAC-paraphrase	27.8	87.3	67.8
COMET			
COMPAC	**37.9**	**96.4**	**87.3**