

Transfer Learning in Personalized Dialogue Generation

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A Simple Question

- What is the relation between **Pre-Training** and **Transfer Learning** ?

A Simple Question

- What is the relation between **Pre-Training** and **Transfer Learning** ?
 - **Pre-Training \subseteq Transfer Learning**
 - Transfer Learning has a wider scope. Details please refer to *A Survey on Transfer Learning*
 - In NLP, Pre-Training is the highlight of Transfer Learning
 - Word2Vec
 - BERT

Paper List

1. Neural Personalized Response Generation as Domain Adaptation, WWW Journal 2019
2. TransferTransfo-A Transfer Learning Approach for Neural Network Based Conversational Agents, AAI 2019
3. Large-scale transfer learning for natural language generation, ACL 2019
4. A Pre-training Based Personalized Dialogue Generation Model with Persona-sparse Data, AAI 2020

Background

Rank	Creator	PPL	Hits@1	F1
1 🍏	🤗 (Hugging Face)	16.28 🍏	80.7 🍏	19.5 🍏
2 🍏	ADAPT Centre	31.4	-	18.39
3 🍏	Happy Minions	29.01	-	16.01
4 🍏	High Five	-	65.9	-
5 🍏	Mohd Shadab Alam	29.94	13.8	16.91
6 🍏	Lost in Conversation	-	17.1	17.77
7 🍏	Little Baby(AI小奶娃)	-	64.8	-

2. AAI 2019

3. ACL 2019

- NeurIPS 2018 Conversational Intelligence Challenge 2 (ConvAI2)
- <http://convai.io/>

Background

任务二：个性化对话竞赛排行榜

排名	更新日期	系统名称	机构名称	BLEU	Perplexity	Distinct
1	2019/7/14	persona-translator	彩云科技&句子互动	0.0130	101.98	0.1689
2	2019/7/5	foxi persona	网易伏羲实验室	0.0061	292.67	0.2160
3	2019/7/6	Persona-dialogue	中国科学院深圳先进技术研究院	0.0055	232.60	0.0520
4	2019/7/15	wizare_smp	华南理工大学-CIKE实验室	0.0055	354.23	0.0872
5	2019/7/15	smp	WRFML LAB	0.0042	503.46	0.0467
6	2019/7/3	PAA_dialog	东北大学	0.0024	450.73	0.0447
7	2019/7/14	SIMPLE-Dialogue	NEU NLP LAB	0.0049	189.96	0.0325
8	2019/7/15	baseline1	复旦大学大数据学院	0.0009	1540.31	0.0437

4. AAI 2020

- SMP 2019 The 3rd Evaluation of Chinese Human-Computer Dialogue Technology (SMP-ECDT 3)

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1. Domain Adaptation-Information

- **Title:** Neural Personalized Response Generation as Domain Adaptation
- **Authors:** Wei-Nan Zhang, Ting Liu, Yifa Wang, Qingfu Zhu
- **Affiliation:** Harbin Institute of Technology

1. Domain Adaptation-Details

- **Goal:** To generate personalized dialogues based on Seq2Seq Model

Table 1: An example of the responses of different personality to a given post.

Post	Is it a proper dress for the first date?
Response #1	Yep.
Response #2	Honey, it is very suitable!
Response #3	It is better to wearing a silk scarf.

- No explicit persona texts are given

1. Domain Adaptation-Details

- **Models:** a two-phase approach, **initialization** and **adaptation**

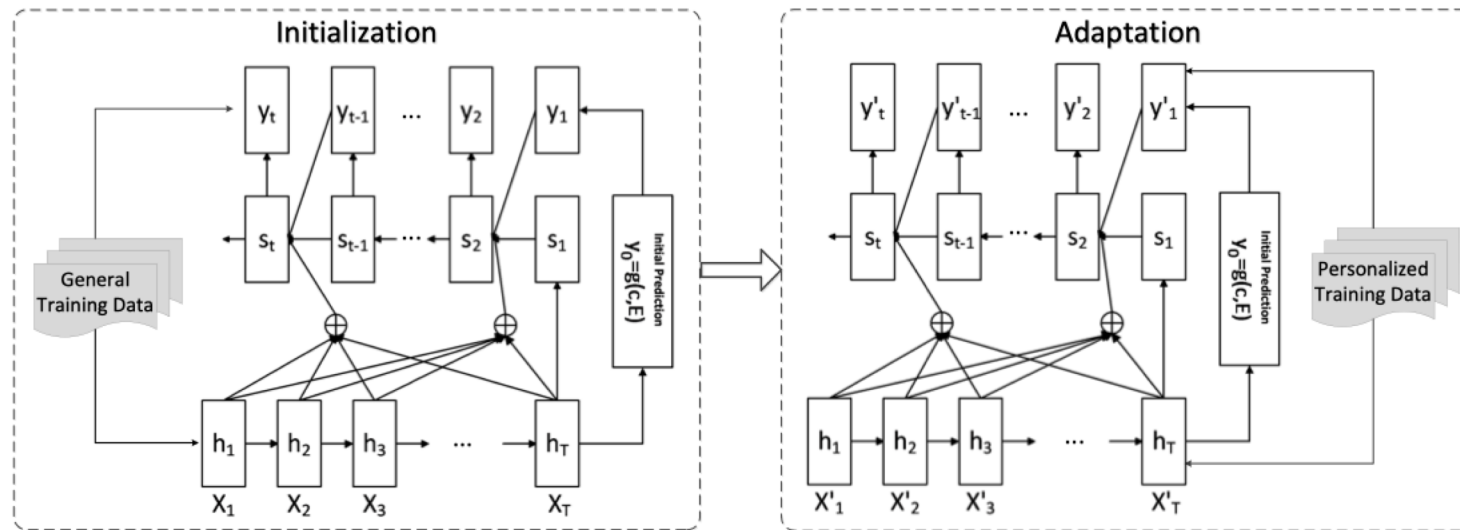


Figure 1: The framework of the proposed approach.

1. Domain Adaptation-Details

- **Dataset Collection**

- General Data

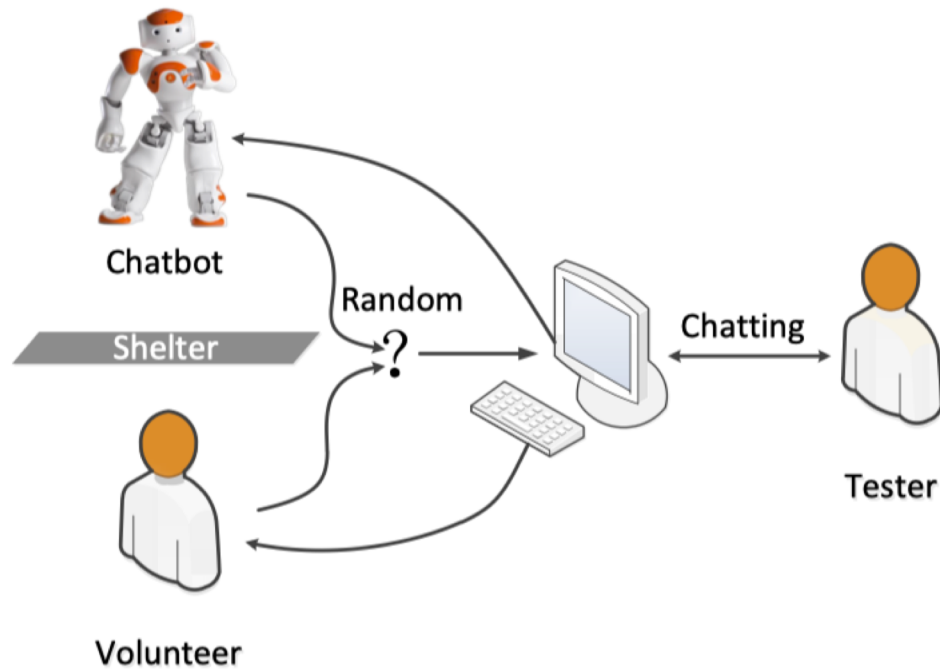
- 1 million one-to-one post-response pairs from several Chinese online forums, such as Weibo and Douban.

