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Empathetic Conversational Artificial Intelligence Systems: *Recent Advances and New Frontiers*

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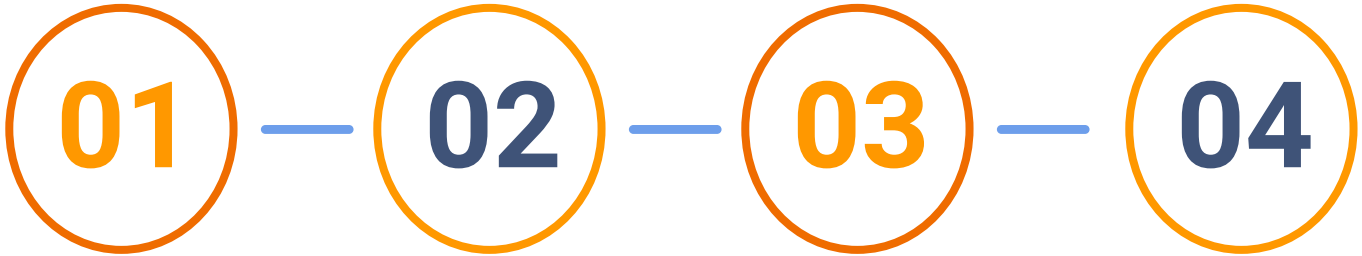
Outline



Background

Empathetic Conversational Artificial Intelligence Systems

Empathetic Conversational Artificial Intelligence Systems for Social Good

Conclusion and Future Direction

01

Conversational AI: A brief Introduction

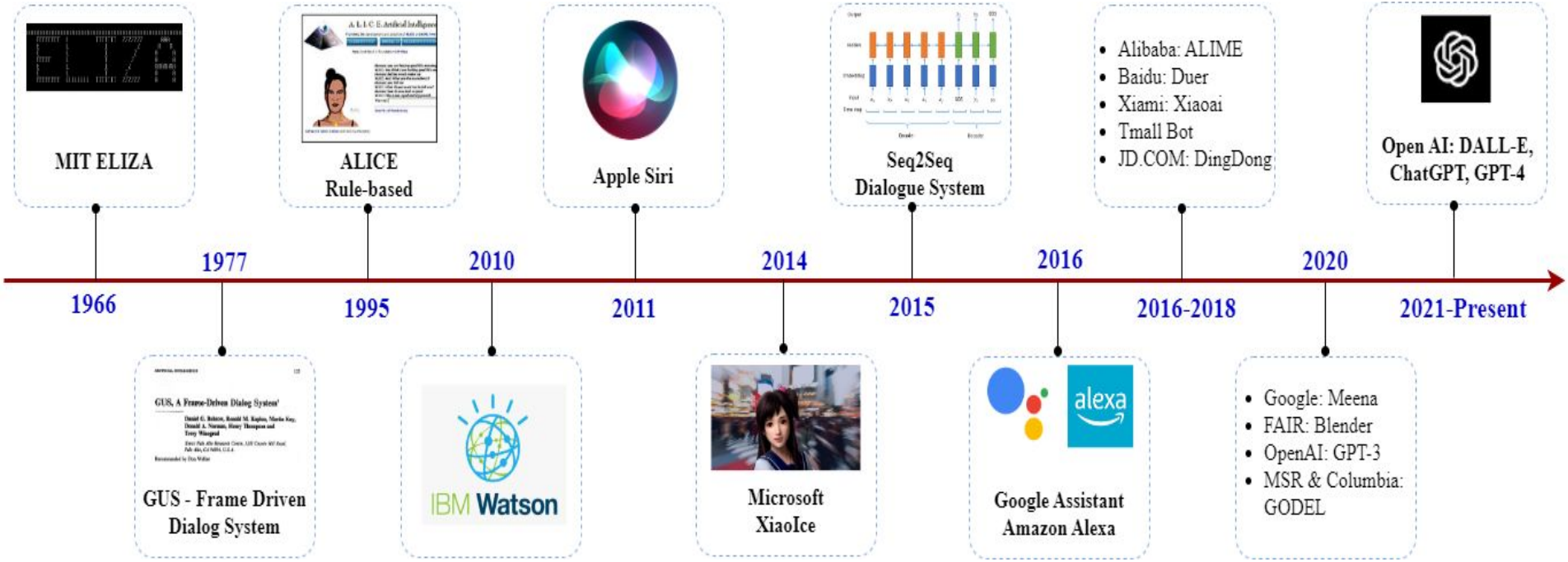
Artificial Intelligence and Conversational Systems

- ***Artificial intelligence (AI)*** is one of the most-discussed technology topics among the researchers, consumers and enterprises today.
- **Conversational AI powered by NLP and ML** has been in the centre of AI revolution during the last few years.

Examples: Conversational AI Systems
Phone-based Personal Assistants : SIRI, Cortana, Google

Now,
- ➔ Talking to your car
- ➔ Communicating with robots
- ➔ Clinical uses for mental health
- ➔ Chatting for fun

History of Conversational Systems



Types of Conversational Systems

- **Open Chit-Chat Agents (Open IE)**
  - Designed for extended conversations, set up to mimic the unstructured conversational or 'chats' characteristic of human-human interaction
  - NOT focused on a particular task like airline reservation etc.
  - Systems often have an entertainment value, such as *Microsoft's XiaoIce*
- **Task-oriented Dialog Agents**
  - Designed for a particular task and set up to have short conversations to get information from the user to help complete the task
  - E.g. Digital assistants like Siri, Cortana, Alexa, Google Now/Home, etc.
  - Agents can give travel directions, control home appliances, find restaurants, or help make phone calls or send texts

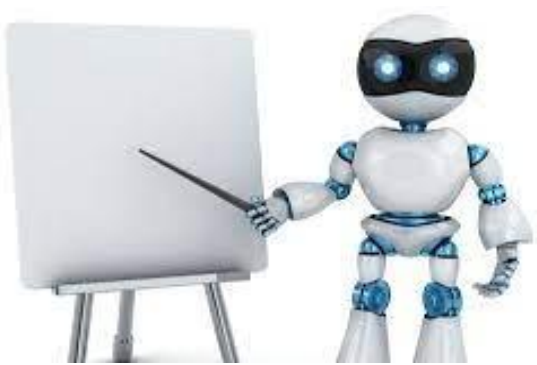
Application of Conversational Systems

Smart Home

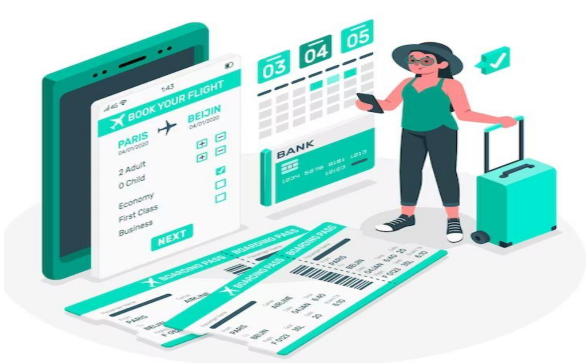
Product Recommender

In-car Assistant

Medical Diagnosis

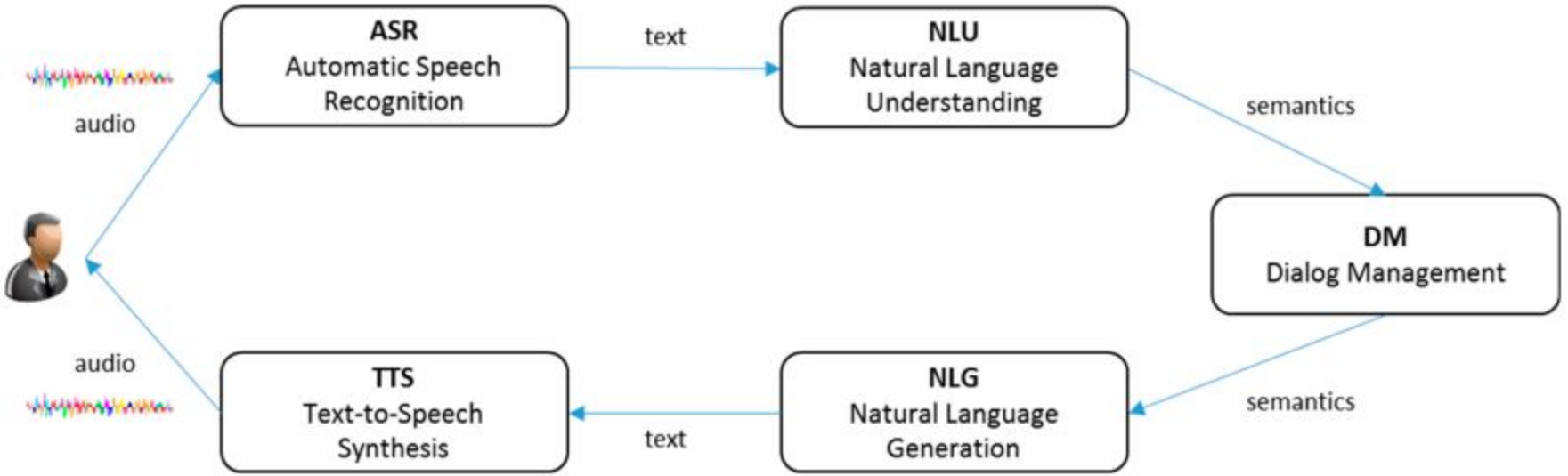


Intelligent Tutor



Travel Agent

Modules in a Task-Oriented Conversational System



The most simplest form of Conversational System: Chatbot

Chatbot: Impact

- The chatbot market size is projected to grow from $2.6 billion in 2019 to $9.4 billion by 2024 at a compound annual growth rate (CAGR) of 29.7% (BusinessInsider)
- By 2022, banks can automate up to 90% of their customer interactions using chatbots (Chatbot Report 2019: Global Trends and Analysis)
- 80% of businesses are expected to have some sort of chatbot automation by 2020 (Outgrow)
- There are over 300,000 chatbots on Facebook (Venture Beat)
- Over 50% of customers expect a business to be open 24/7 (Oracle)
- Chatbots can save up to 30% in customer support costs (Invespcro)

Today's Chatbot: A Long way from ELIZA (1960)

- Nowadays, ***Chatbots*** have grown into a full-blown industry with constant innovations bridging the human-to-machine communication gap
  - *Going beyond simple tasks like playing a song or booking an appointment*
- Beyond knowledge-based conversational agents that match a query to a predefined set of answers
- Chatbot should mimic the dynamics of human conversations

BUT how?

Today's Chatbot: A Long way from ELIZA

- **Generating coherent and engaging responses in conversations**
  - Through Deep Language Understanding and Reasoning
- **Should understand a user's need, context and mood**
- **Should be able to respond with** *personalization, sentimental and emotional analysis*
- **Balancing human-like aspects such as specificity and empathy**
- **Need advanced NLP and ML Systems**
  - Beyond understanding a single sentence or taking discrete actions
  - Understanding long-form sentences in specific contexts

Empowering AI for Human-like Conversation

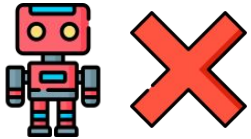
AI has to master the art of conversation at human level, then it has an uphill task ahead (*Facebook AI*)

- **Consistency:** *to ensure that it generates appropriate response without missteps, such as contradictions*
- **Specificity**: *generating specific response*
- **Empathy: Affect-awareness (Sentiment-aware, Emotion-aware), Courteousness etc.**
- **Knowledgeability**: *should be able to take into account the external knowledge and facts, and generate response accordingly*
- **Multimodal understanding**: *should be able to operate with text, image, audio, video etc.*

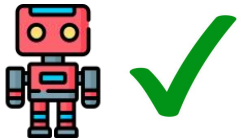
Communication of Empathy

I finally got promoted today at work!!

Why would anyone promote you?



Congrats!! That's great!!



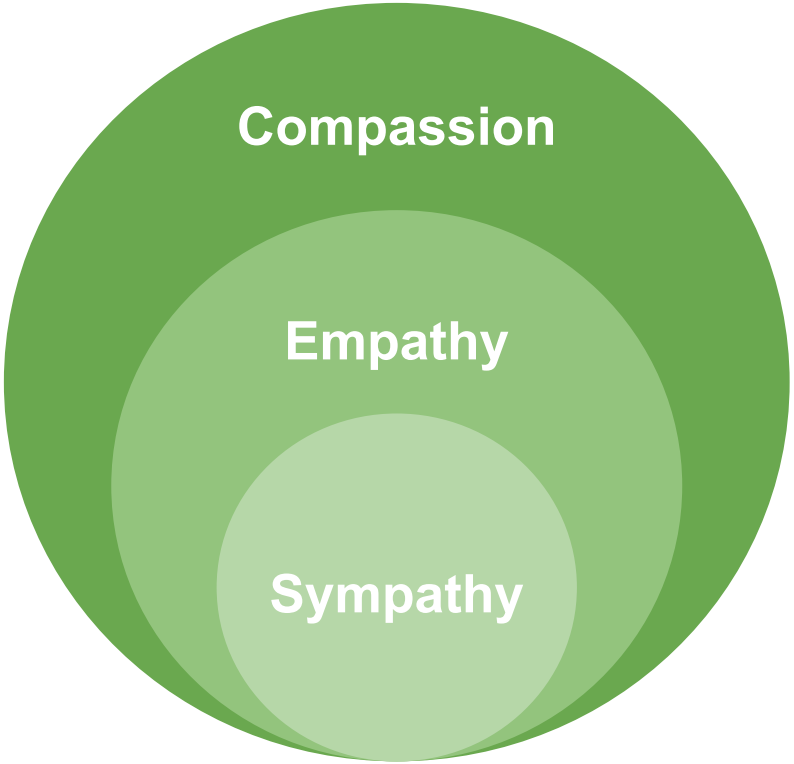
Communication of Empathy

https://www.purpleslate.com/how-conversational-ai-enhances-interactions/

Wondering!!

What the Empathy is??

Understanding Empathy



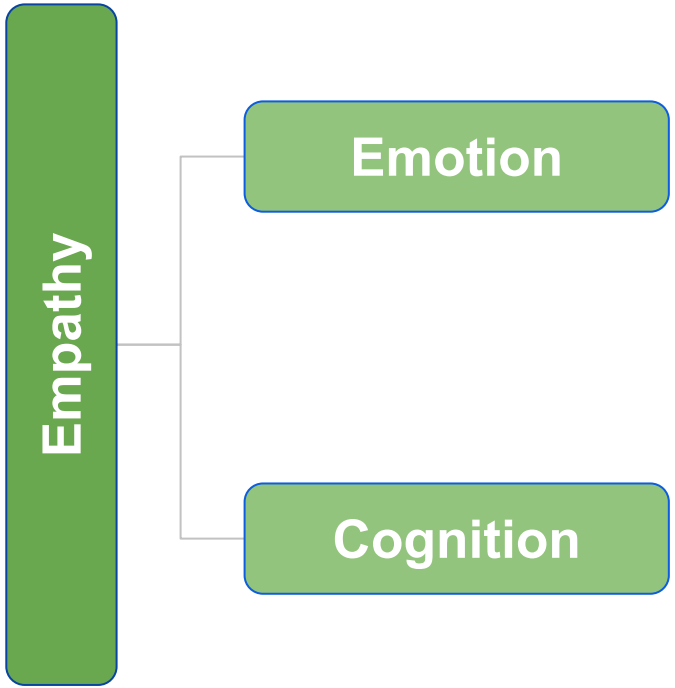
Seeing with the ***eyes of another***, listening with the ***ears of another*** and feeling with the ***heart of another***.

Sympathy: "I'm sorry that happened to you."

Empathy: "I see your pain and I understand."

Compassion: "How do you need me to help?"

Empathy as Two-dimensional Construct

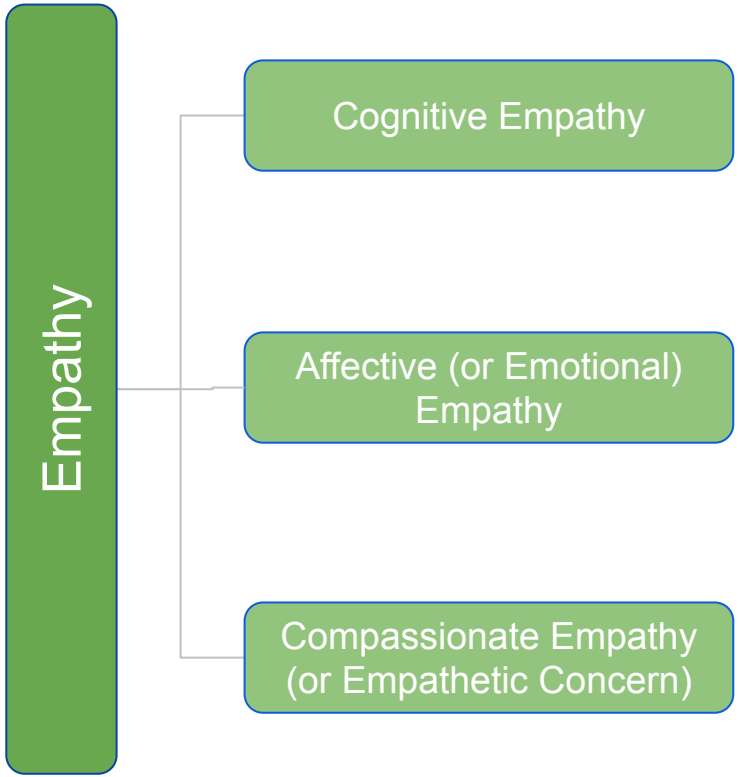


Relates to the *emotional stimulation in reaction to the experiences and feelings* expressed by a user

A more deliberate process of *understanding and interpreting the experiences and feelings* of the user and communicating that understanding to them

Mark H. Davis 1980. A multidimensional approach to individual differences in empathy. In American Psychological Association Washington, DC.

