第_8_次汇报

		工作	F汇总				
完成内容	[1]Zhang S, Dinan E, Urbanek J, et al. Personalizing Dialogue Agents: I have a						
	dog, do you have pets too?[J]. 2018.						
内容描述	1. Motivation: 过去的模型缺乏 consistent 的性格,长期记忆缺失,经常出						
	I don't know 的回答,作	者认为	这些问是	的一个原[因之一	-是没有	好的数据集。
	2. Method: 作者创建了三种数据集,分别是 Personas, Revised Personas, 和						
	Persona Chat。作者考虑了分别考虑了两种模型:生成式和检索式,在训练时,						
	将以上三种数据集加入到模型中进行训练。						
	3. Result:						
	J. Result						
	Method	No Per ppl l		iginal Persona pl hits@1	Revise ppl	d Persona hits@1	ı
	Generative Models	FF-	F		FF-		_
	Seq2Seq Profile Memory	38.08 38.08		.53 0.084 .54 0.125	40.65 38.21	0.082 0.108	
	Ranking Models	30.00	0.092 34	.54 0.125	30.21	0.106	_
	IR baseline	-	0.214	0.410	-	0.207	
	Starspace Profile Memory	-	0.318	- 0.491 - 0.509	-	0.322	
	KV Profile Memory	-		- 0.511	-	0.351	_
	Table 3: Evaluation of dialog u	iterance	prediction v	vith various me	odels in t	three settir	igs: without
	**.* *						
	conditioning on a persona, conditi		he speakers				
	persona that does not have word o		he speakers				or a revised
			<u> </u>	given persona ("	Original		
	persona that does not have word o	verlap.	<u> </u>	given persona (" Engagingne	Original	Persona"),	or a revised Persona
	Method Model Human Generative PersonaChat Models	verlap. Profile Self	Fluency 4.31(1.07	Engagingne 4.25(1.06)	Original ess Cor 4.3	Persona"), nsistency 86(0.92)	Persona Detection 0.95(0.22)
	Method Model Human Generative PersonaChat Models Seq2Seq	verlap. Profile Self	4.31(1.07)	Engagingne (1) 4.25(1.06) (2) 3.18(1.41)	ess Cor	Persona"), nsistency 86(0.92)	Persona Detection 0.95(0.22)
	Method Model Human Generative PersonaChat Models	Profile Self None	Fluency 4.31(1.07	Engagingne (1) 4.25(1.06) (2) 3.18(1.41)	ess Cor	Persona"), nsistency 86(0.92)	Persona Detection 0.95(0.22)
	Method Model Human Generative PersonaChat Models Seq2Seq Profile Memory Ranking PersonaChat Models KV Memory	Profile Self None Self None	3.17(1.10 3.08(1.40 3.81(1.14	Engagingne (1) 4.25(1.06) (2) 3.18(1.41) (3) 3.13(1.39) (4) 3.88(0.98)	Original 2.9 3.1 3.3	Persona"), nsistency 86(0.92) 98(1.45) 14(1.26)	Persona Detection 0.95(0.22) 0.51(0.50) 0.72(0.45)
	Method Model Human Generative PersonaChat Models Seq2Seq Profile Memory Ranking PersonaChat Models KV Memory KV Profile Memory	Profile Self None Self None Self	3.17(1.10 3.08(1.40 3.81(1.14 3.97(0.94	Engagingne (1) 4.25(1.06) (2) 3.18(1.41) (3) 3.13(1.39) (4) 3.88(0.98) (5) 3.50(1.17)	Original ess Cor 4.3 2.9 3.1 3.3 3.3 3.4	Persona"), nsistency 86(0.92) 98(1.45) 14(1.26) 86(1.37) 14(1.30)	Persona Detection 0.95(0.22) 0.51(0.50) 0.72(0.45) 0.59(0.49) 0.81(0.39)
	Method Model Human Generative PersonaChat Models Seq2Seq Profile Memory Ranking PersonaChat Models KV Memory KV Profile Memory Twitter LM OpenSubtitles 2018 LM	Profile Self None Self None	3.17(1.10 3.08(1.40 3.81(1.12 3.97(0.94 3.21(1.52 2.85(1.40	Engagingne (1) 4.25(1.06) (2) 3.18(1.41) (3) 3.13(1.39) (4) 3.88(0.98) (5) 3.50(1.17) (6) 1.75(1.04) (7) 2.13(1.07)	Original 2.9 3.3 3.3 3.4 1.9 2.1	Persona"), nsistency 86(0.92) 98(1.45) 14(1.26) 86(1.37) 14(1.30) 95(1.22) 15(1.08)	Persona Detection 0.95(0.22) 0.51(0.50) 0.72(0.45) 0.59(0.49) 0.81(0.39) 0.57(0.50) 0.35(0.48)
	Method Model Human Generative PersonaChat Models Seq2Seq Profile Memory Ranking PersonaChat Models KV Memory KV Profile Memory Twitter LM OpenSubtitles 2018 LM OpenSubtitles 2009 LM	Profile Self None Self None Self None None None	3.17(1.10 3.08(1.40 3.81(1.12 3.97(0.94 3.21(1.54 2.85(1.40 2.25(1.37)	Engagingne (1) 4.25(1.06) (2) 3.18(1.41) (3) 3.13(1.39) (4) 3.88(0.98) (5) 3.50(1.17) (6) 1.75(1.04) (7) 2.13(1.07) (7) 2.12(1.33)	Original 2.9 3.3 3.3 1.9 1.9 1.9	Persona"), nsistency 86(0.92) 98(1.45) 14(1.26) 86(1.37) 144(1.30) 95(1.22) 15(1.08) 96(1.22)	Persona Detection 0.95(0.22) 0.51(0.50) 0.72(0.45) 0.59(0.49) 0.81(0.39) 0.57(0.50) 0.35(0.48) 0.38(0.49)
	Method Model Human Generative PersonaChat Models Seq2Seq Profile Memory Ranking PersonaChat Models KV Memory KV Profile Memory Twitter LM OpenSubtitles 2018 LM OpenSubtitles 2009 LM OpenSubtitles 2009 KV Memory	Profile Self None Self None Self None None None None	3.17(1.10 3.08(1.40 3.81(1.14 3.97(0.94 3.21(1.54 2.85(1.40 2.25(1.37 2.14(1.20	Engagingne (** Engagingne (**) 4.25(1.06) 3.18(1.41) 3.13(1.39) 3.88(0.98) 3.50(1.17) 1.75(1.04) 2.13(1.07) 2.12(1.33) 2.22(1.22)	Original ess Cor 3.3 3.3 3.4 1.9 2.1 1.9 2.0 2.0	Persona"), nsistency 86(0.92) 98(1.45) 14(1.26) 86(1.37) 14(1.30) 95(1.22) 15(1.08) 96(1.22) 96(1.29)	Persona Detection 0.95(0.22) 0.51(0.50) 0.72(0.45) 0.59(0.49) 0.81(0.39) 0.57(0.50) 0.35(0.48) 0.38(0.49) 0.42(0.49)
	Method Model Human Generative PersonaChat Models Seq2Seq Profile Memory Ranking PersonaChat Models KV Memory KV Profile Memory Twitter LM OpenSubtitles 2018 LM OpenSubtitles 2009 LM	Profile Self None Self None Self None None None None None None None None	3.17(1.10 3.08(1.40 3.81(1.14 3.97(0.94 3.21(1.54 2.25(1.37 2.14(1.20	Engagingne (** Engagingne (**) 4.25(1.06) 3.18(1.41) 3.13(1.39) 3.88(0.98) 3.50(1.17) 1.75(1.04) 2.13(1.07) 2.12(1.33) 2.22(1.22) models, along v	Original ess Cor 3.3 3.3 3.4 1.9 2.1 1.9 2.0 with a cor vith a cor	Persona"), nsistency 86(0.92) 98(1.45) 14(1.26) 36(1.37) 14(1.30) 95(1.22) 15(1.08) 96(1.22) ob(1.29) mparison to	Persona Detection 0.95(0.22) 0.51(0.50) 0.72(0.45) 0.59(0.49) 0.81(0.39) 0.57(0.50) 0.35(0.48) 0.38(0.49) 0.42(0.49)
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	Method Model Human Generative PersonaChat Models Seq2Seq Profile Memory Ranking PersonaChat Models KV Memory KV Profile Memory Twitter LM OpenSubtitles 2018 LM OpenSubtitles 2009 LM OpenSubtitles 2009 KV Memory Table 4: Human Evaluation of vaformance, and Twitter and OpenS 1、从最后的实验结果来 persona 的模型会更加 co	Profile Self None Self None None None None None Trious PER ubtitles be arious PER ubtitles be arious PER ubtitles be first A nsisten 居集的:	4.31(1.07) 3.17(1.10) 3.08(1.40) 3.81(1.14) 3.97(0.94) 3.21(1.54) 2.85(1.44) 2.25(1.37) 2.14(1.20) SONA-CHATassed models 上基寸 大便缺少	Engagingne (** Engagingne (** 4.25(1.06) (** 3.18(1.41) (** 3.13(1.39) (** 3.88(0.98) (** 3.50(1.17) (** 2.13(1.07) (** 2.12(1.33) (** 2.22(1.22) (** models, along v (last 4 rows), st Persona C (** Persona C (** engaging, aging, agent 能更	Sess Cor	Persona"), nsistency 36(0.92) 98(1.45) 14(1.26) 36(1.37) 14(1.30) 95(1.22) 15(1.08) 96(1.22) nparison to eviation in 模型, 用 Person	Persona Detection 0.95(0.22) 0.51(0.50) 0.72(0.45) 0.59(0.49) 0.81(0.39) 0.57(0.50) 0.35(0.48) 0.38(0.49) 0.42(0.49) o human perparenthesis. 能够访问到 ona Chat 的模