- Personalized Data:

- 5 volunteers, each shared 2,000 messages of their chatting history.
 - Then retrieve posts, which have similar responses to the personalized messages, from general data. The post-message pairs are the personalized data.

1. Domain Adaptation-Details

- Experiment Results – imitation rate



$$r_{imi} = \frac{n_{imi}}{n_{gr}}$$

1. Domain Adaptation-Details

- Experiment Results – Human Evaluation

Table 3: The experimental results of the proposed approach to personalized response generation. n_{gr} and n_{vr} represents the number of responses that are generated by the chatbot and the volunteer respectively. n_{test} is the total number of posts for testing. n_{imi} denotes the number of responses that is generated by the chatbot but are judged as the responses of the volunteer. r_{imi} denotes the imitation rate, which is defined in Equation (9).

	Volunteer #1	Volunteer #2	Volunteer #3	Volunteer #4	Volunteer #5	Sum
n_{gr}	29	26	21	33	33	142
n_{vr}	21	24	29	17	17	106
n_{test}	50	50	50	50	50	250
n_{imi}	11	9	8	13	9	50
r_{imi}	37.93%	34.62%	38.10%	39.40%	27.27%	35.21%

1. Domain Adaptation-Details

- Experiment Results – Human Evaluation

Table 4: The evaluation results of the 5 personalized response generation models by human judgement. n_{gr} represents the number of responses that are generated by the chatbot. n_{imi} denotes the number of responses that is generated by the chatbot but are judged as the responses of the volunteer. r_{imi} denotes the imitation rate, which is defined in Equation (9). PRM is short for the personalized responding model.

	PRM #1	PRM #2	PRM #3	PRM #4	PRM #5
n_{gr}	50	50	50	50	50
n_{imi}	6	8	8	13	10
r_{imi}	12%	16%	16%	26%	20%

1. Domain Adaptation-Details

- Experiment Results – Word Statistics

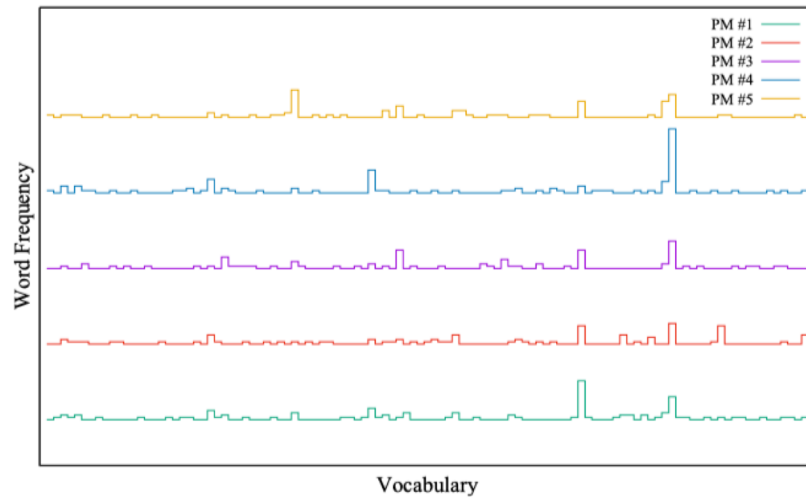


Figure 3: The distributions of the responding words on the vocabulary.

Table 6: The percentage of the overlapping words between the volunteer’s responses and the chatbot generated responses for a same post set. “V” is short for “Volunteer”.

	PRM #1	PRM #2	PRM #3	PRM #4	PRM #5
V #1	20.00%	17.86%	8.73%	14.78%	9.65%
V #2	15.45%	18.64%	8.13%	12.00%	10.83%
V #3	17.65%	10.75%	22.22%	14.77%	9.57%
V #4	17.63%	16.82%	8.28%	17.92%	11.32%
V #5	12.12%	12.96%	6.73%	10.28%	18.52%

1. Domain Adaptation-Details

• Experiment Results – Some Cases

Table 5: The real cases of the same post with different responses generated by PRM #1 - #5 models.

Post	Models	Responses
在哪能租到房子? (Where can I rent a house?)	PRM #1	我不知道那个网站。(I don't know the website.)
	PRM #2	去找一个吧。(To hunt a house.)
	PRM #3	市区。(The downtown.)
	PRM #4	联系中介吧。(You can contact the accommodation agency.)
	PRM #5	我这有地方住。(I have somewhere to stay.)
什么编程语言最好? (What is the best programming language?)	PRM #1	日语。(Japanese.)
	PRM #2	通常来说是Java。(Generally speaking, it is Java.)
	PRM #3	计算机语言。(The computer language.)
	PRM #4	不用。(I don't need.)
	PRM #5	PHP。(PHP.)
洗衣服好累啊。 (It is too tired to wash the clothes.)	PRM #1	用洗衣机洗。(Use the washing machine.)
	PRM #2	累。(I'm tired.)
	PRM #3	我能。(I can.)
	PRM #4	恩。(Yes.)
	PRM #5	去休息吧。(Have a rest.)

1. Domain Adaptation-Summaries

- This work was initialized at the end of 2016. At that time, transfer learning and pre-training in dialogues are not as ubiquitous as today.
- This work is suitable as a baseline:
 - It is a published paper
 - Easy to implement
 - Easy to outperform

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4. A Pre-training Based Personalized Dialogue Generation Model with Persona-sparse Data, AAI 2020

2. TransferTransfo-Information

- **Title:** TransferTransfo: A Transfer Learning Approach for Neural Network Based Conversational Agents
- **Authors:** Thomas Wolf, Victor Sanh, Julien Chaumond and Clement Delangue
- **Affiliation:** HuggingFace Inc.

2. Transfer Transfo-Motivation

- **The well-known challenges in open-domain dialogues:**
 - The lack of a consistent personality
 - The absence of a long-term memory
 - A tendency to produce consensual and generic responses

2. TransferTransfo-Details

- **Goals**

- To generate persona-based responses (a generative model)
- To select 1 response from 20 candidates (a retrieval model)

- **Metrics**

- Perplexity, F1, Hits@1
- Real-time human interactive evaluation

2. TransferTransfo-Details

- **Model**

- TransferTransfo → Transfer Transformer
- A 12-layer decoder-only transformer with masked self-attention heads (768 dimensional states and 12 attention heads)
- It is in the same architecture to the openAI GPT. But the GPT 2018 did not prove its effectiveness in generation tasks (only verified on NLU tasks).

2. TransferTransfo-Details

- Dataset

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

2. TransferTransfo-Details

- 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.