Empathy as Three-dimensional Construct



Ability to understand another person's point of view or perspective (*"putting oneself in others' shoes"*)

Ability to feel what someone else feels (*"your pain in my heart"*)

Ability to sense what another person needs from you and do something helpful (*"demonstrates helpful behaviors"*)

D. Goleman 1995. Emotional intelligence: Emotional intelligence: Why it can matter more than IQ.

Empathy Summarized…

"An emotional response (affective), dependent upon the interaction between trait capacities and state influences. Empathic processes are automatically elicited but are also shaped by top-down control processes. The resulting emotion is similar to one's perception (directly experienced or imagined) and understanding (cognitive empathy) of the stimulus emotion, with the recognition that the source of the emotion is not one's own" - *Benjamin MP Cuff*

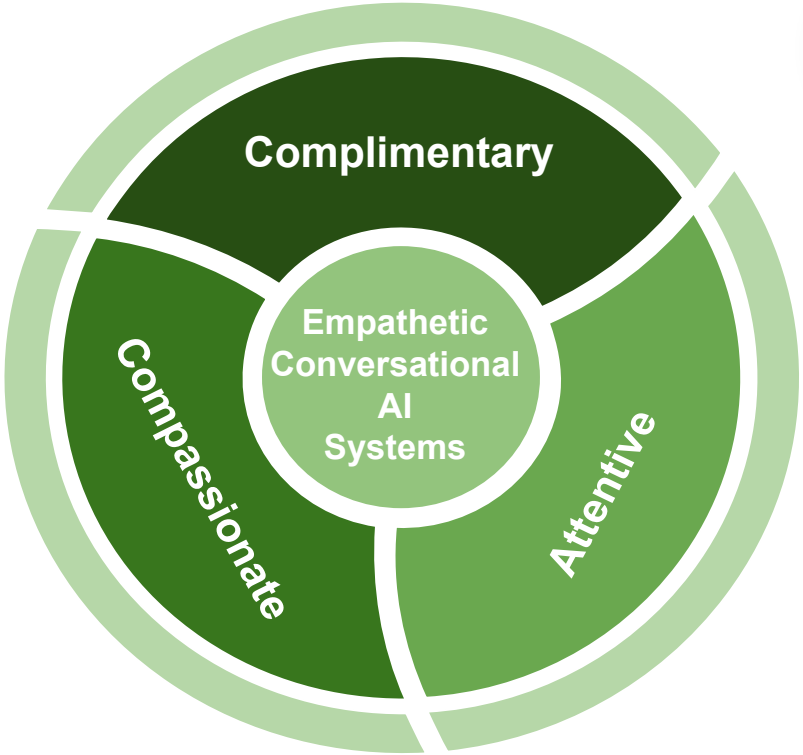
Cuff et al. Empathy: A review of the concept. In *Emotion review* 8.2 (2016).

02

Empathetic Conversational Artificial Intelligence Systems

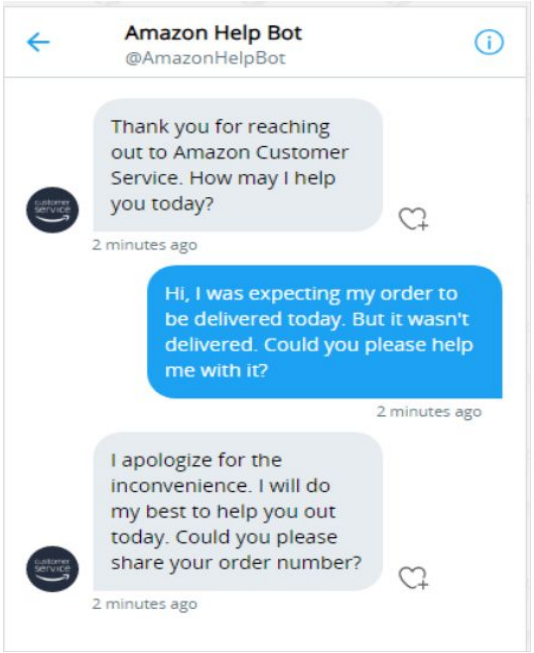
Why do we need Empathy in Conversational AI Systems?

Empathy in Conversational AI: Importance

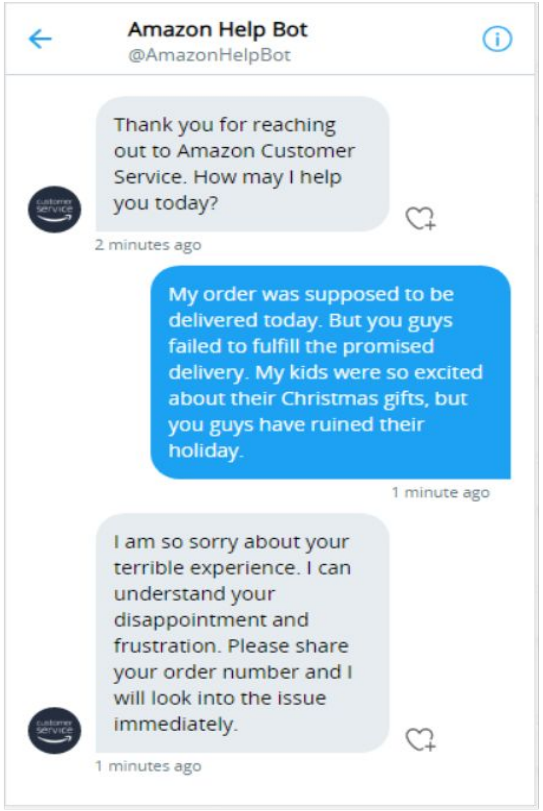


- Human-like systems (bridge human-machine gap)
- Better and more meaningful user engagement
- Enhances emotional bond with users
- Perceived as social actors by users
- Leads to positive user experience and effective communication

Amazon Help Bot



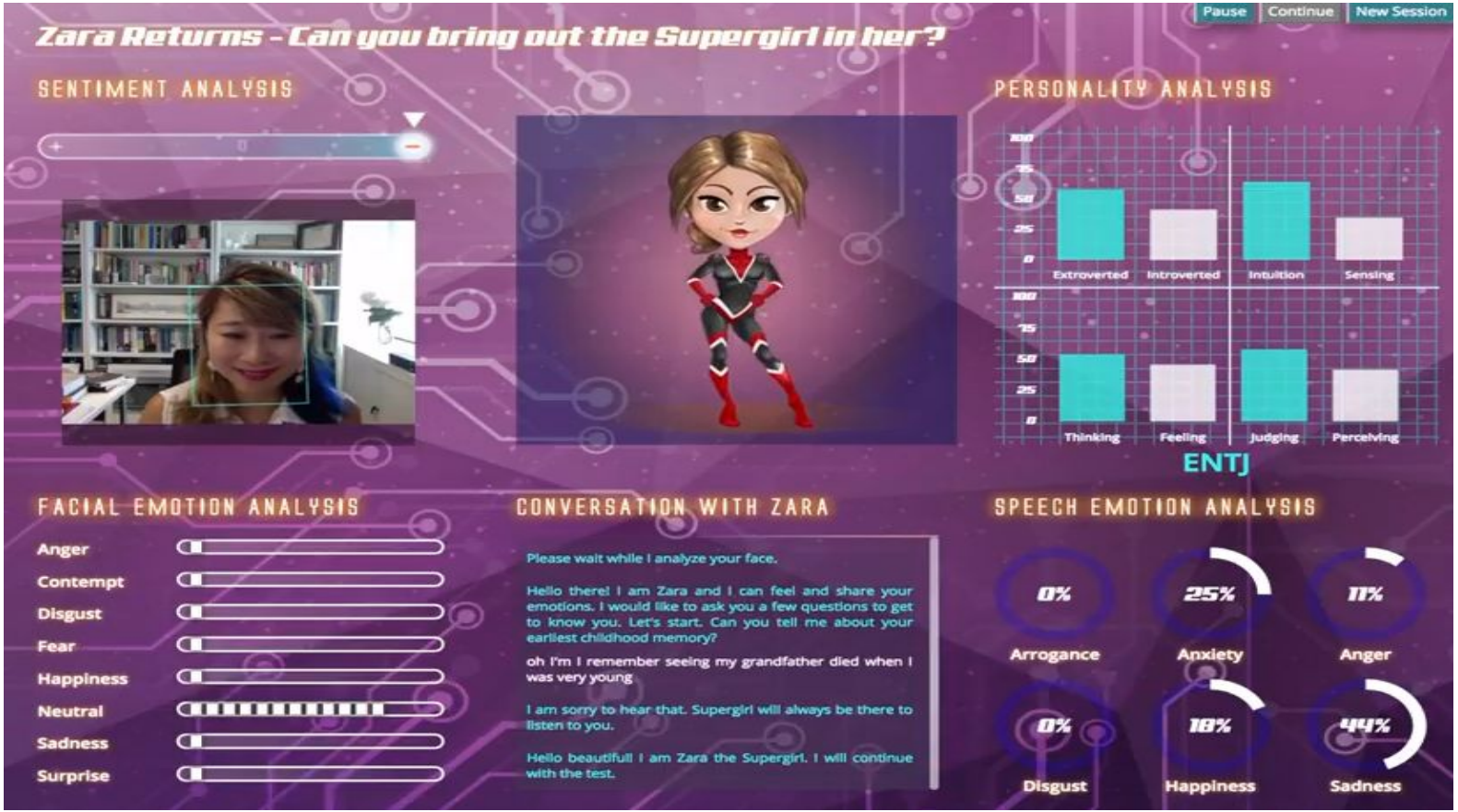
Scenario 1



Scenario 2

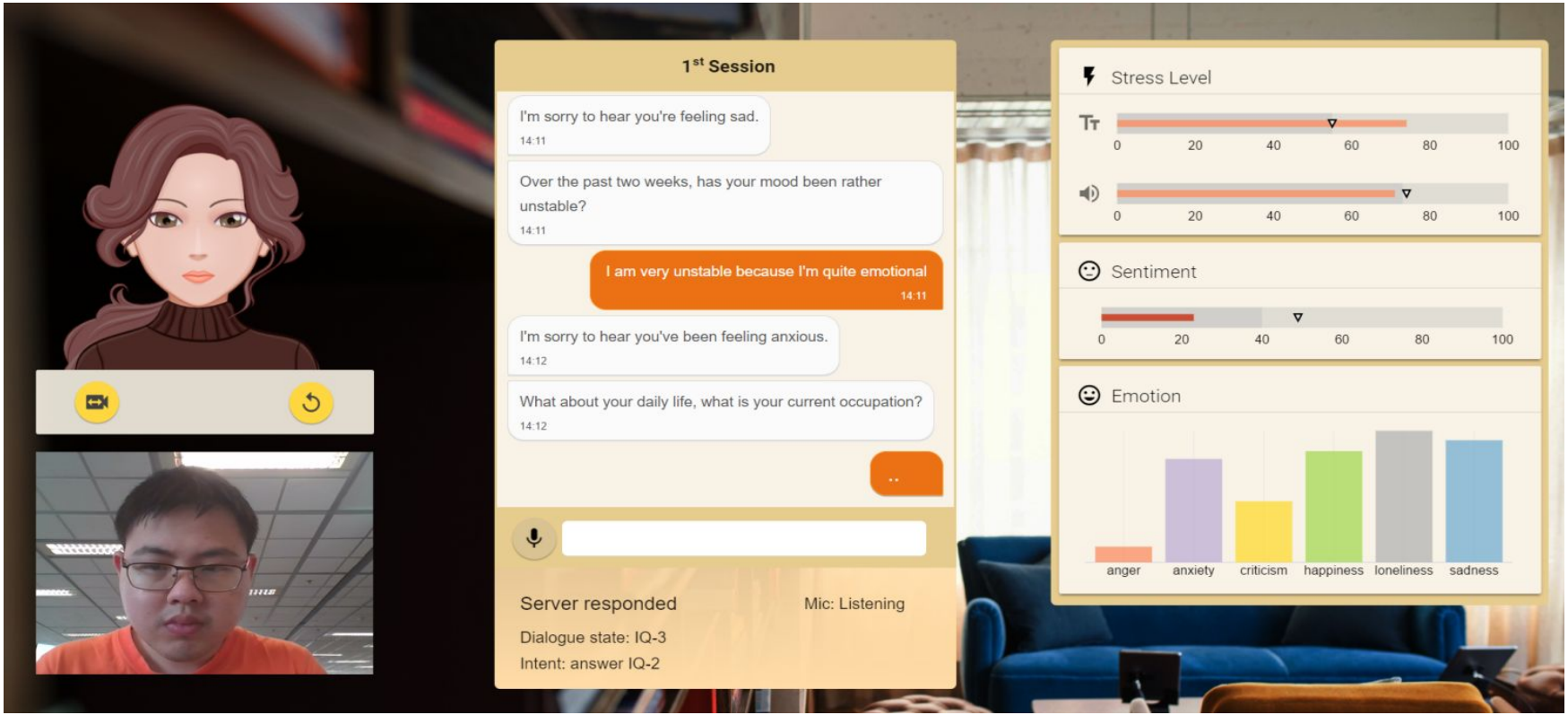
Source: https://blog.reachsumit.com/posts/2020/12/generating-empathetic-responses/

Zara- The SuperGirl



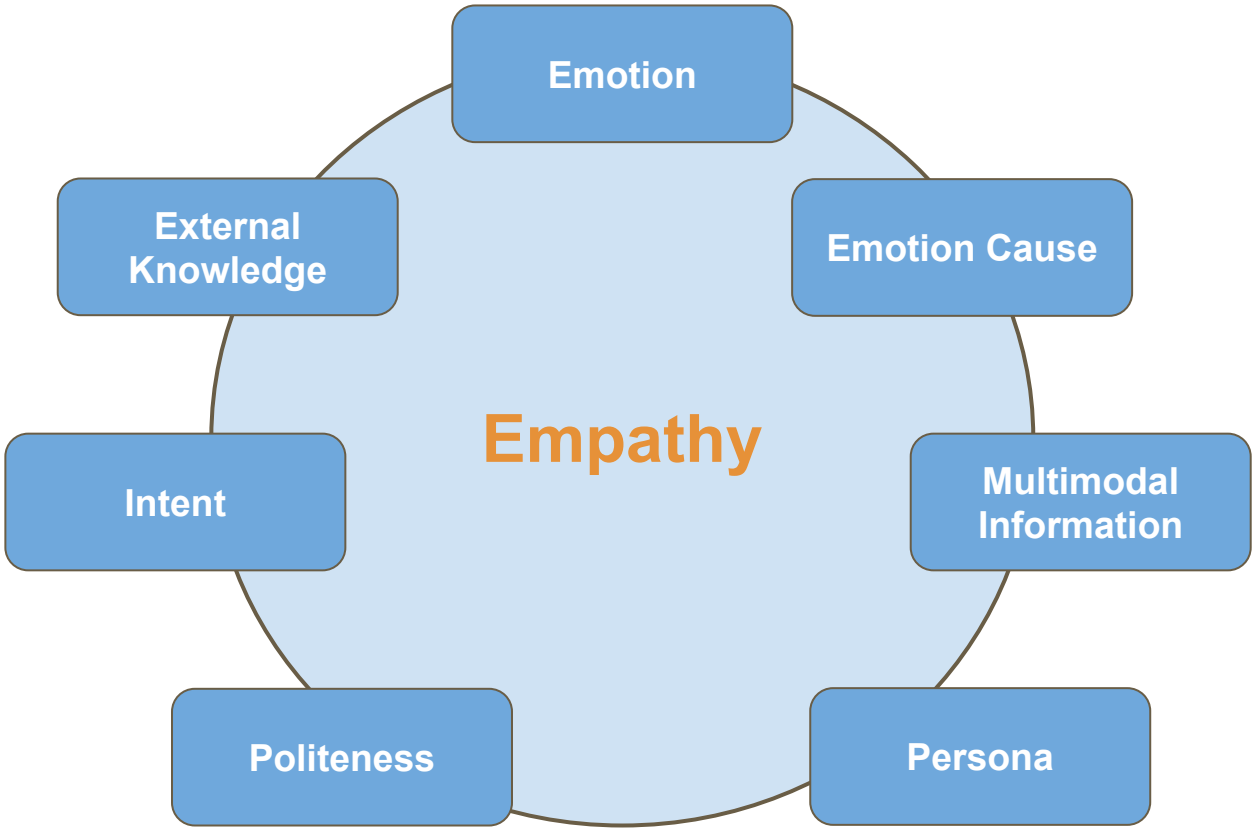
Source: https://blog.reachsumit.com/posts/2020/12/generating-empathetic-responses/

Nora- *the Empathetic Psychologist*



Source:: https://blog.reachsumit.com/posts/2020/12/generating-empathetic-responses/

Empathy and Related Concepts



Concept 1

Emotion

Emotion and Empathy

I've been hearing some strange noises around the house at night.

oh no! That's scary! What do you think it is?

I don't know, that's what's making me anxious.

I'm sorry to hear that. I wish I could help you figure it out.

Listener acknowledges the speaker's underlying emotion (fear) in an empathetic way.

Rakshin et al. Towards Empathetic Open-domain Conversation Models: a New Benchmark and Dataset. In ACL 2019.

Sentiment and Empathy

What do you do for career? (Neutral)

I like to watch kids. (Positive)

I actually play guitar and do a lot of welding. (Neutral)

That's a great job, as I play guitar and do welding for a career. (Positive)

More empathetic compared to the response in red (Happy Undertone)

Major Highlights

- Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory. (Zhou et. al., AAAI 2018)

- More the Merrier: Towards Multi-Emotion and Intensity Controllable Response Generation. (Firdaus et. al., AAAI 2021)

- Modelling Context Emotions using Multi-task Learning for Emotion Controlled Dialog Generation. (Varshney et. al., EACL 2021)

Highlight 1

Emotional chatting machine: Emotional conversation generation with internal and external memory. (Zhou et. al., AAAI 2018)

Emotional Response Generation: An Example

User: Worst day ever. I arrived late because of the traffic.

Basic Seq2Seq: You were late. **(Response without Emotion)**

ECM (Like): I am always here to support you.

ECM (Happy): Keep smiling! Things will get better.

ECM (Sad): It's depressing.

ECM (Disgust): Sometimes life just sucks.

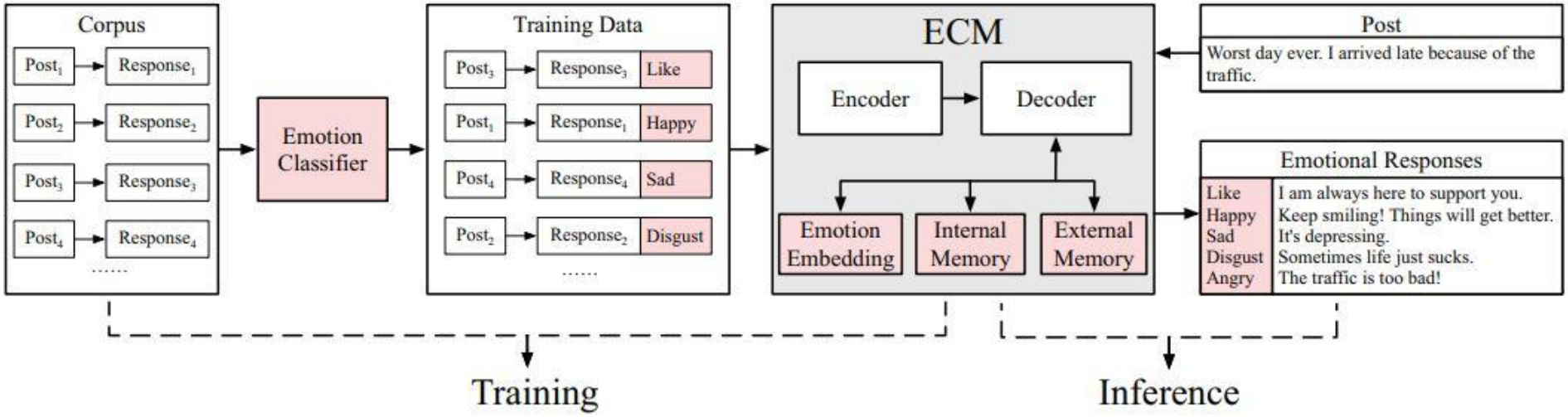
ECM (Angry): The traffic is too bad!