	工作汇总
完成内容	[2]Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova. BERT:
	Pre-training of Deep Bidirectional Transformers for Language Understanding.
	CoRR abs/1810.04805 (2018)

人,也就是个人的专属服务,个人的特性化服务,不适合于泛化场合。

内容描述 1、BERT 的模型架构基于多层双向转换解码,因为 decoder 是不能获要预测 的信息的,模型的主要创新点都在 pre-traing 方法上,即用了 Masked LM 和 Next Sentence Prediction 两种方法分别捕捉词语和句子级别的 representation。 其中"双向"表示模型在处理某一个词时,它能同时利用前面的词和后面的词 两部分信息,这种"双向"的来源在于 BERT 与传统语言模型不同,它不是在 给你大牛股所有前面词的条件下预测最可能的当前词,而是随机遮掩一些 词,并利用所有没被遮掩的词进行预测。 2、模型架构: Bert: 输入部分的处理 Token Embeddings E, E₄ E₃ 未解决问 1、BERT 的收敛速度较慢。 题 2、能捕捉到真正意义上的上下文信息。

论文汇总 论文列表 [1]Zhang S , Dinan E , Urbanek J , et al. Personalizing Dialogue Agents: I have a dog, do you have pets too?[J]. 2018. [2]Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. CoRR abs/1810.04805 (2018)

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