2. TransferTransfo-Details

- **Pre-training Data**

- The BooksCorpus dataset (Zhu et al., 2015), containing over 7,000 unpublished books (about 800M words) from a variety of genres.
- Using the document-level corpus rather than a shuffled sentence-level corpus.
- Taking advantage of long contiguous sequences and paragraphs and learn to condition on long-range information.

2. TransferTransfo-Details

- **Input Representation**

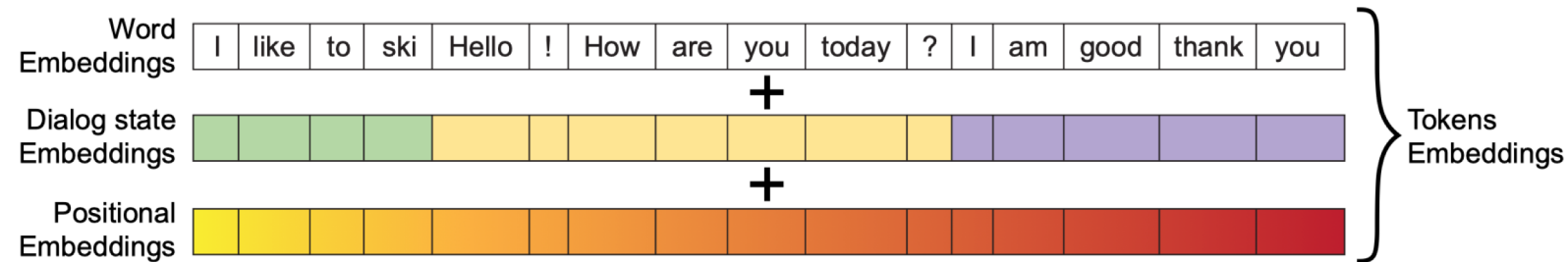


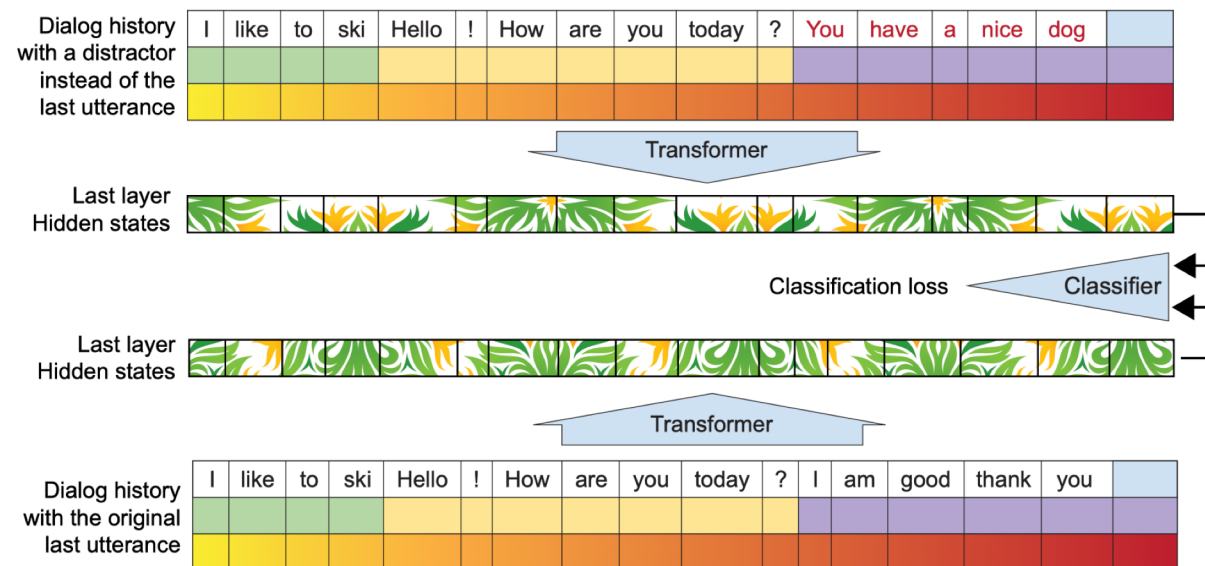
Figure 1: TransferTransfo's input representation. Each token embedding is the sum of a word embedding, a dialog state embedding and a positional embedding.

- input sequence = persona texts + dialogue history
- dialogue history = speak_A_1 + speak_B_1 + speak_A_2 + ...
- reusing the same positional embeddings for each persona texts to promote an invariance to persona texts ordering

2. TransferTransfo-Details

- **Multi-task learning**

- A language model loss (cross-entropy)
- A next-utterance classification loss



Similar to the Next Sentence Prediction task in BERT (a parallel work):

Training a head to distinguish a correct next utterance appended to the input sequence from a set of randomly sampled distractors (in practice between 2 and 6 randomly sampled utterances).

2. TransferTransfo-Details

- **Fine-tuning details**

- batch size of 32, an average of 250 tokens
- 200,000 steps, about 2 epochs on PersonaChat
- Adam with a learning rate of $6.25e-5$, $\beta_1 = 0.9$, $\beta_2 = 0.999$
- dropout probability of 0.1 on all layers
- 10 hours on four K80 GPUs

2. TransferTransfo-Details

- Results

Model	Eval			Test		
	PPL	Hits@1	F1	PPL	Hits@1	F1
Generative Profile Memory (Zhang et al., 2018)	34.54	12.5	–	–	–	–
Retrieval KV Profile Memory (Zhang et al., 2018)	–	51.1	–	–	–	–
Seq2Seq + Attention (ConvAI2 baseline ⁵)	35.07	12.5	16.82	29.8	12.6	16.18
Language Model (ConvAI2 baseline ⁴)	51.1	–	15.31	46.0	–	15.02
KV Profile Memory (ConvAI2 baseline ⁵)	–	55.1	11.72	–	55.2	11.9
TransferTransfo (this work)	17.51	82.1	19.09	16.28	80.7	19.5

- Hits@1 of two retrieval models (on the hidden Test set):

4 🍏	High Five	–	65.9	–
7 🍏	Little Baby(AI小奶娃)	–	64.8	–

2. TransferTransfo-Details

- Are these metrics good ? (excerpt from competition summary)

LESSONS?

- *How good are these automated metrics?*

- There was **some** correlation between PPL and hits@1 and human evaluation



- **However, Major ISSUE with F1:**

- Mega-dumb baseline pick a combination of frequent words:

- “**i am you to do the a, and your is like!?**”

each turn would give the **best F1 score in the competition** 😂

(**19.6** on the test set and **20.5** on the valid set compared to Hugging Face’s 19.5 and 19.1)



- In any case, shown not be correlated well with human metrics (Liu et al, 2016)

2. TransferTransfo-Summaries

- This paper presented their work in ConvAI2, and its superior performance largely benefits from the pretrained GPT.
- This work is an early attempt in leveraging pre-trained LM for dialogue generation. Before BERT (Oct. 2018) and GPT (Jun. 2018), few people knew the power of pretrained transformers.
- Although it is a short paper, it has been cited by 38 times since 2019 and has an impact on later work such as DialogueGPT.