Responses with Emotion

Emotionally-involved conversations demonstrates more empathy

Zhou et al. Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory. In AAAI 2018

Architecture



Overview of ECM (the grey unit). The pink units are used to model emotion factors in the framework.

Zhou et al. Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory. In AAAI 2018

Experimental Details

Dataset: STC [Short-Text Conversation (STC) dataset with emotion categories : Angry, Disgust, Fear, Happy, Like, Sad, Surprise, and Other]

Training	Posts	217,905	
	Responses	Angry	234,635
		Disgust	689,295
		Happy	306,364
		Like	1,226,954
		Sad	537,028
		Other	1,365,371
Validation	Posts	1,000	
Test	Posts	1,000	

Evaluation Metrics:

- **Automatic Metrics**
  - BLEU Score
  - Perplexity
- **Human Evaluation**
  - Content (0,1,2): To check if the appropriateness and naturalness of the generated response
  - Emotion (0,1): To assess if the emotion expression of a response agrees with the given emotion category

Results: Automatic Evaluation

Method	Perplexity	Accuracy
Seq2Seq	68.0	0.179
Emb	62.5	0.724
ECM	65.9	**0.773**
w/o Emb	66.1	0.753
w/o IMem	66.7	0.749
w/o EMem	**61.8**	0.731

Observations:

- ECM obtains the best performance in emotion accuracy
- The performance in perplexity is better than Seq2Seq but worse than Emb.
- Emotion accuracy is more important than perplexity considering that the generated sentences are already fluent and grammatical with the perplexity of 68.0

Zhou et al. Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory. In AAAI 2018

Results: Manual Evaluation

Method (%)	2-1	1-1	0-1	2-0	1-0	0-0
Seq2Seq	9.0	5.1	1.1	37.6	28.0	19.2
Emb	22.8	9.3	4.3	27.1	19.1	17.4
ECM	**27.2**	**10.8**	4.4	24.2	15.5	17.9

Observations:

- Results are shown in the percentage of responses in manual evaluation with the score of Content-Emotion
- ECM obtains best score for content and emotion

Zhou et al. Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory. In AAAI 2018

Generated Examples

Post	Model		Response(Original)	Response(Translated)
承诺，就是一个骗子说给一个傻子听的。 A promise is what a cheater says to a fool.	Seq2Seq		承诺，就是一个骗子说给一个傻子听的。	A promise is what a cheater says to a fool.
	ECM	Like	承诺是一个**专一**的傻子	Promise is a **single-minded** fool
		Happy	我就是一个**开心**的傻子	I'm just a **happy** fool
		Sad	我就是一个**悲伤**的傻子	I am a **sad** fool
		Disgust	一个**骗子**说给一个**傻子**听	A **cheater** says to a **fool**
		Angry	不管你信不信，反正我信了！	Whatever you believe or not, I trust in it!
知道真相的我眼泪笑下来 Knowing the truth, I laughed myself to tears	Seq2Seq		知道真相的我眼泪掉下来。	After knowing the truth, I burst into tears.
	ECM	Like	太**可爱**了，太**可爱**了！	Too **lovely**, it's too **lovely**.
		Happy	笑得我眼泪都出来了。	I can't help laugh myself to tears.
		Sad	知道真相的我**眼泪**掉下来。	After knowing the truth, I burst into **tears**.
		Disgust	这是真的还是假的？	Is this true?
		Angry	什么意思？没看懂。	What do you mean? I don't understand.

Zhou et al. Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory. In AAAI 2018

Highlight 2

More the Merrier: Towards Multi-Emotion and Intensity Controllable Response Generation. (Firdaus et. al., AAAI 2021)

Multi-Emotion Generation: Why is relevant?

- Utterance in a dialogue often has multiple emotions
  - **Example:** *Oh my God!!! How could you treat them in this manner!* ***(surprise, anger)***

- In the absence of one of the emotions the entire meaning of the utterance is left incomplete

  Here, ***"Oh my God"*** is crucial for emphasizing the fact that the ***anger*** of the user is due to ***unawareness*** of the situation leading to ***surprise*** emotion as well

Firdaus et al. More the merrier: Towards multi-emotion and intensity controllable response generation. In AAAI 2021

Emotion Intensity in Generation: Why is relevant?

- Intensity of emotion varies, especially in case of multi-emotion generation

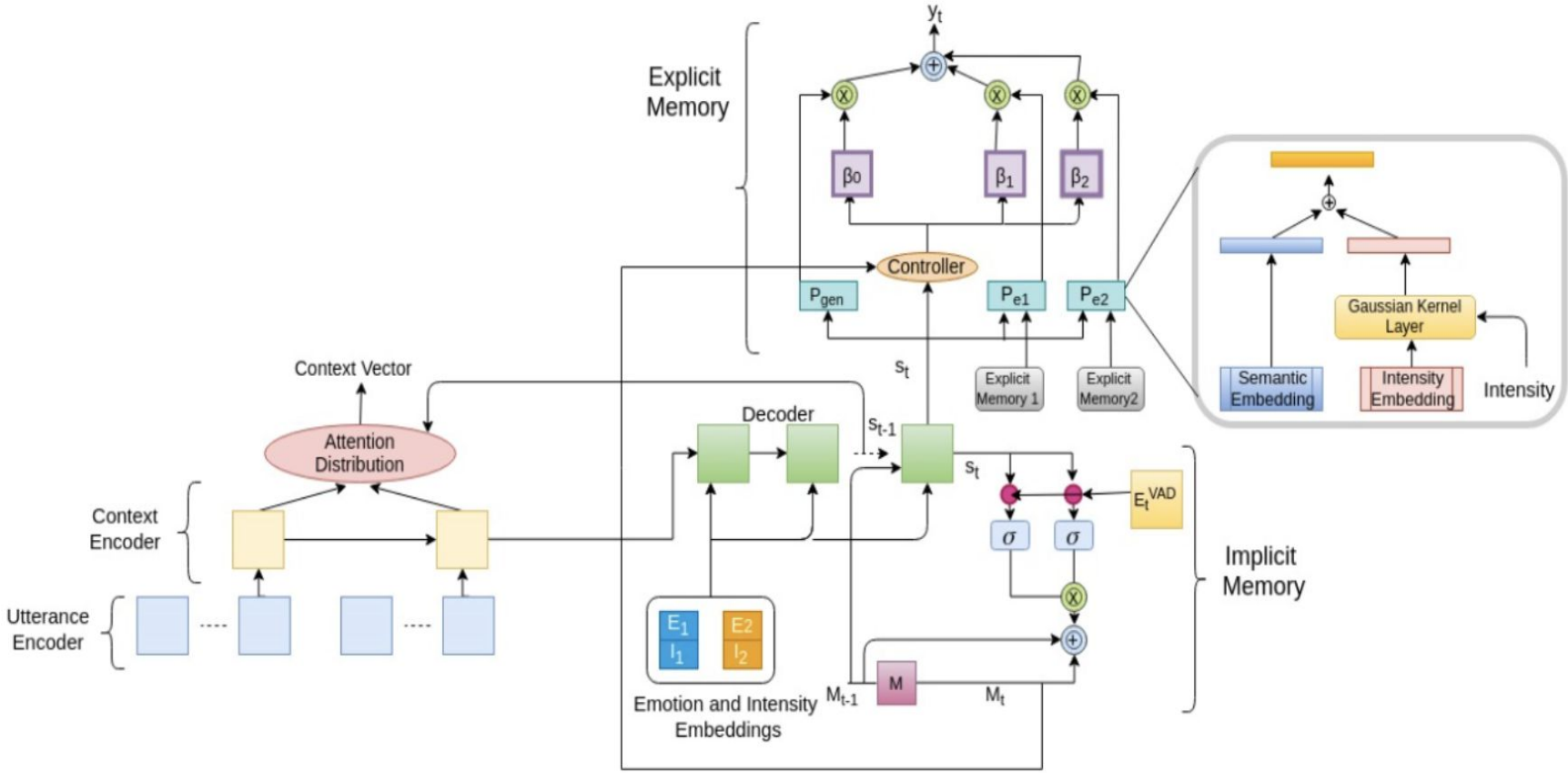
Example:
It's amazing, I am thrilled you got promoted
[**Surprise (0.3), Joy (0.9)**]

I am sorry this could be an infection or cancer
[***Sadness (0.6), Fear (0.3)***]

I am afraid but I know you could help me
[***Acceptance (0.3), Fear (0.6)***]

Firdaus et al. More the merrier: Towards multi-emotion and intensity controllable response generation. In AAAI 2021

Architecture



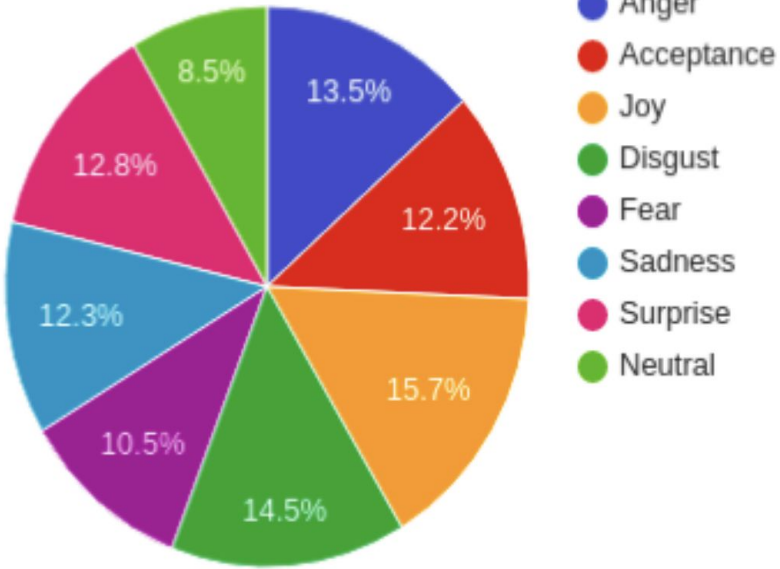
Firdaus et al. More the merrier: Towards multi-emotion and intensity controllable response generation. In AAAI 2021

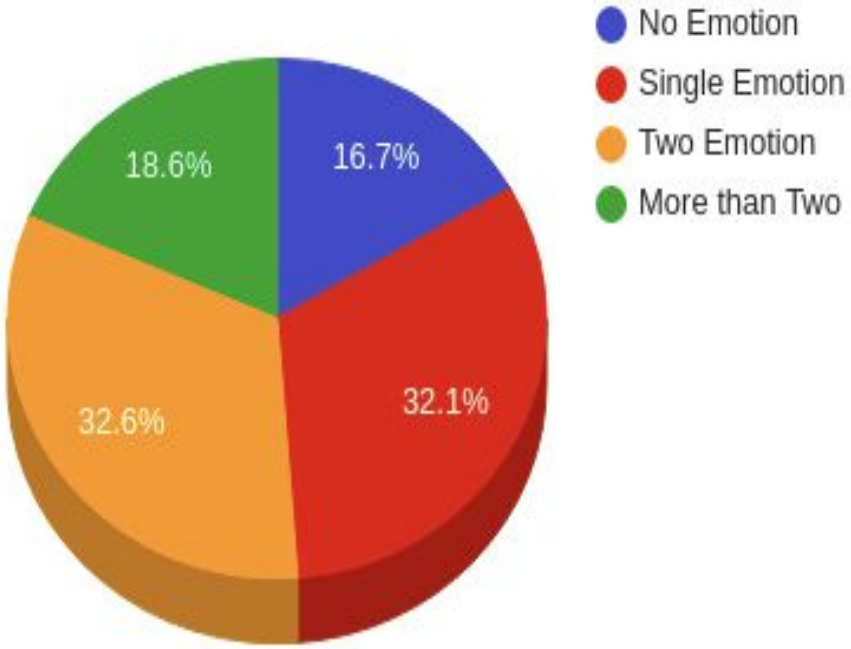
Dataset Statistics

Show	Genre	# Seasons	# Episodes	# Dialogues	# Utterances	# Main Speakers	Avg. Turns per Dialogue	Avg. Utterance Length	# of Emotions per Dialogue	Avg. emotions per Utterance
Breaking Bad	Drama	5	62	1659	32653	11	20.16	14.2	3.5	2
Castle	Drama	5	105	5172	102394	9	21.11	13.8	4.2	2
Friends	Comedy	10	236	4228	82353	6	23.40	10.6	5.5	2
Game of Thrones	Drama	7	67	2263	47471	30	22.50	13.7	3.8	2
Grey's Anatomy	Drama	6	126	4428	86104	15	22.17	14.5	4.1	2
House M.D.	Drama	8	177	6476	126780	12	21.43	13.6	3.3	2
How I Met Your Mother	Comedy	9	208	4968	96314	6	22.33	12.8	5.4	2
The Big Bang Theory	Comedy	10	207	5410	86913	7	21.98	12.5	5.3	2
Total	**-**	**60**	**1188**	**34604**	**660982**	**96**	**21.88**	**13.21**	**4.4**	**2**

Firdaus et al. More the merrier: Towards multi-emotion and intensity controllable response generation. In AAAI 2021

Emotion distribution





Firdaus et al. More the merrier: Towards multi-emotion and intensity controllable response generation. In AAAI 2021

Results: Automatic Evaluation

Models	PPL	Embedding			Emotion Content	
		Average	Greedy	Extreme	E-F1	IP-Corr
No Emotion						
HRED	80.7	0.491	0.360	0.371	0.39	0.26
Single Emotion						
HRED + emb	75.2	0.493	0.361	0.373	0.61	-
ECM (Zhou et al. 2018)	74.6	0.519	0.375	0.381	0.63	-
EMOTICONS (Colombo et al. 2019)	74.3	0.523	0.381	0.385	0.63	-
EmoDS (Song et al. 2019)	74.1	0.526	0.389	0.387	0.65	-
MEI-DG (Ours)	73.9	0.533	0.409	0.399	**0.67**	-
Single Emotion + Intensity						
HRED + emb	75.2	0.493	0.361	0.373	0.63	0.44
Affect-LM (Ghosh et al. 2017)	73.1	0.526	0.389	0.387	0.66	0.50
MEI-DG (Ours)	72.7	0.544	0.419	0.411	**0.69**	**0.57**
Multiple Emotion + Intensity						
HRED + emb	73.2	0.498	0.369	0.376	0.57	0.41
HRED + IM	72.9	0.512	0.396	0.413	0.59	0.48
HRED + EM - GK	74.1	0.531	0.412	0.407	0.60	0.43
HRED + EM	73.6	0.539	0.428	0.415	0.62	0.51
MEI-DG(HRED+EM+IM)	**71.2**	**0.552**	**0.443**	**0.428**	0.66	0.54

Observations:

- Our proposed MEI-DG framework have a lower perplexity of 71.2 than all the other baselines
- For all the metrics, our proposed framework outperforms the existing approaches significantly

Results: Human Evaluation

Models	Fluency	Relevance	Emotion	Intensity
No Emotion				
HRED	3.17	2.89	15.9%	13.6%
Single Emotion				
HRED + emb	3.25	2.93	28.3%	-
ECM (Zhou et al. 2018)	3.45	3.08	36.7%	-
EMOTICONS (Colombo et al. 2019)	3.48	3.05	37.5%	-
EmoDS (Song et al. 2019)	3.47	3.12	39.2%	-
MEI-DG (Ours)	3.49	3.13	45.1%	-
Single Emotion + Intensity				
HRED + emb	3.52	3.21	32.5%	30.6%
Affect LM (Ghosh et al. 2017)	3.58	3.26	41.7%	34.2%
MEI-DG (Ours)	3.60	3.28	**47.3%**	**40.1%**
Multiple Emotion + Intensity				
HRED + emb	3.66	3.33	35.4%	32.9%
HRED + IM	3.71	3.40	40.7%	35.4%
HRED + EM - GK	3.69	3.38	38.6%	33.1%
HRED + EM	3.73	3.41	42.9%	36.8%
MEI-DG(HRED+EM+IM)	**3.82**	**3.48**	43.9%	37.2%

Observations:

- Obtains the highest emotion and intensity score of 43.9% and 37.2%, respectively
- Single emotion and intensity-based MEI-DG model have the highest scores in terms of emotion and intensity
- Although the emotion scores are less in multiple emotion models, the fluency and relevance scores are better

Generated Examples

Conversational History	Model	Emotion	Intensity	Generated Response
It was an amazing night. You think it looked amazing?	HRED	-	-	Yes, I think so.
	MEI-DG	Joy	0.6	Yes it was really fascinating, I enjoyed it.
	MEI-DG	Joy	0.3	Yes it was a nice night.
	MEI-DG	Sadness	0.3	I found the night gloomy.
	MEI-DG	Sadness	0.9	The whole night I cried all alone.
	MEI-DG	Joy, Sadness	0.3, 0.6	It was nice but I terribly missed my friend.
	MEI-DG	Joy, Sadness	0.9, 0.3	The night was really great only had a little trouble in finding cab.
I invented the game of Cups as a way to give Joey money. And now you want that money back.	HRED	-	-	I want it back.
	MEI-DG	Anger	0.6	What the hell is wrong with you?
	MEI-DG	Anger	0.9	I would kill you if I don't get my money back.
	MEI-DG	Surprise	0.3	Wow, I didn't know about it.
	MEI-DG	Surprise	0.9	Oh my God! I left the money in the room.
	MEI-DG	Anger, Surprise	0.3, 0.6	It's not a game! Stop it and give me the money.
	MEI-DG	Anger, Surprise	0.6, 0.3	Oh you please stop annoying me.