Paper List

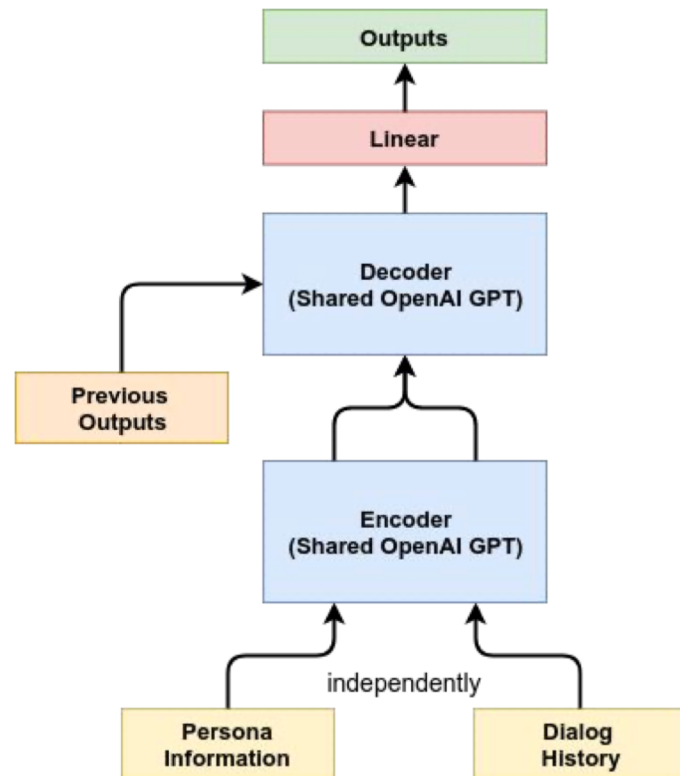
1. Neural Personalized Response Generation as Domain Adaptation, WWW Journal 2019
2. TransferTransfo-A Transfer Learning Approach for Neural Network Based Conversational Agents, AAI 2019
3. **Large-scale transfer learning for natural language generation, ACL 2019**
4. A Pre-training Based Personalized Dialogue Generation Model with Persona-sparse Data, AAI 2020

3. Lost in Conversation-Information

- **Title:** Large-Scale Transfer Learning for Natural Language Generation
- **Authors:** Sergey Golovanov, Rauf Kurbanov, Sergey Nikolenko et al.
- **Affiliation:** Neuromation OU, Estonia; Steklov Mathematical Institute at St.Petersburg.

3. Lost in Conversation-Details

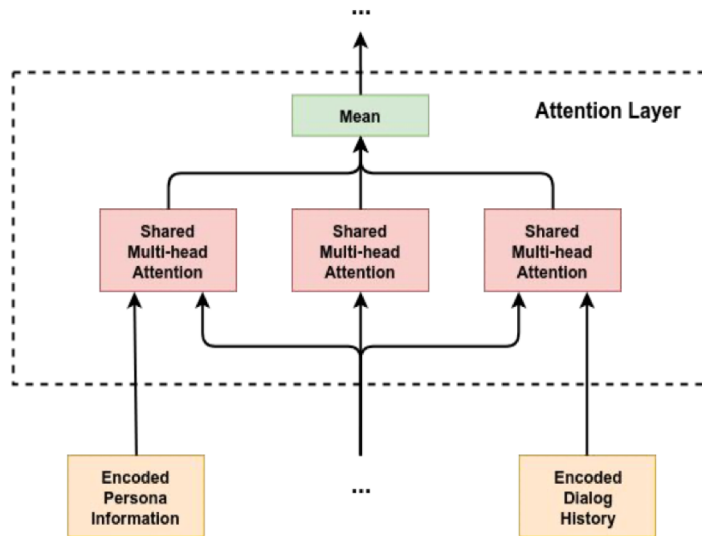
- Model



- Shared encoder and decoder - pretrained OpenAI GPT
- Shared pre-softmax linear layer and token embeddings
- Beam-search with length penalty and annealing for improving answer diversity
- Reduction of persona information and dialog history – first and last 512 tokens respectively

3. Lost in Conversation-Details

- Model



Attention layer modifications:

- Shared multi-head attention layers
- Parallel computation of attention for inputs
- Merge of attentions - mean

3. Lost in Conversation-Details

- **Dataset:** PersonaChat
- **Pre-Training Dataset**
 - DailyDialog
 - Li Y. et al. DailyDialog: A Manually Labelled Multi-turn Dialogue Dataset
 - Reddit comments dataset
 - files.pushshift.io/reddit/comments

3. Lost in Conversation-Details

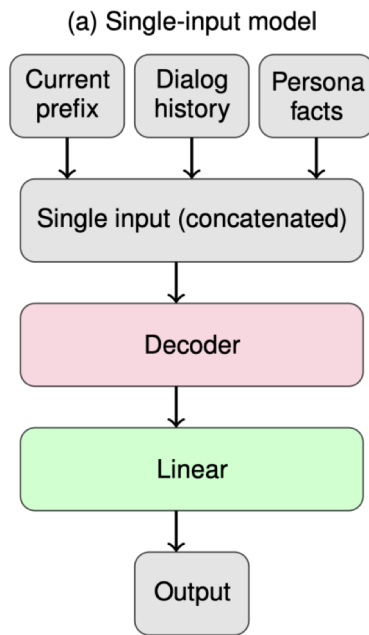
- **Training Settings**

- batch size: 256
- learning rate: $6.25e-5$
- warmup: 16000
- label smoothing: 0.1
- dropout: 0.1

- First stage: one week on Nvidia GTX 1080TI
- Finetuning stage: about two days on Nvidia GTX 1080TI

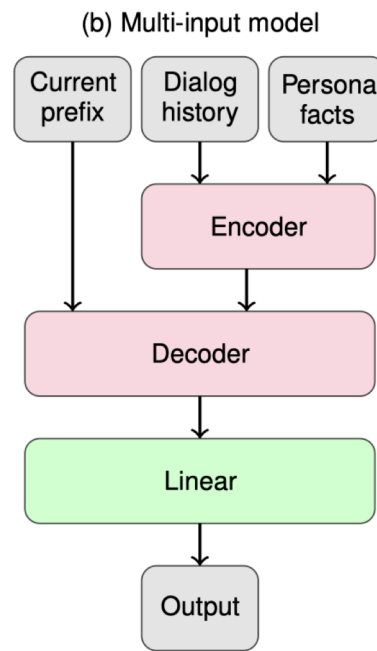
3. Lost in Conversation-Details

- The Interesting Part of This Paper: Compare two architectures



Decoder-Only

VS



Encoder-Decoder

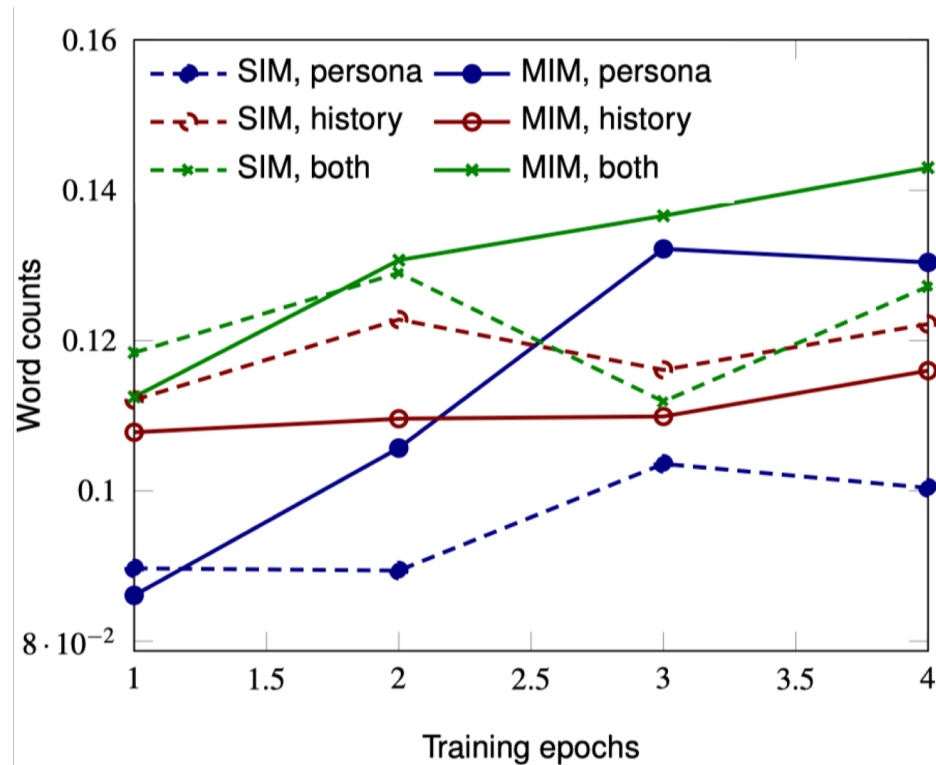
3. Lost in Conversation-Details

- **The Interesting Part of This Paper: Compare Two Architectures**
 - Both architectures reach comparable performances on the automatic metrics

Model	METEOR	NIST-4	BLEU	Entropy-4	Distinct-2	Average Length
Single-input (zero-shot)	0.07727	1.264	2.5362	9.454	0.1759	9.671
Single-input (additional embeddings)	0.07641	1.222	2.5615	9.234	0.1614	9.43
Multi-input	0.07878	1.278	2.7745	9.211	0.1546	9.298

3. Lost in Conversation-Details

- The Interesting Part of This Paper: Compare Two Architectures



Words are labeled to three categories:

1. words that were mentioned in the **persona texts**;
2. words that were mentioned in the **dialog history**;
3. words that were mentioned in **both**

Conclusion:

1. **Single-input** stays closer to the **dialog history**
2. **Multi-input** stays closer to **persona texts**

Possible Reasons:

Persona texts are **not ordered**. In Single-input model, they are handled sequentially. Older history becomes less relevant.

3. Lost in Conversation-Summaries

- This model got the best human evaluation results in ConvAI2 final round.

Rank	Creator	Rating
1 🥑 🍌	Lost in Conversation [code]	3.11 🍌
2 🥑 🍎 🍎 🍎	😊 (Hugging Face)	2.68
3 🥑	Little Baby(AI小奶娃)	2.44

- It is an educated guess that encoder-decoder structure is more suitable for dialogue generation tasks.

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4. Pre-training Persona-sparse Generation

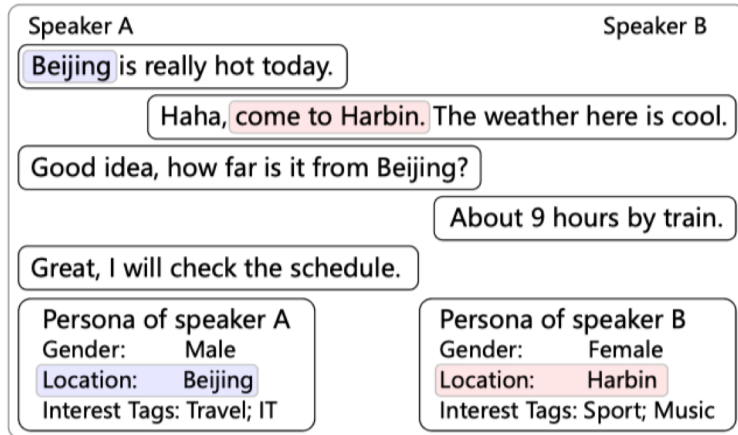
- **Title:** A Pre-training Based Personalized Dialogue Generation Model with Persona-sparse Data
- **Authors:** Yinhe Zheng, Rongsheng Zhang, Xiaoxi Mao, Minlie Huang
- **Affiliation:** Tsinghua University; NetEase Inc.; Samsung Research

4. Pre-training Persona-sparse Generation

- What is “persona-sparse” ?
 - Most speakers in daily conversations are not aiming to exhibit their personas within limited turns of interactions.
 - Data collected from real-world conversations only contain a limited amount of dialogues that relate to speakers’ persona.
 - In contrast, **PersonaChat** is a **persona-dense** dataset. Its collection scheme guaranteed to yield dialogues that cover rich persona features.

4. Pre-training Persona-sparse Generation

• Dataset



Total number of dialogues	5.44 M
Total number of speakers	1.31 M
Total number of utterances	14.40 M
Dialogues with more than 4 utterances	0.81 M
Average utterances per dialogue	2.65
Average tokens per utterance	9.46

- SMP-ECDDT 2019 Dataset
- Collected from Chinese social media Weibo
- Weibo post and its replies, together with a structured profile of each speaker
- **Random test set** contains 10K sessions of randomly sampled dialogues
- **Biased test set** provides contexts which speakers tend to reveal their personas, selected by humans.

4. Pre-training Persona-sparse Generation

- **Pre-training Dataset**

- A dataset collected from a set of Chinese novels, which covered a variety of genres (including Comedy, Romance, Mystery).
- The final pre-training corpus contains about 0.5 billion tokens.
- a character-level language model with a vocabulary size of 13,084.

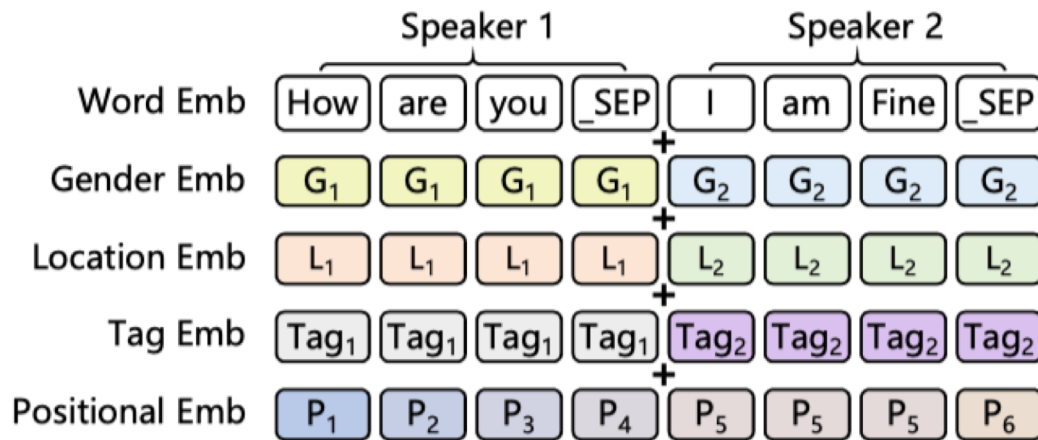
4. Pre-training Persona-sparse Generation

- **Solutions**

- a pre-training based method that can utilize persona-sparse data
- an **attention routing mechanism** to weigh persona features dynamically in the decoder

4. Pre-training Persona-sparse Generation

- Encoding Persona



- Sum of a word embedding, a positional embedding and attribute embeddings
- Attribute embedding is obtained by utilizing look-up tables
- Interest Tags is computed as the average of all the tag embeddings