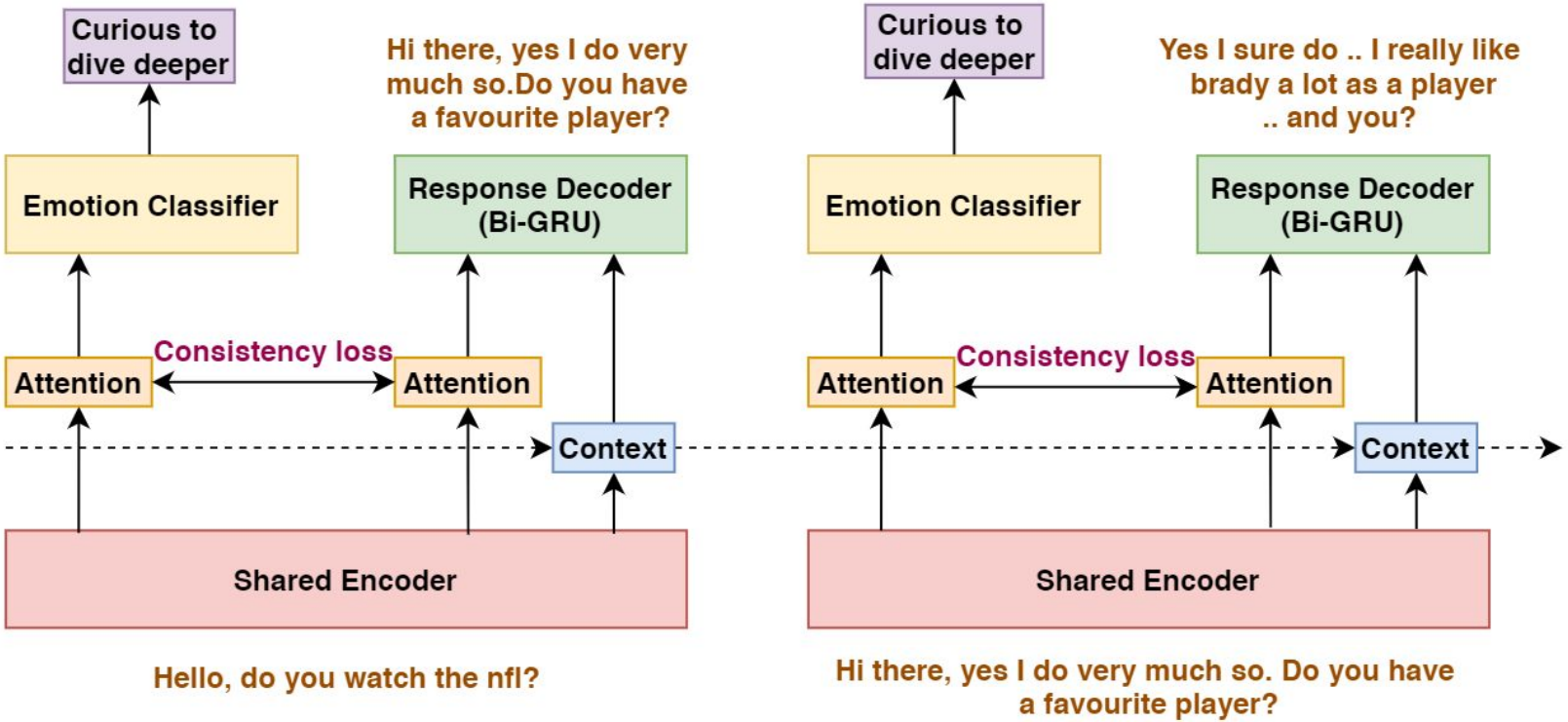
Highlight 3

Modelling Context Emotions using Multi-task Learning for Emotion Controlled Dialog Generation. (Varshney et. al., EACL 2021)

Task Description: An Example

Agent 1	**Do you like wearing hats? It has so many functions.**	Curious
Agent 2	I don't like them on myself but I know a lot of people that can pull them off.	Neutral
Agent 1	Yes me as well. In the military hats denote a nationality, branch of service, rank or regiment.	Curious
Agent 2	Yes. I love hats! I have a wide variety of hats and wear them for different reasons.	Happy
Agent 1	Yes. . . Even I like it too !! Specially I am on vacation, roaming around I do carry 2–3 hats. And I wear it according to my dressing style.	Happy

Architecture



Dataset Details

	#Conversation	#Utterances
Train	8628	188378
Valid Frequent	539	11681
Valid Rare	539	11692
Test Frequent	539	11760
Test Rare	539	11770

Tropical Chat Dataset Statistics

Emotion Classes	Original Count
Curious to dive deeper	101162
Surprised	38254
Disgusted	1848
Sad	3070
Neutral	51796
Happy	36845
Angry	1133
Fearful	1174

Distribution of emotion classes in topical chat dataset

A Conversational Example from the dataset

Agent 1	Are you **afraid** of snakes?	Curious
Agent 2	Hi, I am a little! but I was surprised there are none in New Zealand!	Happy
Agent 1	Sounds like a perfect place for me lol, I'm **terrified** of them	Fearful
Agent 2	Wow! I can understand , I am more **terrified** of crocodiles but it seems they are closer to birds than to snakes!	Fearful
Agent 1	Some snakes can even fly to catch their prey so thats **scary**	Curious
Agent 2	Wow, I would **like** to see that! And did you know its head is designed to swallow prays larger than them	Happy
Agent 1	Yeah I did know that, thats actually a bit disgusting, watching them eat prey	Disgusted
Agent 2	It looks like monkeys are terrified of snakes too!	Happy
Agent 1	They are? monkey are smart, they should stay as far as they can of snakes, dangerous animals	Fearful
Agent 2	Maybe you are terrified of snakes! But do you like dancing?	Happy

Results: Automatic and Manual Evaluation

Models	PPL (*Freq/Rare*)	BLEU% (*Freq/Rare*)	F1% (*Freq/Rare*)	Div.(n=1) (*Freq/Rare*)	Div.(n=2) (*Freq/Rare*)	Fluency (*Freq/Rare*)	Adequacy (*Freq/Rare*)	EA (*Freq/Rare*)
HRED	45.61 / 70.30	2.4 / 1.9	0.14 / 0.10	0.88 / 0.87	0.89 / 0.88	1.65 / 1.60	0.85 / 0.70	0.50 / 0.45
HRED-A	41.42 / 71.31	2.3 / 1.8	0.15 / 0.11	**0.91 / 0.90**	**0.90 / 0.90**	1.70 / 1.65	0.90 / 0.84	0.52 / 0.54
HRED-SA	36.63 / 54.87	2.1 / 1.8	0.21 / 0.15	0.83 / 0.82	0.84 / 0.84	1.70 / 1.65	0.98 / 0.88	0.60 / 0.55
EmoHRED-A-FL-CL	36.08 / 51.06	2.1 / 1.7	0.23 / 0.12	0.87 / 0.87	0.87 / 0.88	1.85 / 1.80	1.45 / 1.35	0.74 / 0.64
EmoHRED-SA-FL-CL	**35.45 / 50.45**	**2.6 / 2.1**	0.23 / **0.19**	0.88 / 0.87	0.89 / 0.88	**1.95 / 1.90**	**1.50 / 1.45**	**0.80** / 0.60
EmoHRED-SA-FL	36.34 / 54.82	2.3 / 1.9	**0.25** / 0.13	0.86 / 0.82	0.86 / 0.84	1.80 / 1.80	1.01 / 0.95	0.64 / **0.65**
EmoHRED-SA	36.04 / 52.98	2.3 / 1.8	0.24 / 0.13	0.88 / 0.83	0.83 / 0.84	1.83 / 1.81	0.93 / 0.81	0.53 / 0.51

- **Observation:**
  - High unigram and bi-gram diversities, demonstrating that the models learn to decode fluent and informative responses with great diversity
  - Significant improvement in BLEU and F1-scores in multi-task learning architecture
  - Model outperforms the other baseline models in terms of human evaluation metrics

Case Study

Utterance 1	**do you enjoy sports?**	**Neutral**
EmoHRED-SA-FL-CL	i do! it's very interesting. i used to play video games when i was a kid i don't have any time.	Happy
HRED	i do. do you ?	Curious
Utterance 2	**i enjoy the getting together with friends part of it but i could take or leave the actual sports events except when i am watching my children play. how about you what's your favorite sport?**	**Happy**
EmoHRED-SA-FL-CL	i do too.	Neutral
HRED	i enjoy watching football games as well.	Happy
Utterance 3	**i would say football**	**Neutral**
EmoHRED-SA-FL-CL	nice! speaking of football, did you know women were not allowed to play at the same time ?	Curious
HRED	i don't really like football, but i don't think i've ever heard of it, what about you?	Curious
Utterance 4	**that is the favorite sport in my household as well! tom brady is quite the dedicated player both on and off the field, don't you think?**	**Curious**
EmoHRED-SA-FL-CL	i don't know much about him.	Neutral
HRED	i do not have a favorite team but i don't really follow it.	Neutral
Utterance 5	**yes, he is arguably the greatest steal in nfl history**	**Neutral**
EmoHRED-SA-FL-CL	i can't believe he has never eaten a strawberry ha ha. have you ever heard of him ?	Surprised
HRED	i think it's cool that the nfl has no written rule against female players. i don't know how that's possible.	Surprised

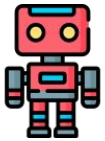
Concept 2

Emotion Cause

Emotion Cause and Empathy

I'm upset.

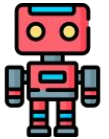
Everything will be okay.



Non-empathetic response

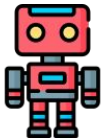
I'm upset

Sorry to hear that. What happened?



We *broke up.*

Oh dear, it must be hurt. Did you active listening argue for something?



Empathetic Response

Li et al. Towards an Online Empathetic Chatbot with Emotion Causes. In SIGIR 2021.

Major Highlights

- Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. (Kim et al. , EMNLP 2021)

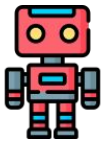
Highlight 1

Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. (Kim et al. , EMNLP 2021)

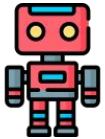
Emotion Cause: Improves Empathy

I had a severe headache.

Are you Okay?



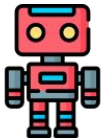
It's just terrible, isn't it?



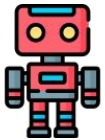
Weak Empathy - Generic expressions in response

I had a severe headache.

How is your headache, any better?



You must be worried about your job interview.

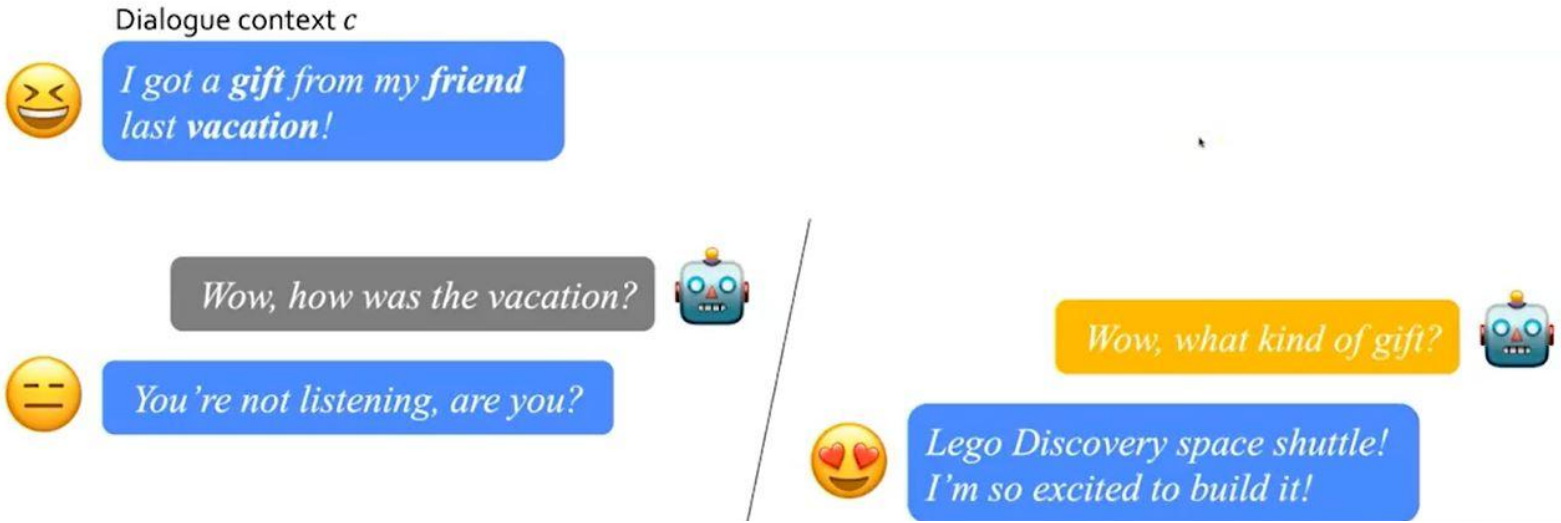


Stronger Empathy - Reason behind the emotion

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

Empathetic response need to

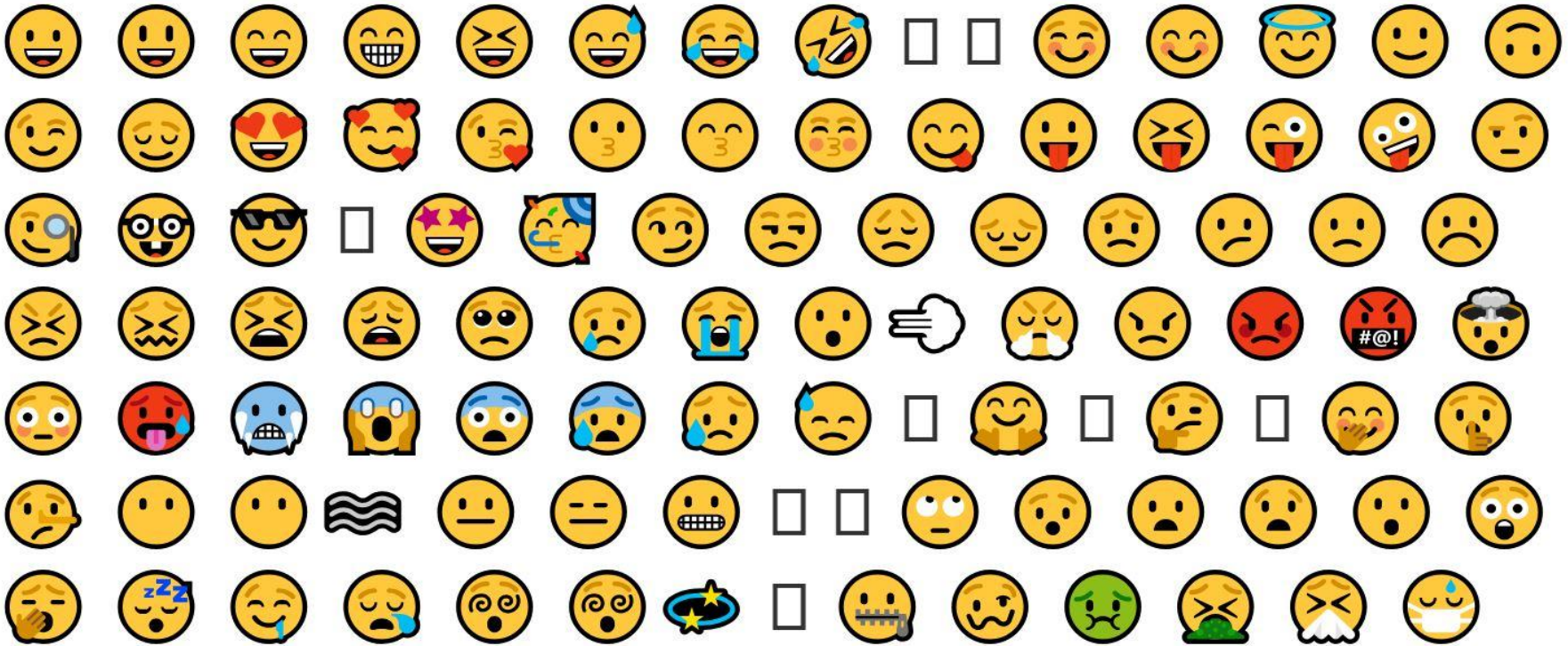
- Recognize emotion cause words in dialogue utterances
- Focus on these targeted words



Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.c

Existing works for emotion cause recognition

Annotating all those emotion causes is super demanding



Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.c

How do we humans recognize emotions?

Do we use emotion cause labels? 🤔

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.c

We put ourselves in the other's shoes

Simulating what it would be like if we were in that situation

Perspective-taking

The act of perceiving a situation or understanding a concept from alternating point of view

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

The work aims to reason the emotion-cause weight of each word in utterances, while satisfying the following three desiderata

[A] Do not require word-level supervision

We human do not need them

[B] Simulate the observed interlocutor's situation within the model

Much evidence for this behavior is found from cognitive science including empathetic perspective-taking and mirror neurons

[C] Reason other's internal emotional states in Bayesian fashion

Studies from cognitive science argue that affective reasoning can be described via Bayesian inference [1]

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

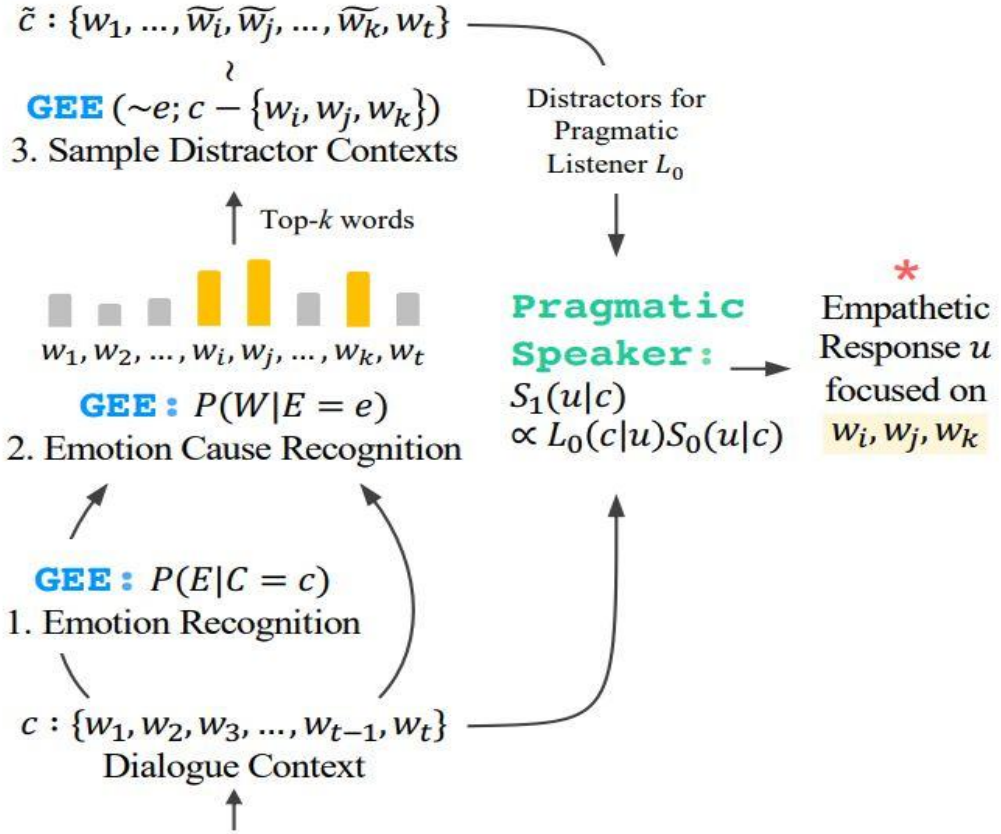
Overview of the proposed Approach

Generative Emotion Estimator (GEE) models P(C, E) = P(E)P(C|E) with text sequence (e.g. context) C and emotion E

First, the generative estimator computes the likelihood of C by generating C given E, which can be viewed as a simulation of C.