4. Pre-training Persona-sparse Generation

- Model

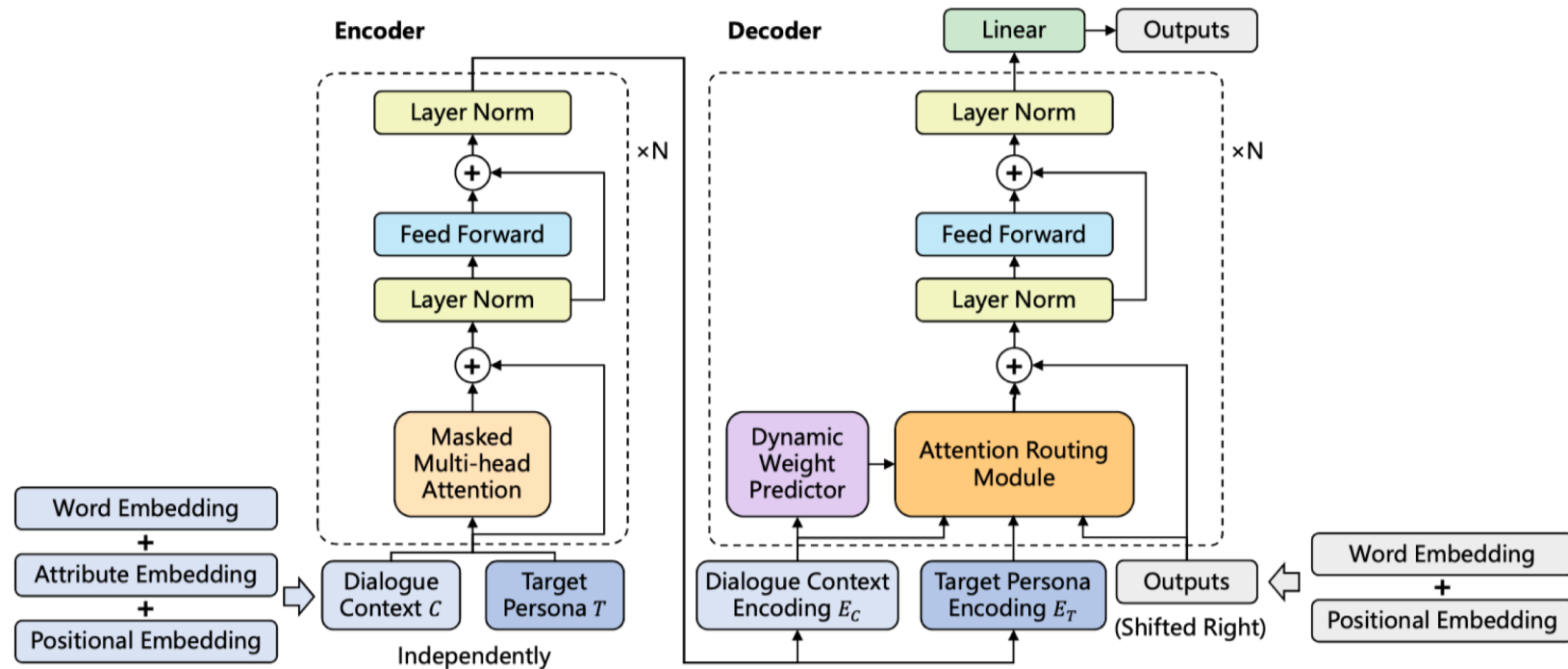


Figure 2: The framework of the proposed personalized dialogue generation model. The encoder and decoder share the same set of parameters. The dialogue context and the target persona are encoded independently using the encoder and their encodings are fed into the attention routing module in each decoder block. A dynamic weight predictor is trained to weigh the contribution of each route.

4. Pre-training Persona-sparse Generation

• Attention Routing

$$O_T = \text{MultiHead}(E_{prev}, E_T, E_T) \quad (2)$$

$$O_C = \text{MultiHead}(E_{prev}, E_C, E_C) \quad (3)$$

$$O_{prev} = \text{MultiHead}(E_{prev}, E_{prev}, E_{prev}) \quad (4)$$

$$O_{merge} = \alpha O_T + (1 - \alpha) O_C + O_C + O_{prev} \quad (5)$$

- E_{prev} previous decoded words
- E_T target profile
- E_C dialogue context
- α the confidence of the response is persona related

4. Pre-training Persona-sparse Generation

- Automatic Results

Table 2: Automatic evaluation on the random test set.

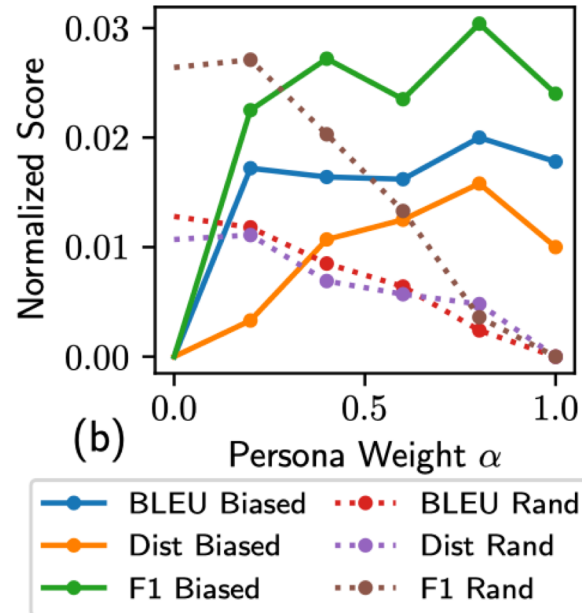
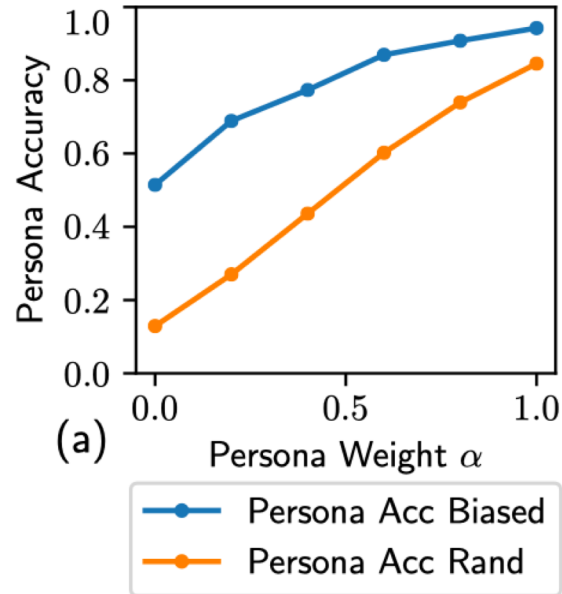
Model	Acc.	BLEU	F1	Dist.	ppl.
Att+PAB	13.99	1.61	8.60	0.130	69.30
Trans.	7.80	3.97	12.51	0.132	43.12
TTransfo	8.80	4.06	12.63	0.169	32.12
TTransfo+P	43.05	3.44	11.28	0.158	43.78
LConv	9.45	4.19	12.99	0.157	32.64
LConv+P	48.00	3.56	11.46	0.136	42.00
Ours	32.80	4.18	12.52	0.171	35.06
Ours, $\alpha=1$	84.55	3.45	10.96	0.154	38.56
Ours, $\alpha=0$	12.90	4.56	13.02	0.171	33.71
w/o PreT	27.10	3.86	11.62	0.146	48.48
w/o AEmb	31.85	4.15	12.56	0.164	35.75
w/o DWP	30.70	4.15	12.34	0.169	34.10
+ HW	32.55	3.50	11.90	0.151	38.52

Table 3: Automatic evaluation on the biased test set.