Second, it estimates P(E|C) via Bayes' rule.

Finally, the association between the emotion estimate and each word comes for free by using the likelihood of each words; without using any word-level supervision *(weakly supervised)*.



Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

Dataset

- To train GEE, the **EmpatheticDialogues** dataset [2] was used
  - a multiturn English dialogue dataset
  - the speaker talks about an emotional situation and the listener expresses empathy
  - 24,850 conversations in total
  - 32 emotion labels that are evenly distributed.

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

Automatic Evaluation: *Recognize emotion cause words*

EmoCause

- Evaluation set to measure the performance of GEE
- Annotate emotion cause words on the situations in **EmpatheticDialogues** [2] validation and test sets

Metrics

Report the **Top-1, 3, 5 recall scores**

Emotion	Situation
Surprised	Man, I did not expect to see a bear on the road today.
Afraid	I have to take a business trip next week, I'm not looking forward to flying.
Sad	I feel sad that I am spending so much time this late on the internet.
Joyful	I'm excited I get to go to Disney in October!

Examples of annotated emotion cause words

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

Results: Automatic Evaluation

Model	Top-1 Recall	Top-3 Recall	Top-5 Recall
Human	41.3	81.1	95.0
Random	10.7	30.6	48.5
EmpDG	13.4	36.2	49.3
RAKE	12.7	35.8	55.0
BERT-Attention	13.8	40.6	61.2
GEE (Ours)	**17.3**	**48.1**	**68.4**

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

Results: Automatic Evaluation

Model	Coverage	Exploration ↑	Interpretation ↑
MIME (Majumder et al., 2020)			
S_0	0.22	0.12	0.05
Plain S_1	0.22	0.23	0.10
Focused S_1	**0.24**	**0.24**	**0.13**
DodecaTransformer (Shuster et al., 2020)			
S_0	0.34	0.25	0.24
S_0+Emotion	0.34	0.21	0.20
Plain S_1	0.43	0.30	0.23
Focused S_1	**0.49**	**0.32**	**0.30**
Blender (Roller et al., 2021)			
S_0	0.35	0.28	0.22
S_0+Emotion	0.34	0.31	0.20
Plain S_1	0.43	0.37	0.21
Focused S_1	**0.54**	**0.38**	**0.26**

Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

Results: Manual Evaluation

Model	Empathy ↑	Relevance ↑	Fluency ↑
MIME (Majumder et al., 2020)			
S_0	2.94	3.17	2.75
Focused S_1	**3.09**	**3.21**	**2.83**
DodecaTransformer (Shuster et al., 2020)			
S_0	2.53	3.47	2.56
Focused S_1	**2.71**	**3.57**	**2.75**
Blender (Roller et al., 2021)			
S_0	2.91	3.12	3.46
Focused S_1	**3.00**	**3.25**	**3.57**

Generated Examples

Emotion: Angry

Context: I just moved to this neighborhood and some dumb criminals shot my neighbors and ran into the woods!

Emotion cause words from GEE:

dumb, neighbors, shot, moved, ran

S_0: That's terrible. Did you get a chance to talk to them?

Plain S_1:

Oh my god, that is horrible! Where are they?

Focused S_1:

Oh my god, that is horrible! Did they get *caught*?

Emotion: Trusting

Context: I'm a big believer in listening to your gut. Sometimes I might wonder where my intuition is leading me, but it always seems to be spot on.

Emotion cause words from GEE:

believer, leading, intuition, wonder, spot

S_0: That's great. I'm glad you have a good intuition.

Plain S_1:

Good for you. I have a gut feeling about a lot of things.

Focused S_1:

That's great! I'm a big *believer* in *intuition* too.

Emotion: Proud

Context: We were living overseas at the times – the most impressive part was crossing the Grand Canal over a pontoon of boats to finish the marathon ;-)

Emotion cause words from GEE:

impressive, Canal, Grand, part, finish

S_0: Wow, that sounds like a lot of fun! I'm glad you had a good time!

Plain S_1:

Wow, that sounds amazing! I bet you were so excited!

Focused S_1:

Wow, that sounds amazing! I've never been to *Europe*, but I've heard of it.

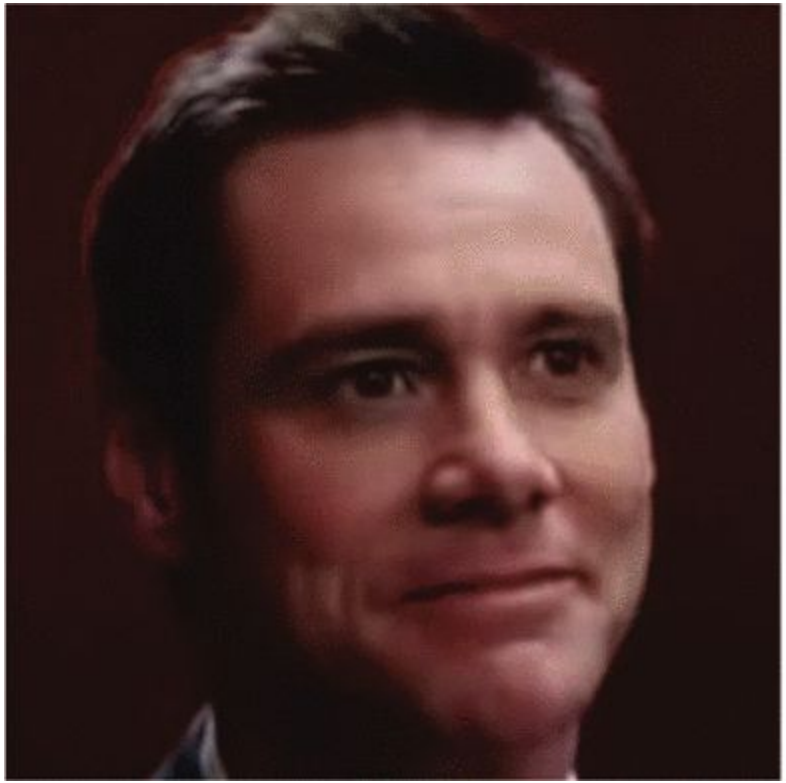
Kim et al. Perspective-taking and Pragmatics for Generating Empathetic Responses Focused on Emotion Causes. In EMNLP 2021.

Concept 3

Multimodal Information

Multimodal Information and Empathy

- Comprehensive Context.
- Accurate Emotion Recognition
- Nuanced Expression
- Personalization
- Enhanced Connection
- Reducing Misinterpretation



Facial gestures convey sentiment information. Words have different meanings with different facial gestures. Saying "*thank you*" with different gestures could either express gratitude, or irony. Therefore, a different response should be triggered.

Chu et al. A Face-to-Face Neural Conversation Model. In IEEE/CVF Conference on Computer Vision and Pattern Recognition 2018

Major Highlights

- EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. (Firdaus et al., IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022)

- Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. (Firdaus et al., ECIR 2022)

Highlight 1

EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. (Firdaus et al., IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022)

Problem Definition

- Generate sentiment and emotion controlled textual responses conditioned on the conversational history
- The dialogue consists of text utterances along with audio and visual counterparts, and given a context of k turns the task here is to generate the next text response
- For the given task, emotion and sentiment categories will be provided to generate the response

Motivation

- Simultaneous use of sentiment and emotion information is useful to generate more human-like responses
- Leads to better user experience and retention
- Multimodal information (audio and video) provide important cues for correctly identifying sentiment and emotion

Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

Sentiment and Emotion aware Multi-modal Dialogue (SEMD) Dataset

- Large-scale multi-party dataset that seamlessly employs multimodal information along with sentiment and emotion in the dialogues.
- Dataset was created utilizing the 10 famous TV shows belonging to different genres:
  - ***Comedy:*** *Friends, The Big Bang Theory, How I Met Your Mother, The Office*;
  - ***Drama:*** *House M.D., Grey's Anatomy, Castle and Game of Thrones, House of Cards, Breaking Bad*
- Total 55k dialogues
- Emotion labels:
  - ***Ekman's six universal emotions:*** *Joy, Sadness, Anger, Fear, Surprise, and Disgust*
  - ***Extended Emotion annotation list:*** *Acceptance and Neutral*
- Sentiment labels: Positive, Negative and Neutral

Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

An Example from SEMD dataset

You know, we had all this cool stuff in basement.
(Surprise, Positive)

No no, I am paddling away.
(Disgust, Positive)

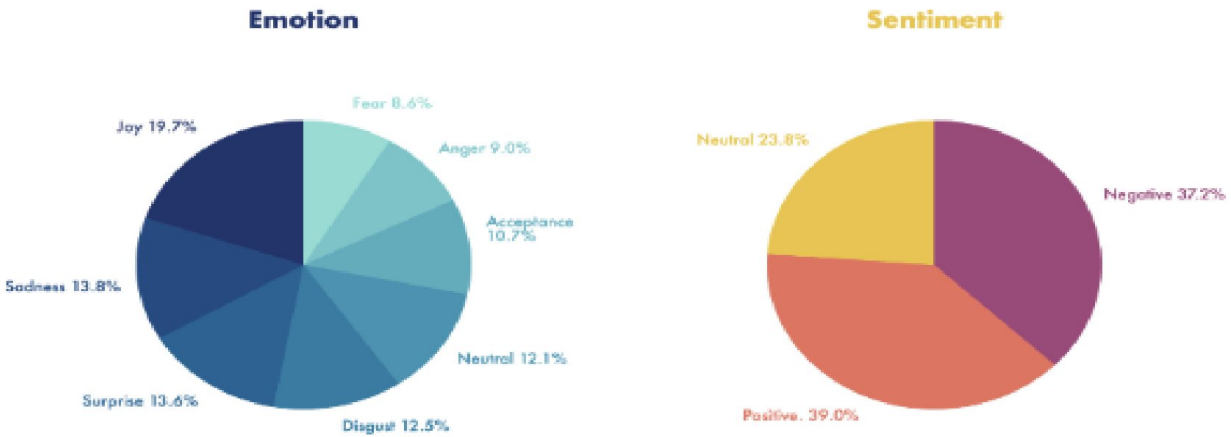
See, Yeah
(Joy, Positive)

Really, you got all this rustic crap for free.
(Anger, Negative)

Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

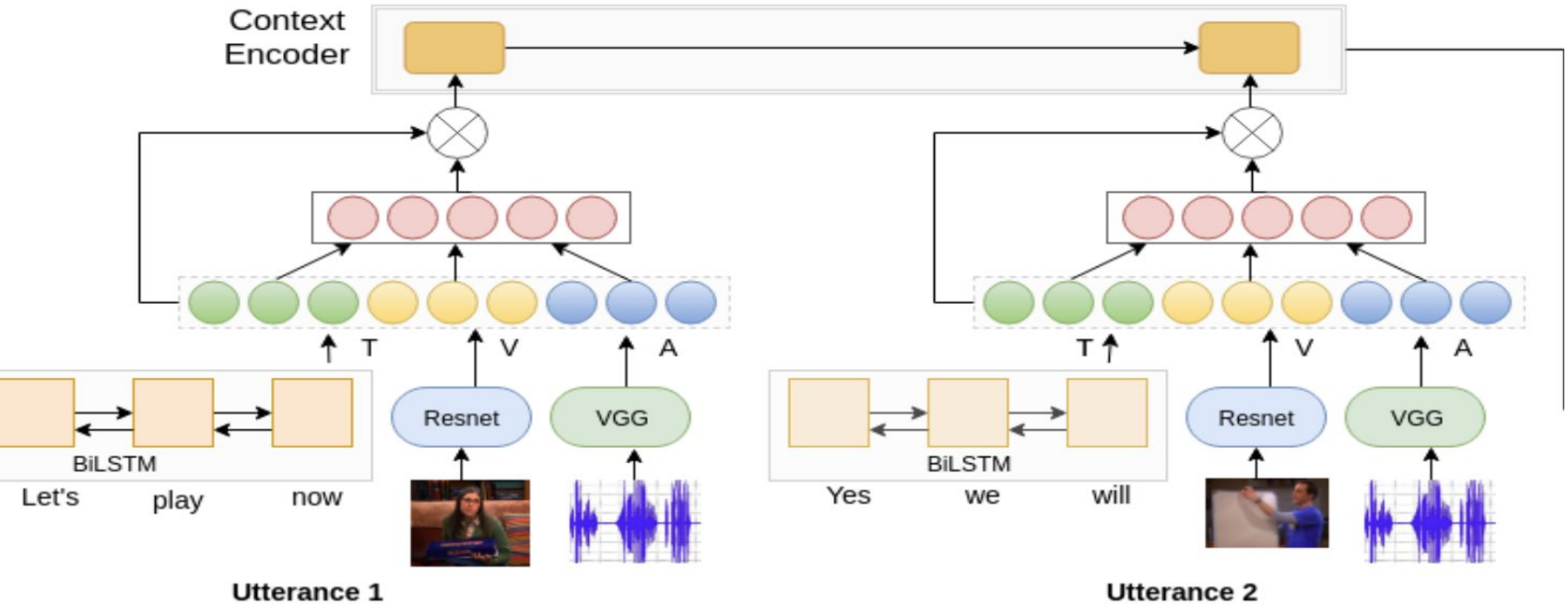
Data Annotation

- We create a balanced dataset (SEMD-annotated) by manually annotating all the 10 TV series.
- For annotating the dataset, we consider Ekman's six universal emotions, viz. *Joy, Sadness, Anger, Fear, Surprise, and Disgust* as emotion labels for all the utterances in dialogue. The annotation list has been extended to incorporate two more emotion labels, namely *acceptance and neutral*.
- We label every utterance in a dialogue with sentiment labels (*positive, negative, and neutral*).



Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

Multimodal Hierarchical encoder with Attention

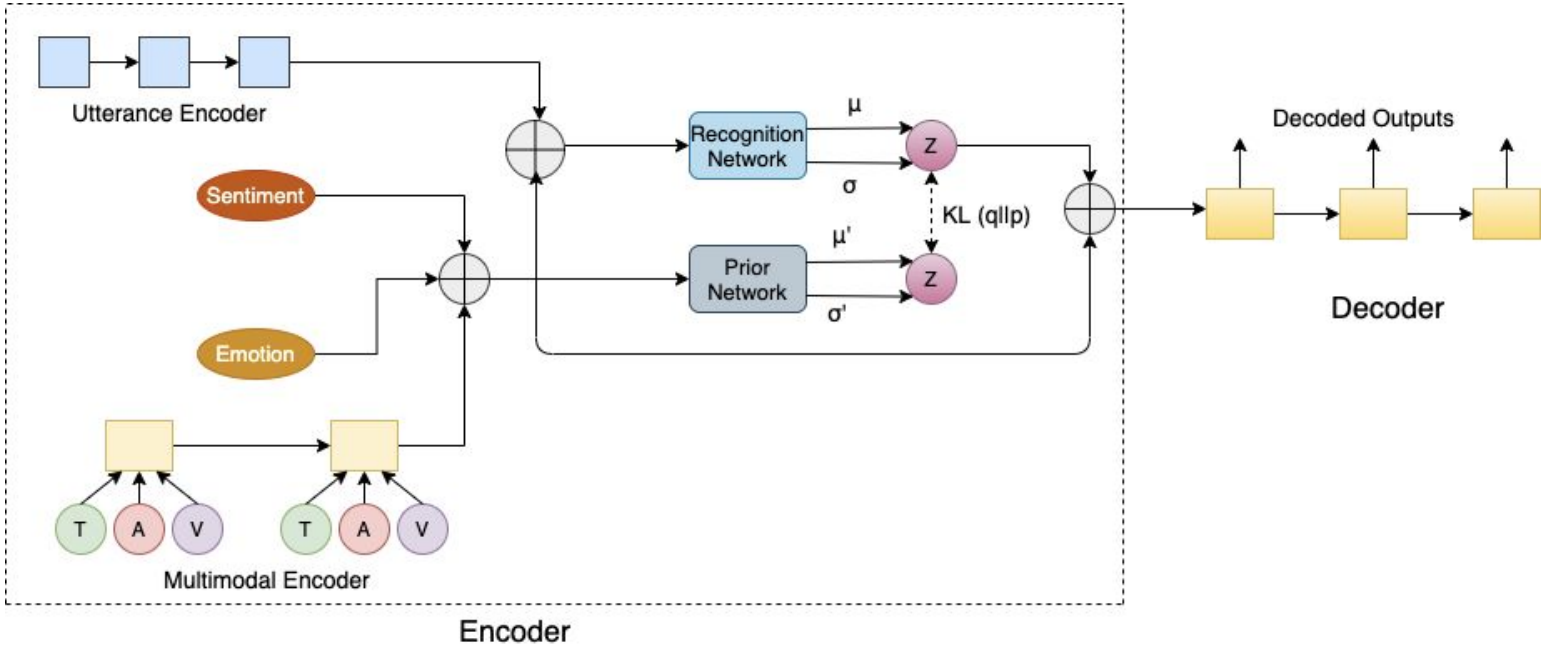


The attended utterance representation(with features from all the three modality) is passed to the context encoder

Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

Multimodal Conditional Variational Autoencoder (M-CVAE)

- In M-CVAE, dialog response *y* is generated conditioned on dialog context h_c along with the desired emotion V_e and sentiment V_s embedding and latent variable *z*.



Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

Results: Automatic Evaluation

Model Description		Modality			W/o S & E			Only S		Only E		S + E		
		T	*A*	*V*	*PPL*	*SA*	*EA*	*PPL*	*SA*	*PPL*	*EA*	*PPL*	*SA*	*EA*
Amodal Baselines	*HRED*	√			73.8	0.40	0.35	72.1	0.60	71.8	0.64	70.5	0.61	0.65
	HRED		√		120.2	0.31	0.20	120.6	0.35	119.5	0.28	119.1	0.35	0.30
	HRED			√	118.4	0.31	0.22	117.9	0.34	117.5	0.29	116.8	0.33	0.30
Bimodal Baselines	*MHRED*	√	√		69.4	0.41	0.36	67.9	0.63	66.2	0.66	65.1	0.64	0.68
	MHRED	√		√	68.8	0.40	0.36	66.3	0.63	64.7	0.65	64.2	0.66	0.66
	MHRED		√	√	102.7	0.33	0.23	101.9	0.34	100.8	0.31	100.2	0.34	0.31
Trimodal Baselines	*MHRED*	√	√	√	65.8	0.43	0.37	64.1	0.65	63.2	0.68	62.1	0.68	0.71
	MHRED + Attn	√	√	√	63.1	0.44	0.38	60.8	0.66	60.1	0.68	59.4	0.68	0.72
OurProposed Approach	*M-CVAE*	√			46.4	0.42	0.40	45.8	0.72	44.7	0.69	44.1	0.78	0.74
	M-CVAE		√		95.3	0.31	0.25	93.9	0.36	93.1	0.32	92.4	0.36	0.34
	M-CVAE			√	93.5	0.33	0.27	92.7	0.34	91.8	0.33	91.4	0.36	0.35
	M-CVAE	√	√		44.9	0.42	0.41	42.9	0.74	42.0	0.72	41.2	0.77	0.76
	M-CVAE	√		√	44.2	0.43	0.41	43.7	0.73	42.6	0.72	41.8	0.78	0.75
	M-CVAE		√	√	91.2	0.35	0.27	90.5	0.35	90.1	0.35	89.4	0.36	0.35
	M-CVAE	√	√	√	43.2	0.46	0.41	41.4	0.75	40.7	0.74	37.5	0.81	0.78
	M-CVAE + Attn (EmoSen)	√	√	√	**42.7**	**0.47**	**0.43**	**39.5**	**0.77**	**38.2**	**0.75**	**35.9**	**0.83**	**0.79**
	M-CVAE + Attn + GMP (EmoSen)	√	√	√	**42.1**	**0.47**	**0.44**	**38.7**	**0.79**	**37.1**	**0.76**	**34.8**	**0.85**	**0.80**

1. Here, T: Text, A: Audio, V: Visual features, S: Sentiment, E: Emotion, PPL: Perplexity, SA: Sentiment Accuracy, EA: Emotion Accuracy; GMP: Gaussian Mixture Prior network

Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

Results: Manual Evaluation

Model Description	Fluency			Sentiment		Emotion	
	0	*1*	*2*	*0*	*1*	*0*	*1*
MHRED + Attn (only S)	18.23	43.7	38.07	43.5	56.5	-	-
MHRED + Attn (only E)	16.85	40.3	42.85	-	-	42.8	57.2
MHRED + Attn (S + E)	17.64	39.2	43.16	41.7	58.3	40.5	59.5
M-CVAE + Attn (S + E)	14.7	38.5	46.8	35.4	64.6	34.6	65.4

Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

Case Study

Conversational History	Model	Emotion	Sentiment	Generated Response
Did he hear anything, at least? He was listening to his Ipod. Nothing like a little quality time with daddy. How could this happen in our own home?	MHRED	-	-	I am not sure about it.
	EmoSen	Sadness	-	I am sorry I could not hear anything.
	EmoSen	-	Positive	We like it to be at our home.
	EmoSen	Sadness	Positive	Oh no have been was looking for it, good I found it here.
	EmoSen	Surprise	-	Wow was it supposed to be like this?
	EmoSen	-	Negative	I hate to search this stuff around here at this time.
	EmoSen	Surprise	Negative	Oh my God! I am shocked by the sound coming from that room.
Call me crazy, but I don't think he was looking at Random's picture. It was like he was checking out that document. Oh, you mean, "the world's least-interesting doodle"?	MHRED	-	-	Yes you are right.
	EmoSen	Joy	-	That's really funny I love to doodle all the time.
	EmoSen	-	Positive	I am interested and want to finish these documents today.
	EmoSen	Joy	Positive	That's great I enjoyed taking the pictures of the doodles.
	EmoSen	Anger	-	Are you mad? this is not the way to say these things.
	EmoSen	-	Negative	Not a fan of these hobbies especially doodling.
	EmoSen	Anger	Negative	Don't screw up these documents or else I will kill you.
Oh no-no-no, give me some specifics. I love the specifics, the specifics were the best part! Hey, what about the scene with the kangaroo? Did-did you like that part?	MHRED	-	-	Sure I did like it.
	EmoSen	Disgust	-	That scene was horrible I almost puked.
	EmoSen	-	Positive	It was amazing I enjoyed it thoroughly.
	EmoSen	Disgust	Positive	Hey it was awfully good I never saw this coming.
	EmoSen	Fear	-	I was afraid when I saw it at first.
	EmoSen	-	Negative	Its not right I suppose it was very irritating.
	EmoSen	Fear	Negative	That movie scares the hell out of me especially the end part.
Chris says they're closing down the bar. No way! Yeah, apparently they're turning it into some kinda coffee place.	MHRED	-	-	Not heard of it yet.
	EmoSen	Surprise	-	When did this happen? I have no idea.
	EmoSen	-	Positive	Coffee is good I like it.
	EmoSen	Surprise	Positive	Wow it will be great I love coffee.
	EmoSen	Like	-	That's nice to hear it will be a good place.
	EmoSen	-	Negative	I hate coffee I have never been to a cafe.
	EmoSen	Like	Negative	I like this place alot but don't want it to become a cafe.

Firdaus et al. EmoSen: Generating Sentiment and Emotion Controlled Responses in a Multimodal Dialogue System. In IEEE TRANSACTIONS ON AFFECTIVE COMPUTING 2022.

Highlight 2

Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. (Firdaus et al., ECIR 2022)

Problem Definition

- Propose the task of sentiment guided aspect controlled response generation for multimodal dialogue systems

Motivation

- Growing requirements in various fields require conversational agents to communicate by incorporating information from the different modalities to build a robust system
- Users are the ultimate evaluators of dialogue systems. Therefore, research on the dialogue framework should aspire for greater user satisfaction

Firdaus et al. Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. In ECIR 2022.

Sentiment annotated examples from the Multi-domain Multi-modal Dialogue(MDMMD) dataset

Dialogue	Sentiment
User: I don't like the speakers shown so far, could you please show something portable.	Negative
Agent: Don't worry, we have some great portable speakers for you, please have a look. 	Neutral
User: The 2nd one looks great, could you show more in this pattern.	Positive

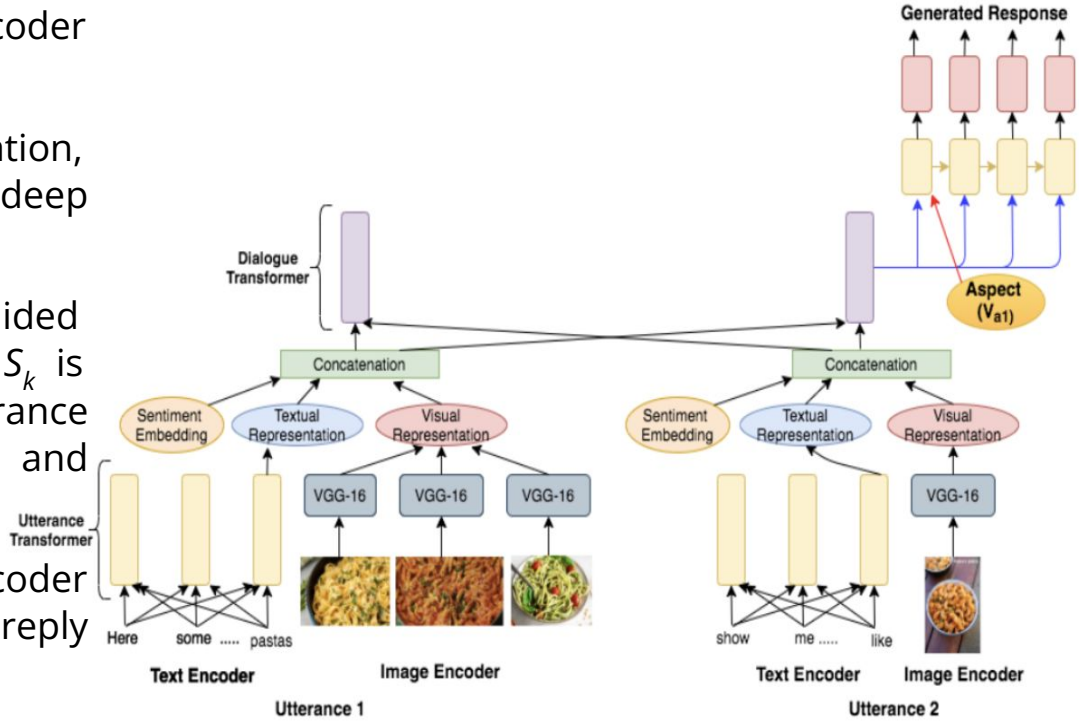
Dialogue	Sentiment
Agent: Great Choice! We have some nice colors for you, please see 	Positive
User: I love red! Please show the 3rd one from different orientations.	Positive
Agent: Nice to know, but we don't have any images of the 3rd one to show.	Neutral

- Providing extra feedback from the user in the form of sentiment
  - guide the model to adapt to user behaviour
  - assist in generating appropriate and accurate responses according to the user requirements

Firdaus et al. Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. In ECIR 2022.

Proposed Framework

- **Utterance Encoder:** A transformer encoder is used to encode the textual utterances
- **Visual Encoder:** For visual representation, the pre-trained VGG-16 having 16-layer deep convolutional network is used
- **Context Encoder:** For sentiment guided response generation, sentiment label S_k is concatenated with the final utterance representation having both textual and visual representation.
- **Aspect conditioned Decoder:** RNN decoder is used to construct the next textual reply using the specified aspect embedding



Firdaus et al. Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. In ECIR 2022.

Dataset

This work is built upon the Multi Domain Multi Modal Dialogue (MDMMD) dataset that comprises of 130k chat sessions between the customer and sales agent

Data Annotation

- Due to the absence of sentiment labels in the MDMMD dataset, a semi-supervised approach is used for labeling it with sentiments for which we annotate a portion of the dataset
- Create a balanced dataset (MDMMD-annotated) by manually annotating 10k dialogues for all the three domains
- Label every utterance in a dialogue with three sentiment labels, *positive, negative, and neutral*

Sentiment Classifier:

- Apply a semi-supervised approach for annotating the entire MDMMD dataset with sentiment labels
- For labeling the entire MDMMD dataset, the best-performing classifier, RoBERTa is used

Results: Automatic Evaluation

Model Description		Modality U	Modality M	Perplexity	BLEU-4	SA	Aspect F1
Existing Baselines	*Seq2Seq + Attn [41]*	√	-	1.0341	0.4378	45.36	51.59
	HRED [37]	√	-	1.0293	0.5206	48.33	56.83
	HVMN [5]	√	-	1.0189	0.5453	50.14	60.26
	GCN [3]	√	-	1.0119	0.5821	53.75	64.53
	Global-to-local [50]	√	-	1.0169	0.5785	54.66	64.29
	Working Memory [7]	√	-	1.0173	0.5692	55.27	63.78
	MHRED [35]	-	√	1.0142	0.5537	57.48	61.86
	OAM [4]	-	√	1.0136	0.5746	58.35	65.71
	M-GCN + A [14]	-	√	1.0112	0.6014	62.85	67.71
Proposed Approach	*M-HierTrans + RL + A + S*	-	√	**1.0043**	**0. 7287**	**72.58**	**80.55**
Ablation Study	*Transformer*	√	-	1.0123	0.6077	54.69	66.18
	Transformer + A	√	-	1.0117	0.6198	57.42	69.34
	Transformer + A + S	√	-	1.0111	0.6295	62.18	71.32
	M- Transformer	-	√	1.0085	0.6534	56.78	68.43
	M- Transformer + A	-	√	1.0077	0.6748	61.39	71.59
	M - Transformer + A + S	-	√	1.0069	0.6927	66.83	73.45
	HierTrans	√	-	1.0116	0.6382	57.23	69.11
	HierTrans + A	√	-	1.0111	0.6577	65.11	73.87
	HierTrans + A + S	√	-	1.0096	0.6825	69.47	76.36
	M- HierTrans	-	√	1.0058	0.6890	59.37	73.69
	M - HierTrans + A	-	√	1.0053	0.7033	67.84	77.51
	M - HierTrans + A + S	-	√	1.0049	0.7101	70.56	78.83

Firdaus et al. Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. In ECIR 2022..

Results: Manual Evaluation

Model Description		Modality U	Modality M	AC	SA	F	R	I
Existing Baselines	*Seq2Seq + Attn [41]*	√	-	25.9%	27.1%	2.17	2.21	2.19
	HRED [37]	√	-	34.1%	28.3%	2.54	2.63	2.69
	HVMN [5]	√	-	37.3%	30.1%	2.69	2.71	2.82
	GCN [3]	√	-	44.5%	31.7%	2.75	2.83	3.02
	Global-to-local [50]	√	-	47.1%	33.5%	2.88	2.91	3.19
	Working Memory [7]	√	-	46.5%	33.2%	2.86	2.90	3.15
	MHRED [35]	-	√	53.9%	36.1%	3.15	3.07	3.32
	OAM [4]	-	√	57.8%	38.2%	3.38	3.25	3.51
	M-GCN + A [14]	-	√	58.2%	38.7%	3.74	3.69	3.93
Proposed Approach	*M-HierTrans + RL + A + S*	-	√	**68.7%**	**52.2%**	**3.95**	**3.86**	**4.12**
Ablation Study	*Transformer*	√	-	49.1%	37.8%	2.91	3.02	3.37
	Transformer + A	√	-	51.3%	38.3%	2.94	3.06	3.41
	Transformer + A + S	√	-	53.5%	40.1%	2.97	3.08	3.47
	M- Transformer	-	√	59.4%	39.5%	3.70	3.59	3.69
	M- Transformer + A	-	√	61.2%	40.9%	3.73	3.63	3.75
	M - Transformer + A + S	-	√	63.7%	43.2%	3.78	3.66	3.83
	HierTrans	√	-	55.3%	41.3%	3.25	3.34	3.51
	HierTrans + A	√	-	57.9%	43.8%	3.28	3.37	3.56
	HierTrans + A + S	√	-	61.1%	46.4%	3.33	3.40	3.63
	M- HierTrans	-	√	65.3%	45.3%	3.80	3.79	3.99
	M - HierTrans + A	-	√	67.2%	48.3%	3.83	3.81	4.05
	M - HierTrans + A + S	-	√	67.7%	50.1%	3.87	3.83	4.07

Firdaus et al. Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. In ECIR 2022.

Generated Examples

Example 1 **Sys:** With the 2nd image, these beverages will be good please have a look  **Usr:** Its great! Show we more like the 3rd one but in some other flavour.	
M-HierTrans + A	Sure let me check other flavours for you.
M-HierTrans + A + S	We have in strawberry flavour, would you like it?
M-HierTrans + RL + A + S	Your choice is good! There are three available flavours you will love it.
Example 2 **Sys:** We have got you the latest smart watches available with best features  **Usr:** I don't prefer plastic, could you tell what is the strap material of the 3rd image?	
M-HierTrans + A	This watch has rubber strap.
M-HierTrans + A + S	The material of the strap is rubber and its very comfortable.
M-HierTrans + RL + A + S	Plastic is not good, but the strap is made of black rubber material and is very trendy.

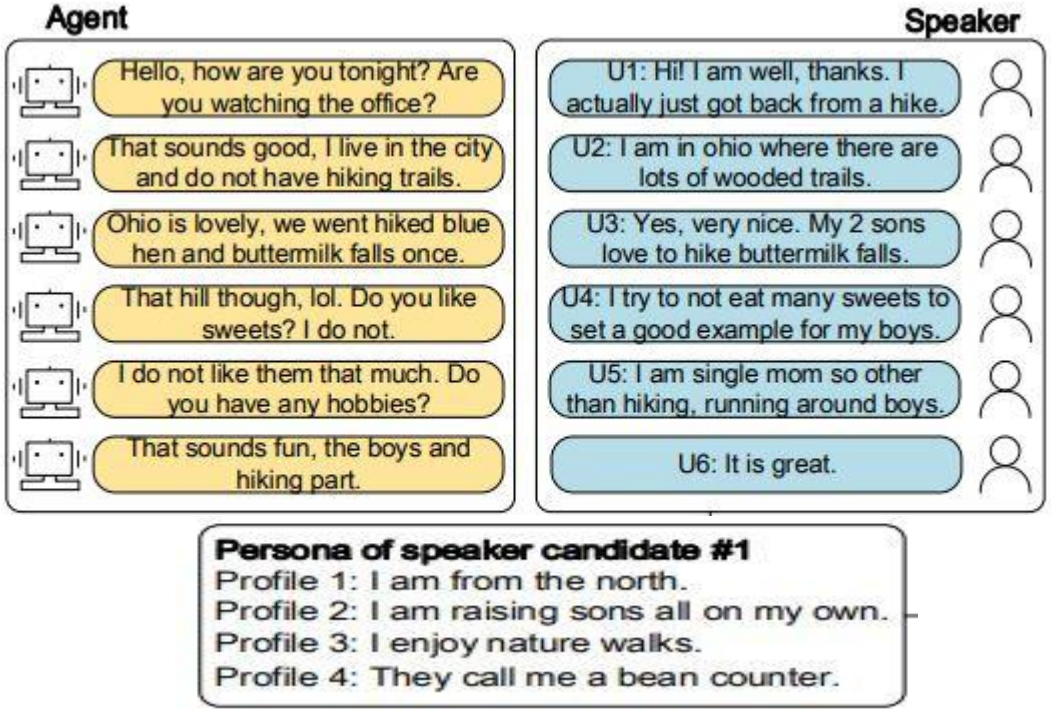
Firdaus et al. Sentiment guided Aspect conditioned Dialogue Generation in a Multimodal System. In ECIR 2022.

Concept 4

Persona

Persona

- Every individual has a personality (persona)
- Useful in response generation
  - Establishing a connection
  - Building trust
  - Improving user experience
  - Guiding the conversation



Gu et al. Detecting Speaker Personas from Conversational Texts. In EMNLP 2021.