Model	Acc.	BLEU	F1	Dist.	ppl.
Att. + PAB	47.60	3.08	12.50	0.133	94.38
Trans.	34.93	7.06	15.38	0.203	85.80
TTransfo	45.87	8.68	17.39	0.260	34.83
TTransfo+P	61.61	9.10	18.41	0.257	38.07
LConv	44.34	8.47	17.08	0.238	37.44
LConv+P	59.88	9.82	18.91	0.231	41.68
Ours	92.13	10.53	19.47	0.256	38.68
Ours, $\alpha=1$	94.24	11.63	20.51	0.262	39.74
Ours, $\alpha=0$	51.44	9.00	17.44	0.249	40.89
w/o PreT	71.74	9.36	18.29	0.222	95.00
w/o AEmb	73.51	10.51	19.41	0.247	39.36
w/o DWP	73.90	10.61	19.26	0.256	37.08
+ HW	69.87	9.01	19.81	0.232	36.37

4. Pre-training Persona-sparse Generation

- Effect of α



- α controls the persona information
- In the persona-sparse scenario, too many persona information could lead to the decrease of performance

4. Pre-training Persona-sparse Generation

• Human Evaluations and Cases

Model	Utterance Fluency		Persona Consistency		Context Coherency	
	Rand	Biased	Rand	Biased	Rand	Biased
Trans.	1.852	1.810 [†]	0.997 [†]	1.068 [†]	1.428 [†]	1.500
TTransfo	1.832 [†]	1.890	1.015 [†]	1.100 [†]	1.498	1.517
TTransfo+P	1.802 [†]	1.837 [†]	1.125 [†]	1.195 [†]	1.217 [†]	1.483 [†]
LConv	1.863	1.882	1.028 [†]	1.147 [†]	1.490	1.550
LConv+P	1.832 [†]	1.875 [†]	1.093 [†]	1.173 [†]	1.238 [†]	1.478 [†]
Ours	1.837 [†]	1.912	1.092 [†]	1.198 [†]	1.487	1.563
Ours, $\alpha=1$	1.835 [†]	1.900	1.248	1.268	1.303 [†]	1.467 [†]
Ours, $\alpha=0$	1.890	1.880 [†]	0.997 [†]	1.085 [†]	1.535	1.463 [†]
Gold Resp	1.928	1.922	1.015	1.423	1.758	1.807

[†] significant difference with the best result (t-test, p -value <0.05)

* with scale 0, 1, 2

Dialogue	I am free this weekend. It that OK? (我这周末闲, 好不)
Context:	(Gender: Female, Location: Nanjing, Interest Tags: Cate)
Target Persona:	(Gender: Male, Location: Nanjing , Interest Tags: Null)
Trans. :	I'm also free, but I don't know what's going on. (我也闲, 但是我不知道怎么回事)
TTransfo :	Great, come here and we can have a meal together. (好呀, 你来了我们一起吃个饭呗)
TTransfo+P :	I am free this weekend. It that Okay? (我这周末闲, 好不好?)
LConv :	It is not OK. (不好)
LConv+P :	Are you in Nanjing or Nanjing ? (你在 南京 还是 南京 啊?)
Ours :	Ok, are you coming to Nanjing ? (好啊, 你来 南京 吗?)
Ours, $\alpha = 1$:	Come to Nanjing , I will treat you to dinner and film. (来 南京 , 我请你吃饭看电影)
Ours, $\alpha = 0$:	Ok, where are you? I will go back tomorrow. (好啊, 你在那呢? 我明天就回去了)
Gold Resp :	OK, come to Nanjing ! (好, 来 南京 !)

Conclusion

Neural Personalized Response Generation as Domain Adaptation

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Abstract

In this paper, we focus on the personalized response generation for conversational systems. Based on the sequence to sequence learning, especially the encoder-decoder framework, we propose a two-phase approach, namely initialization then adaptation, to model the responding style of human and then generate personalized responses. For evaluation, we propose a novel human aided method to evaluate the performance of the personalized response generation models by online real-time conversation and offline human judgement. Moreover, the lexical divergence of the responses generated by the 5 personalized models indicates that the proposed two-phase approach achieves good results on modeling the responding style of human and generating personalized responses for the conversational systems.

Keywords: Personalized Response Generation, Conversational Systems, Sequence to Sequence Learning, Domain Adaptation

1. Introduction

Conversational system, which is also called conversational robot, virtual agent or chatbot, etc, is an interesting and challenging research of artificial intelligence. It can be applied to a large number of scenarios of human-computer interaction, such as question answering [1], negotiation [2, 3], e-commerce [4], tutoring [5], etc. Recently, conversational system usually plays the role of virtual companion or assistant of hu-

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TransferTransfo: A Transfer Learning Approach for Neural Network Based Conversational Agents

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Abstract

We introduce a new approach to generative data-driven dialogue systems (e.g. chatbots) called *TransferTransfo* which is a combination of a *Transfer* learning based training scheme and a high-capacity *Transfo*-former model. Fine-tuning is performed by using a multi-task objective which combines several unsupervised prediction tasks. The resulting fine-tuned model shows strong improvements over the current state-of-the-art end-to-end conversational models like memory augmented seq2seq and information-retrieval models. On the privately held PERSONA-CHAT dataset of the Conversational Intelligence Challenge 2, this approach obtains a new state-of-the-art, respectively pushing the perplexity, Hit@1 and F1 metrics to 16.28 (45% absolute improvement), 80.7 (46% absolute improvement) and 19.5 (20% absolute improvement).

Introduction

Non-goal-oriented dialogue systems (chatbots) are an interesting test-bed for interactive Natural Language Processing (NLP) systems and are also directly useful in a wide range of applications ranging from technical support services to entertainment. However, building intelligent conversational agents remain an unsolved problem in artificial intelligence research. Recently, recurrent neural network based models with sufficient capacity and access to large datasets attracted a large interest when first attempted. Vinyals and Le [2015] showed that they were capable of generating meaningful responses in some chat-chat settings. Still, further inquiries in the capabilities of these neural network architectures and developments (Serhan et al. 2019; Miao, Yu, and Bhanuani, 2015; Sordani et al. 2015; Serhan et al. 2017; Li, Monroe, and Jurafsky 2016; Li et al. 2017) indicated that they were limited which made communicating with them a rather unsatisfying experience for human beings.

The main issues with these architectures can be summarized as:

- (i) the wildly inconsistent outputs and the lack of a consistent personality (Li and Jurafsky 2019).
- (ii) the absence of a long-term memory as these models have difficulties to take into account more than the last dialogue utterance; and

- (iii) a tendency to produce consensual and generic responses (e.g. I dont know) which are vague and not engaging for humans (Li, Monroe, and Jurafsky 2019).

In this work, we make a step toward more consistent and relevant data-driven conversational agents by proposing a model architecture, associated training and generation algorithms which are able to significantly improve over the traditional seq-2-seq and information-retrieval baselines in terms of (i) relevance of the answer (ii) coherence with a predefined personality and dialog history, and (iii) grammaticality and fluency as evaluated by automatic metrics.