Persona and Empathy

- Empathy helps understand and relate to the personas of others
- Being empathetic helps recognize the emotions and struggles that others may be experiencing, even if they are not explicitly expressing them through their persona
- Allow to connect with others on a deeper level and build more meaningful relationships

Major Highlights

- Persona aware Response Generation with Emotions. (Firdaus et al., IJCNN 2020)

- I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. (Firdaus et al., IEEE Transactions on Affective Computing 2022)

- SEPRG: Sentiment aware Emotion controlled Personalized Response Generation. (Firdaus et. al., INLG 2021)

Highlight 1

Persona aware Response Generation with Emotions. (Firdaus et al., IJCNN 2020)

Persona-aware Emotional Response Generation

Persona 1	Persona 2
As a child , I won a national spelling bee.	*I'm very athletic.*
I've been published in the new yorker magazine.	*I have brown hair.*
I am a gourmet cook.	*I love bicycling.*
I've perfect pitch.	*I hate carrots.*
[Person 1] Hi! i work as a gourmet cook.	
[Person 2] I don't like carrots. I throw them away.	
[Person 1] Really. But, I can sing pitch perfect .	
[Person 2] I also cook, and I ride my bike to work.	

- Speakers maintain the persona information while conversing with each other
  - Make the conversation interactive and also facilitate building user's trust and confidence.

- Response to Person 1 could be empathetic like "*That's a great job, but I don't like carrots and throw them away.*"

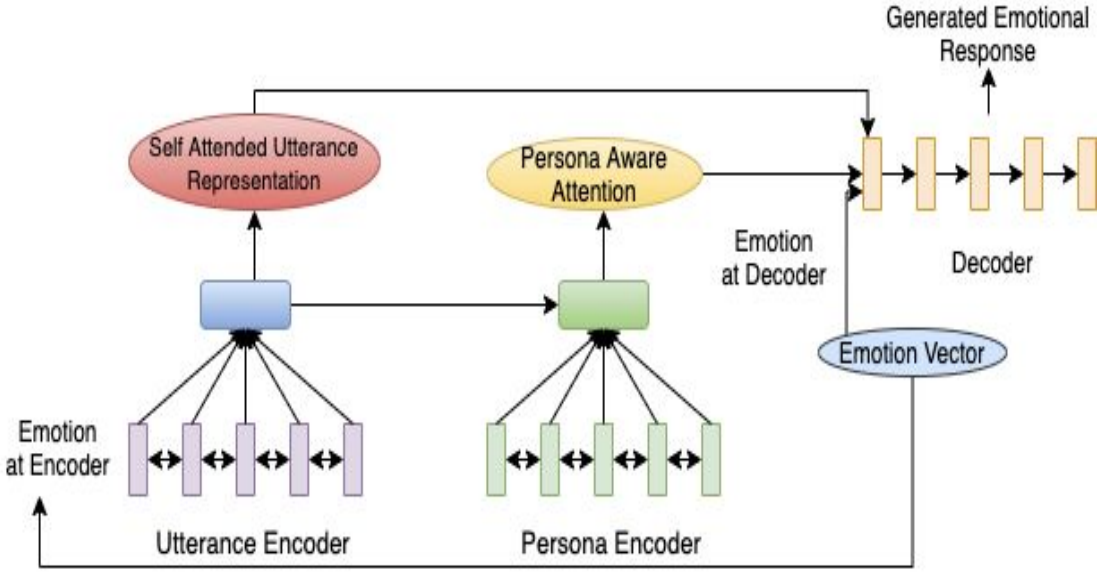
Firdaus et al. Persona aware Response Generation with Emotions. In IJCNN 2020

Dataset

- Used ConvAI2 benchmark dataset, which is an extended version (with a new test set) of the persona-chat dataset
- Dataset Statistics
  - 10,981 dialogues with 164,356 utterances
  - 1,155 personas, each consisting of at least four personality texts.
  - 1,016 dialogues in the testing set and 200 never before seen personas.

Proposed Framework

- Utterance and Persona encoders followed by a decoder for generating the desired emotional responses
- Persona-aware attention enables the model to focus on different personas mentioned in the utterance



Firdaus et al. Persona aware Response Generation with Emotions. In IJCNN 2020

Results: Automatic Evaluation

Model Description		Perplexity	BLEU	Rouge-L	Emotion Accuracy	Distinct-1	Distinct-2
Baseline Approaches	Seq2Seq	59.11	0.042	0.149	0.35	0.0125	0.0464
	Seq2Seq + Attn	58.23	0.047	0.151	0.38	0.0131	0.0472
	Seq2Seq + Attn + PAA	57.60	0.088	0.154	0.42	0.0163	0.0581
	Seq2Seq + Attn + EE	56.87	0.092	0.157	0.58	0.0155	0.0534
	Seq2Seq + Attn + ED	56.39	0.096	0.158	0.61	0.0158	0.0562
Proposed Approaches	**Seq2Seq + Attn + PAA + EE**	**55.59**	**0.099**	**0.162**	**0.65**	**0.0189**	**0.0844**
	Seq2Seq + Attn + PAA + ED	**52.68**	**0.108**	**0.169**	**0.67**	**0.0210**	**0.0923**

Firdaus et al. Persona aware Response Generation with Emotions. In IJCNN 2020

Results: Manual Evaluation

Model Description		Fluency			Emotion		Persona Consistency	
		0	1	2	0	1	0	1
Baseline Approaches	Seq2Seq	27.36	45.83	26.81	75.93	24.07	77.20	22.80
	Seq2Seq + Attn	26.11	44.71	29.18	74.56	25.44	76.14	23.86
	Seq2Seq + Attn + PAA	23.41	42.96	33.63	73.81	26.19	51.64	48.36
	Seq2Seq + Attn + EE	24.17	43.11	32.72	59.33	40.67	70.88	29.12
	Seq2Seq + Attn + ED	23.05	42.88	34.07	57.49	42.51	70.31	29.69
Proposed Approaches	**Seq2Seq + Attn + PAA + EE**	**19.64**	**38.65**	**41.71**	**55.72**	**44.28**	**49.85**	**50.15**
	Seq2Seq + Attn + PAA + ED	**18.15**	**37.32**	**44.53**	**53.91**	**46.09**	**48.11**	**51.89**

Firdaus et al. Persona aware Response Generation with Emotions. In IJCNN 2020

Generated Examples

Dialog Input	Persona Information		Ground-Truth	Generated Response
[Person 1] Hi! i work as a gourmet cook. [Person 2] I don't like carrots. I throw them away. [Person 1] Really. But, I can sing pitch perfect .	Persona 1 As a child, I won a national spelling bee. I've been published in the new yorker magazine. I am a gourmet cook. I've perfect pitch.	Persona 2 I'm very athletic. I have brown hair. I love bicycling. I hate carrots.	I also cook, and I ride my bike to work.	**Seq2Seq:** I also cook. **Seq2Seq+PAA+EE:** Really! I like to cook and ride a bike to work. (surprise) **Seq2Seq+PAA+ED:** Wow that's nice, but I like to cook and ride bike to work. (surprise)
[Person 1] Hi! how are you today? [Person 2] I had the day off, you? [Person 1] I only worked half a day at the bank.	Persona 1 I am a bank teller. I've never been out of the country. My favorite phone is as Iphone. I love to go hiking.	Persona 2 I m from Texas. I like basketball. I work many hours. My favorite band is imagine dragons.	I work a lot.	**Seq2Seq:** I work alot. **Seq2Seq+PAA+EE:** That's nice to hear but I have a busy schedule. (disappointed) **Seq2Seq+PAA+ED:** Ohh good for you but I work alot for my basketball. (disappointed)

Firdaus et al. Persona aware Response Generation with Emotions. In IJCNN 2020

Highlight 2

I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. (Firdaus et al., IEEE Transactions on Affective Computing 2022)

Problem Definition

- Generate empathetic, personalized responses while considering the persona information and implicitly the emotion in the responses through the dialogue context

Motivation

- Social chatbots have gained immense popularity, and their appeal lies in their capacity to respond to diverse requests, and their ability to develop an emotional connection with users
- To develop and promote social chatbots, both the intellectual and emotional quotient needs to be introduced in conversational agents
    - Increases user interaction

Firdaus et al. I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. In IEEE Transactions on Affective Computing 2022

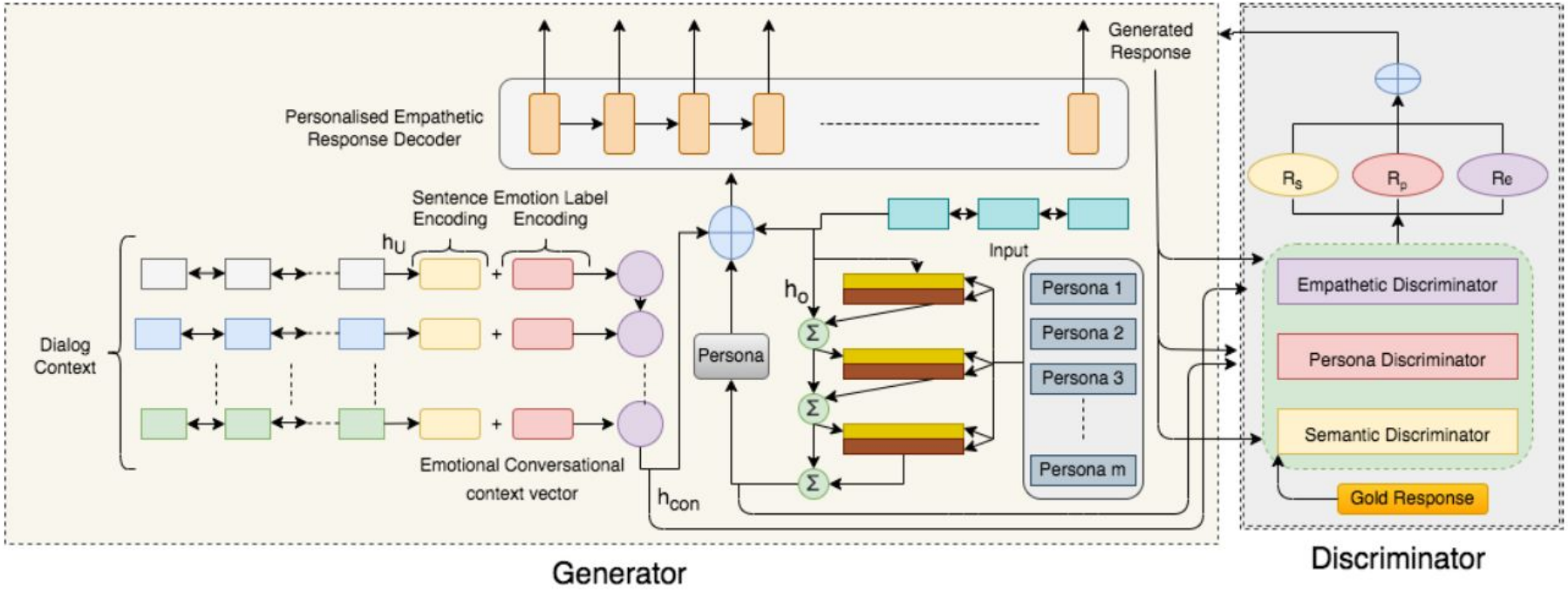
Example from the Dataset

Persona 1	Persona 2
I am primarily a meat eater.	*I've a sweet tooth.*
I am a guitar player.	*I'm a babysitter and drive a mercedes.*
Welding is my career field.	*I'm the middle child of 3 siblings.*
My parents don't know I am gay.	*I'm getting married in six months.*
[Person 1] What do you do for career?	
[Person 2] I like to watch kids.	
[Person 1] I actually play guitar and do a lot of welding.	
[Person 2] What do you weld? houses?	

- Speakers maintain the persona information while conversing with each other
  - Make the conversation interactive and also facilitate building user's trust and confidence.

Firdaus et al. I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. In IEEE Transactions on Affective Computing 2022

Empathy and Persona aware Generative Adversarial Network



Firdaus et al. I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. In IEEE Transactions on Affective Computing 2022

Dataset

- Used ConvAI2 benchmark dataset, which is an extended version (with a new test set) of the persona-chat dataset
- Dataset Statistics
  - 10,981 dialogues with 164,356 utterances
  - 1,155 personas, each consisting of at least four personality texts.
  - 1,016 dialogues in the testing set and 200 never before seen personas.
- Emotion Annotation
  - Semi-supervised approach
  - Used DistilBERT fine-tuned on EmpatheticDialogues dataset with 32 emotion labels

Firdaus et al. I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. In IEEE Transactions on Affective Computing 2022

Results: Automatic Evaluation

Model Description		Perplexity	BLEU-4	Rouge-L	Distinct-1	Distinct-2	Emotion Accuracy
Baseline Approaches	*Seq2Seq [82]*	56.11	0.089	0.196	0.0125	0.0464	0.358
	HRED [25]	55.63	0.096	0.201	0.0128	0.0469	0.376
	Trans [6]	53.17	0.121	0.228	0.0186	0.0749	0.451
	SeqGAN [80]	55.61	0.098	0.203	0.0133	0.0470	0.381
	Seq2Seq + E + P [21]	54.13	0.103	0.189	0.0168	0.0549	0.657
	HRED + E + P	54.85	0.116	0.224	0.0174	0.0592	0.665
	Trans + E + P	52.87	0.132	0.241	0.0203	0.0839	0.681
	CoBERT [22]	51.09	0.138	0.258	0.0210	0.0894	0.693
Proposed Approach	***EP-GAN***	**51.92**	**0.143**	**0.266**	**0.0219**	**0.0987**	**0.715**
Ablation Study	*EP-GAN - SD*	53.47	0.118	0.239	0.0189	0.0883	0.678
	EP-GAN - ED	53.44	0.125	0.242	0.0193	0.0896	0.695
	EP-GAN - PD	52.39	0.129	0.249	0.0199	0.0953	0.683
	EP-GAN - SD + ED	52.26	0.130	0.251	0.0206	0.0976	0.708
	EP-GAN - SD + PD	52.12	0.135	0.257	0.0210	0.0971	0.688

Observations:

- Here, E-Emotion, P-Persona, Ep-GAN-SD: the EP-GAN framework having only the semantic discriminator, EP-GAN-ED: with only emotion discriminator, EP-GAN-PD: with only persona discriminator, EP-GAN - SD+ED: with both semantic and emotion discriminators, EP-GAN - SD+PD: with both semantic and persona discriminators

Firdaus et al. I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. In IEEE Transactions on Affective Computing 2022

Results: Manual Evaluation

Model Description		Fluency	Relevance	Emotion Appropriateness	Persona Consistency
Baseline Approaches	*Seq2Seq [82]*	2.98	2.65	38%	35%
	HRED [25]	3.16	2.89	41%	39%
	Trans [6]	3.51	3.24	45%	59%
	SeqGAN [80]	3.25	2.95	42%	41%
	Seq2Seq + E + P [21]	3.29	3.02	53%	48%
	HRED + E + P	3.45	3.18	59%	55%
	Trans + E + P	3.68	3.51	61%	62%
	CoBERT [22]	3.72	3.59	63%	65%
Proposed Approach	*EP-GAN*	**3.89**	**3.66**	**65%**	**67%**

Observations:

- From the manual evaluation results presented in the table, we can see that the HRED+E+P and Seq2Seq+E+P models show significant improvement from the typical HRED and Seq2Seq model in inducing the persona information while generating the responses.
- There is an enhancement in the proposed EP-GAN system from all of the other baseline systems in the case of the persona consistency metric.

Firdaus et al. I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. In IEEE Transactions on Affective Computing 2022

Generated Examples

Dialog Input	Persona Information		Ground-Truth	Generated Response
[*Person 1*] What do you do for a career? [*Person 2*] I like to watch kids. [*Person 1*] I actually play guitar and do lot of welding.	**Persona 1** I am primarily a meat eater. I am a guitar player. Welding is my career field. My parents don't know I am gay.	**Persona 2** I've a sweet tooth. I'm the middle child of 3 sibling. I'm getting married in six weeks.	What do you weld? houses?	**Seq2Seq:** What is weld? ¡UNK¿ ¡UNK¿ **HRED:** What you weld? **Trans:** Welding houses are you? **SeqGAN:** What are you welding? **Seq2Seq+E+P:** Wow! What you weld mostly? (surprise) **HRED+E+P:** Really! Do you weld houses? (surprise) **Trans + E + P:** Oh my god! you weld houses? (surprise) **EP-GAN - ED:** Do you weld homes? **EP-GAN - PD:** That's nice, what you do? (surprise) **EP-GAN:** Wow that's great, what do you weld mostly, is it houses? (surprise)
[*Person 1*] Hi! do you like turtles? [*Person 2*] I have two cats actually. [*Person 1*] I have a turtle his name is Speedy.	**Persona 1** I don't pick up my toys. I have a pet turtle. I like to play with my dolls. I'm fourteen.	**Persona 2** I love cats and have two cats. My favorite season is winter. I've a hat collection of over 1000 hats.	I am a cat person.	**Seq2Seq:** I have cats. **HRED:** I like cats mostly. **Trans:** Cats are lovely. **SeqGAN:** I am into cats. **Seq2Seq+E+P:** Turtles are nice but I like cats. (joy) **HRED+E+P:** Nice name for a pet, but I love cats. (joy) **Trans + E + P:** Nice turtle name, but I am more in cats. (joy) **EP-GAN - ED:** I have cats only. **EP-GAN - PD:** I love to have pets. (joy) **EP-GAN:** That is an adorable name for a turtle! but I am a cat person. (joy)
[*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!	**Persona 1** I hate Mexican food. I like to ski. I like to eat cheetos. My wife does not like me anymore.	**Persona 2** I am an artist. I have four children. I enjoy walking for exercise. I love watching Game of Thrones.	Do you watch Game of Thrones?	**Seq2Seq:** What you watch? **HRED:** Do you enjoy watching? **Trans:** Did you see Game of Thrones? **SeqGAN:** What you see in Game of thrones?. **Seq2Seq+E+P:** Oh! do you see game? (anxious) **HRED+E+P:** How is it possible for watching game? (anxious) **Trans + E + P:** Ohh no! Game of thrones you like? (anxious) **EP-GAN - ED:** Do you watch any game? **EP-GAN - PD:** I guess you watch game right? (anxious) **EP-GAN:** Oh I hope you watch Game of Thrones? (anxious)
[*Person 1*] What do you usually bake? [*Person 2*] I bake cakes at a local restaurant how about you? [*Person 1*] I used to be a juggler at a carnival.	**Persona 1** I used to work at a carnival. I write short stories for a living. I am afraid of dogs. I like dark superhero movies.	**Persona 2** I love baking. I like playing poker. I enjoy dancing as well. I dont have many friends.	I am a dancer, what do you do?	**Seq2Seq:** What you do? **HRED:** Do you like to dance? **Trans:** I enjoy dancing and you? **SeqGAN:** Are you a dancer? **Seq2Seq+E+P:** Nicee but what you do? (impressed) **HRED+E+P:** I am a dancer but juggling is nice too. (impressed) **Trans + E + P:** Wow but I dance, what you do? (impressed) **EP-GAN - ED:** I dance all the time. **EP-GAN - PD:** I like juggling alot. (impressed) **EP-GAN:** Juggling is wonderful just like I am a dancer but what you do now? (impressed)

Firdaus et al. I enjoy writing and playing, do you: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network. In IEEE Transactions on Affective Computing 2022

Highlight 3

SEPRG: Sentiment aware Emotion controlled Personalized Response Generation. (Firdaus et. al., INLG 2021)

What has been done in this work?