Tasks and evaluation

An interesting challenge to evaluate the quality of open-domain conversation agent is the Conversational Intelligence Challenge 2 (ConvAI2) that was held during the NIPS 2018 conference and which we shortly present here with its associated dataset.

ConvAI2 is based on the PERSONA-CHAT dataset (Zhang et al. 2018), a crowd-sourced dialogue dataset in which each speaker was asked to condition its utterances on a predefined profile computing a few sentences defining a personality as illustrated on figure 1. Paired workers were asked to chat naturally and to get to know each other during the conversation. This produced an interesting dataset with rapid turns of topics as it can be seen on the example we reproduce on table 1.

As automatic evaluation is still an open question in dialogue systems (Li et al. 2016), the PERSONA-CHAT dataset comes with three automated metrics on its evaluation set. The ConvAI2 challenge further evaluated these metrics on a privately held portion of PERSONA-CHAT combined with human evaluation.

The automatic metrics involves three tasks defined on the same dataset which are (i) a *language modeling* task where the metric is the perplexity of gold utterance tokens as computed from the model's next token probability predictions (denoted PPL) (ii) a *next utterance retrieval* task where the associated metric is the accuracy of retrieving a gold next utterance among 19 random distractor responses sampled from other dialogues (denoted Hit@1) and (iii) a *generator* task which consists in generating a response in the dialog setting

<http://convai2.io/>

Large-Scale Transfer Learning for Natural Language Generation

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Abstract

Large-scale pretrained language models define a state of the art in natural language processing, achieving outstanding performance on a variety of tasks. We study how these architectures can be applied and adapted for natural language generation, comparing a number of architectural and training schemes. We focus in particular on open-domain dialog as a typical high entropy generation task, presenting and comparing different architectures for adapting pretrained models with state of the art results.

1 Introduction

Over the past few years, the field of natural language processing (NLP) has witnessed the emergence of transfer learning methods which have significantly improved the state of the art (Dai and Le, 2015; Peters et al., 2018; Howard and Ruder, 2018; Radford et al., 2018; Devlin et al., 2018). These methods depart from classical supervised machine learning where a predictive model for a given task is trained in isolation on a single dataset. Here, a model is pretrained on large text corpora and then fine-tuned on the target task.

Such models are usually evaluated on natural language understanding (NLU) tasks such as text classification or question answering (Wang et al., Rajpurkar et al., 2016), but natural language generation (NLG) tasks such as summarization, dialog, or machine translation remain relatively underexplored. At first glance, large-scale pretrained models appear to be a natural fit for NLG since their pretraining objectives often derive from language modeling. However, interesting questions and problems still arise.

We consider a text-only NLG task where the generation of an output sequence of symbols $y = (y_1, \dots, y_n)$ is conditioned on a context $x = (x^1, \dots, x^k)$ composed of one or several sequences of symbols $x^i = (x^i_1, \dots, x^i_{l_i})$. Several types of contexts may warrant different treatment in the model. E.g., in case of dialog generation they may include: (i) facts from a knowledge base, (ii) dialog history, and (iii) the sequence of already generated output tokens (y_1, \dots, y_{n-1}) . Thus, there arises a general question of how to adapt a *single-input* pretrained model to a *multi-input* downstream generation task.

In this work, we study two general schemes to adapt a pretrained language model to an NLG task. In the *single-input* setting, contexts are concatenated to create a sequence prefix from which the output is decoded as a continuation by the pretrained language model following Radford et al. (2018, 2019). The model can be used as is or with a small number of special token embeddings added to the vocabulary to identify the context. In the *multi-input* setting, the pretrained model is duplicated to form an encoder-decoder structure where the encoder processes contexts while the decoder generates the output.

2 Related work

Unsupervised pretraining for transfer learning has a long history in natural language processing, and a common thread has been to reduce the amount of task-specific architecture added on top of pretrained modules. Most early methods (Mikolov et al., 2013; Pennington et al., 2014) focused on learning word representations using shallow models, with complex recurrent or convolutional networks later added on top for specific tasks. With

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A Pre-training Based Personalized Dialogue Generation Model with Persona-spars Data

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Abstract

Endowing dialogue systems with personas is essential to deliver more human-like conversations. However, this problem is still far from well explored due to the difficulties of both embodying personalities in natural languages and the persona sparsity issue observed in most dialogue corpora. This paper proposes a pre-training based personalized dialogue model that can generate coherent responses using persona-spars dialogue data. In this method, a pre-trained language model is used to initialize an encoder and decoder, and personal attribute embeddings are devised to model richer dialogue contexts by encoding speakers' personas together with dialogue histories. Further, to incorporate the target persona in the decoding process and to balance its contribution, an attention routing structure is devised in the decoder to merge features extracted from the target persona and dialogue contexts using dynamically predefined weights. Our model can utilize persona-spars dialogues in a unified manner during the training process, and can also control the amount of persona-related features to exhibit during the inference process. Both automatic and manual evaluation demonstrates that the proposed model outperforms state-of-the-art methods for generating more coherent and persona consistent responses with persona-spars data.

Introduction

Building a "human-like" conversation system has been an important topic in artificial intelligence, where one of the major challenges is to present a consistent persona so that the system can interact with users in a more natural way to gain users' confidence and trust. The user engagement of a dialogue agent increases when the agent is conditioned on various persona settings, including age, gender, language, location, or even a proper accent (Shim, He, and Li 2018; Wang et al. 2018; Huang, Zhu, and Gao 2019; Zhou et al. 2018). Various approaches have been explored to personalize a dialogue system (Li et al. 2016a; Yuan et al. 2018; Koturu, Wang, and Carvalho 2017).

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Figure 1: An example dialogue session and the persona profile of each speaker. Words in responses are in the same color with the corresponding personal attributes.

Recent advances in pre-training methods have led to state-of-the-art results in a range of natural language processing tasks (Peters et al. 2018; Devlin et al. 2019; Radford et al. 2019; Jeon et al. 2019). Promising results are also obtained by applying these approaches in personalized dialogue generation models, such as fine-tuning a pre-trained model on a small set of persona-related dialogues (e.g. PERSONA-CHAT (Zhang et al. 2018); (Mazare et al. 2018; Wolf et al. 2018; Golovnov et al. 2019)). However, the dialogue data used in the fine-tuning stage of these methods are usually crowd-sourced, where speakers are required to exchange their personas within limited turns of conversation. This data collection scheme is guaranteed to yield dialogues that cover rich persona related features (i.e., "personasense") and thus facilitate fine-tuning directly. However, such a setting is expensive and can only produce a limited amount of dialogues. Further, models fine-tuned using these data tend to over-fit the routine that persona-related features should be exhibited in every response. This does not meet the common practice observed in our daily communication.

As a matter of fact, most speakers in our daily conversations are not aiming to exhibit their personas within limited turns of interactions, namely, real-world dialogues are not always persona-related. For example, as shown in the dialogue session in Figure 1, speaker A and B only reveal their personas in the first turn of the conversation, while

SUMMARY

1. Better language model, better dialogue generation model
2. transfer learning in personalized dialogue is still under-explored

- Domain adaption
- No explicit persona
- RNN-based model
- 2016-2017

- Pre-training + Finetuning
- With explicit persona
- Transformer-based model
- 2016-2020

END

Q & A