- Defining a new task: **Sentiment-aware emotion controlled personalized response generation**
- Annotated PersonaChat Dataset with sentiment information
  -
- **Proposed architecture**
  - A novel Transformer based encoder-decoder framework, with the ability to infuse the sentiment, emotion and persona information in the responses

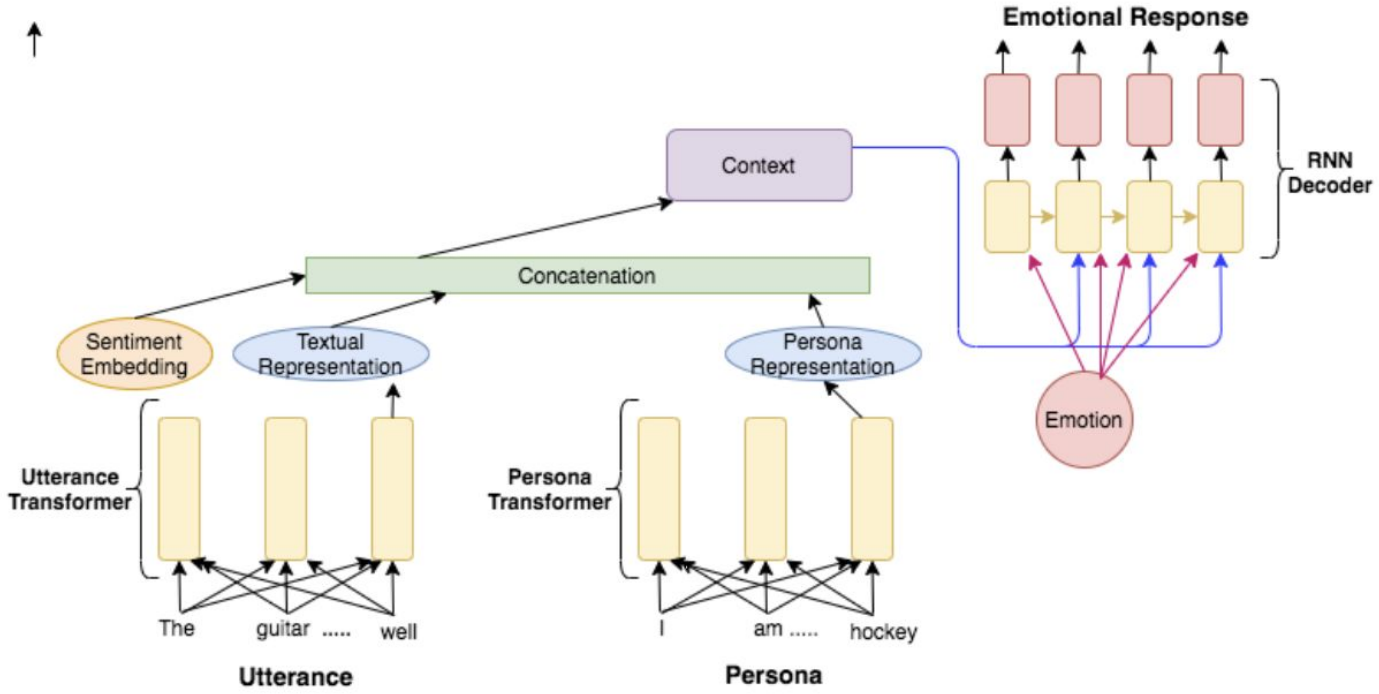
A conversation from the PersonaChat dataset with sentiments

Persona 1	Persona 2
I am primarily a meat eater.	*I've a sweet tooth.*
I am a guitar player.	*I'm a babysitter and drive a mercedes.*
Welding is my career field.	*I'm the middle child of 3 siblings.*
My parents don't know I am gay.	*I'm getting married in six months.*

[Person 1] What do you do for career? (Neutral)
[Person 2] I like to watch kids. (Positive)
[Person 1] I actually play guitar and do a lot of welding. (Positive)
[Person 2] What do you weld? houses?(Neutral)

Firdaus et al. SEPRG: Sentiment aware Emotion controlled Personalized Response Generation. In INLG 2021

Sentiment and Persona guided Emotional Dialogue Generation Framework



Firdaus et al. SEPRG: Sentiment aware Emotion controlled Personalized Response Generation. In INLG 2021

Dataset

Dataset Statistics	Train	Valid	Test
Dialogues	7686	1640	1655
Utterances	124816	19680	19860
Avg. turns per Dialogue	12.51	12.73	12.74
Avg. words in a Response	11.89	9.57	10.75
Emotions per dialogue	7.4	6.5	5.1
Unique words	20322	13415	15781

Results: Automatic Evaluation

Model Description		Perplexity	BLEU-4	Rouge-L	Distinct-1	Distinct-2	Emotion Accuracy
Baseline Approaches	*Seq2Seq* (*Sutskever et al., 2014*)	56.11	0.089	0.196	0.0125	0.0464	0.358
	HRED (*Serban et al., 2017*)	55.63	0.096	0.201	0.0128	0.0469	0.376
	Seq2Seq + E + P (*Firdaus et al., 2020*)	54.13	0.103	0.189	0.0168	0.0549	0.657
	HRED + E + P	54.85	0.116	0.224	0.0174	0.0592	0.665
	Seq2Seq + E + P + S	53.61	0.115	0.203	0.0171	0.0555	0.673
	HRED + E + P + S	52.46	0.127	0.237	0.0186	0.0590	0.689
Proposed Approach	*Trans + E + P + S*	**51.92**	**0.143**	**0.266**	**0.0219**	**0.0987**	**0.715**
Ablation Study	*Trans*	53.47	0.118	0.239	0.0189	0.0883	0.678
	Trans + E + P	53.44	0.125	0.242	0.0193	0.0896	0.695

Firdaus et al. SEPRG: Sentiment aware Emotion controlled Personalized Response Generation. In INLG 2021

Results: Manual Evaluation

Model Description		Fluency	Relevance	Emotion Appropriateness	Persona Consistency	Sentiment Coherence
Baseline Approaches	*Seq2Seq* (*Sutskever et al., 2014*)	2.98	2.65	38%	35%	33%
	HRED (*Serban et al., 2017*)	3.16	2.89	41%	39%	37%
	Seq2Seq + E + P (*Firdaus et al., 2020*)	3.29	3.02	53%	48%	42%
	HRED + E + P	3.45	3.18	59%	55%	47%
	Seq2Seq + E + P + S	3.33	3.21	56%	52%	51%
	HRED + E + P + S	3.52	3.45	61%	58%	55%
Proposed Approach	***Trans + E + P + S***	**3.89**	**3.66**	**65%**	**67%**	**62%**

Generated Examples

Dialog Input	Persona Information		Ground-Truth	Generated Response
[Person 1] What do you do for a career? [Person 2] I like to watch kids. [Person 1] I actually play guitar and do lot of welding.	Persona 1 I am primarily a meat eater. I am a guitar player. Welding is my career field. My parents don't know I am gay.	Persona 2 I've a sweet tooth. I'm a babysitter and drive a mercedes. I'm the middle child of 3 sibling. I'm getting married in six weeks.	What do you weld? houses? Neutral	**Seq2Seq:** What is weld? ¡UNK¿ ¡UNK¿ **HRED:** What you weld? **Seq2Seq+E+P:** Wow! What you weld mostly? (surprise) **HRED+E+P:** Really! Do you weld houses? (surprise) **Proposed:** Wow that's great, what do you weld mostly, is it houses? (surprise)
[Person 1] Hi! do you like turtles? [Person 2] I have two cats actually. [Person 1] I have a turtle his name is Speedy.	Persona 1 I don't pick up my toys. I have a pet turtle. I like to play with my dolls. I'm fourteen.	Persona 2 I love cats and have two cats. My favorite season is winter. I won a gold medal in the 1992 olympics. I've a hat collection of over 1000 hats.	I am a cat person. Positive	**Seq2Seq:** I have cats. **HRED:** I like cats mostly. **Seq2Seq+E+P:** Turtles are nice but I like cats. (joy) **HRED+E+P:** Nice name for a pet, but I love cats. (joy) **Proposed:** That is an adorable name for a turtle! but I am a cat person. (joy)

Firdaus et al. SEPRG: Sentiment aware Emotion controlled Personalized Response Generation. In INLG 2021

Concept 5

Politeness

Politeness and Empathy

- Politeness can drive and enhance empathy
- It helps to create an atmosphere that promotes positive interactions and encourages others to open up and share their thoughts and feelings, thereby fostering empathy
- Practicing both can contribute to healthier relationships, effective communication, and the creation of positive social environments.

Major Highlights

- Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. (Golchha et al., NAACL-HLT 2019)
- Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. (Firdaus et al. LREC 2020)
- PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. (Firdaus et al., COLING 2022)
- Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In (Firdaus et al. , IEEE TCSS 2022)
- Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. (Mishra et al., Neurocomputing 2022)
- GenPADS: Reinforcing Politeness in an End-to-End Dialogue System. (Mishra et al., PLOS ONE 2023)

Highlight 1

Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. (Golchha et al., NAACL-HLT 2019)

Problem Definition

To **transform** a generic chatbot response into a response which uses courteous phrases and emoticons to display appreciation, empathy, apology, assurance, in coherence with the state of conversation

Domain: Customer Care on Twitter

Motivation

To transform a generic chatbot reply into one that:

- Is emotionally aware and intelligent
- Uses courteous phrases and emoticons to display appreciation, empathy, apology, assurance
- End motive is to increase user satisfaction and to build customer relations

Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

Example I (Expressing Apology / Empathy)

somebody from @VerizonSupport please help meeeeee 😩😩😩😩 I'm having the worst luck with your customer service

@115719 How can we help?

@VerizonSupport I finally got someone that helped me, thanks!

@115719 Awesome!

somebody from @VerizonSupport please help meeeeee 😩😩😩😩 I'm having the worst luck with your customer service

@115719 **Help has arrived! We are sorry to see that you are having trouble.** How can we help?

@VerizonSupport I finally got someone that helped me, thanks!

@115719 Awesome! **If you ever need us we are just a tweet away.**

Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

Resource Creation: Data Source and Description

- Source the requisite Twitter data from the dataset made available on Kaggle

- Segment the tweet into sentences
  - Purely courteous (and non-informative) sentences must be removed
  - Purely informative sentences must be retained
  - Informative sentences with courteous expressions must be transformed (to remove only the courteous part from the sentence)

Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

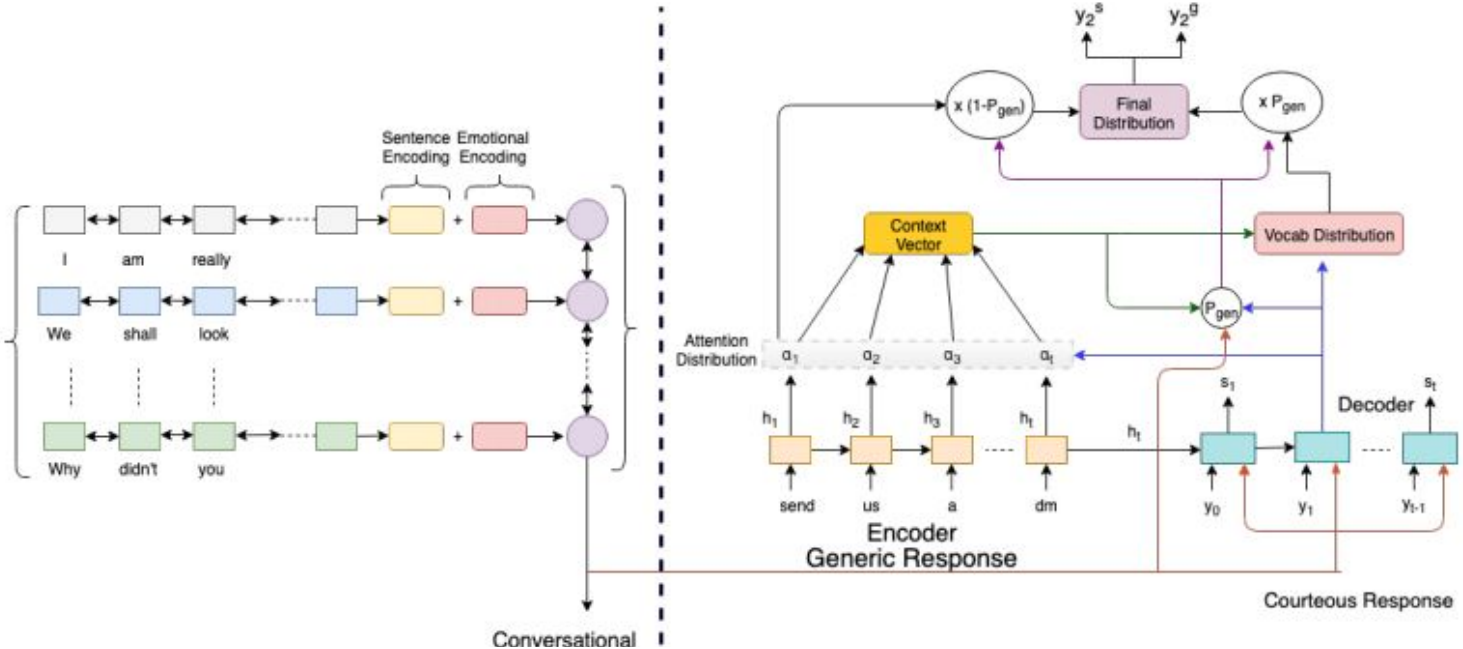
Resource Creation: Scaling up for large data creation

- **Clustering**
  - The vector-semantic representations of sentences are obtained using the sentence encoder trained on the SNLI corpus.
  - Use the K-Means clustering(k = 300) to cluster these sentences.
- **Annotations**
  - purely courteous,
  - purely informative,
  - hybrid
- **Preparing generic responses**
  - Obtain the generic response by removing the courteous sentences, retaining the informative sentences, and replacing the hybrid sentences with the prepared generic equivalents

Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

Proposed Methodology

- Based on a reinforced pointer-generator model for the sequence to sequence task
- The model is also conditioned on a hierarchically encoded and emotionally aware conversational context



Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

Results: Automatic Evaluation

	Model	BLEU	ROUGE			PPL	CP	EA
			1	2	L			
1	*Seq2Seq*	56.80	63.8	59.06	64.52	58.21	68.34	82.43
2	*Seq2Seq + P*	66.11	69.92	64.85	66.40	**42.91**	**77.67**	81.98
3	*Seq2Seq + P + EE*	68.16	72.18	67.92	71.17	43.52	76.05	85.75
4	*Proposed Model*	**69.22**	**73.56**	**69.92**	**72.37**	43.77	77.56	**86.87**

P: Pointer Generator Model; EE: Emotional embedding

Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

Results: Human Evaluation

Model	F			CA			CoA		
	0	1	2	0	1	2	-1	0	1
Model 1	15.70	42.50	41.80	16.21	41.69	42.10	23.71	51.08	25.21
Model 2	14.23	42.77	43.00	15.62	39.65	44.73	22.05	39.43	38.52
Model 3	11.15	44.10	44.75	13.66	41.12	45.22	15.23	41.22	43.55
Our Model	10.05	44.90	44.60	13.85	38.48	47.67	14.11	41.11	44.78

All values are in percentages.

Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

Generated Examples

Generic Input	Model 1	Model 2	Model 3	Our Model
dm us more info and well take a look into it for you	we'll look into it	im sorry to hear this please dm us more info and we'll take a look into it for you	were here to help please dm us more info and well take a look into it for you	were here to help please dm us more info and well take a look into it for you at the earliest
adjust the brightness via your display settings on your device	whos the brightness via your display settings on your device	were here to help adjust the brightness via your display settings on your device	we have several ways to change the display brightness on your device and were happy to help	thanks for reaching out we have several ways to change the display brightness on your device and were happy to help
we'll follow up with the store	we'd like to help well follow up	were here to help well follow up with the store	sorry to hear that well follow up with the store	thats disappointing to hear, we'll follow up with the store
can you confirm which platform you are using for video access ? what is the error ?	what is the error ?	I am sorry for the frustration ! can you confirm which platform you are using for video access ? what is the error ?	I am sorry to hear this can you confirm which platform you are using for video access? what is the error?	I am sorry for any frustration, can you please confirm which platform you are using for video access? Please tell us what is the error.
fill this form <url>	please fill this form <url>	were here to help fill this form <url>and I'll contact you at the earliest a	apologies for the hassle, please fill this form <url>and we'll contact you thank you for reaching out to us we will follow up with the store	i am sorry for the hassle, please fill this form <url> and ill contact you at the earliest

Golchha et al. Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network. In NAACL-HLT 2019

Highlight 2

Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. (Firdaus et al. LREC 2020)

Problem Definition

To **induce** courteous behaviour in generic customer care response (appreciation, empathy, apology, assurance, etc.) in a multi-lingual scenario (Hindi and English languages)

Domain: Customer Care on Twitter

Motivation

- Polite behavior of the agent give humanly essence to the conversational systems
- Develop systems that can converse with humans in their preferred language
    - using polite/courteous response,
    - leading to user satisfaction and high customer retention

Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

Example of Polite Response

Generic Response	Polite Response	Behaviour
Provide your booking info via dm.	We're here to help you, please provide your booking info via dm.	*Assurance*
हम मामले पर गौर करेंगे। (We will look into the matter.)	यह सुनने के लिए निराशाजनक है, कृपया धैर्य रखें जब तक कि हम मामले को न देखें। (That's disappointing to hear, please have patience until we look into the matter.)	*Empathy*
Our team is working on getting your bags.	We're sorry for the extended travel time, our team is working hard on getting your bags, please have patience.	*Apology*
What are you looking for?	Hey good evening, good to have you with us, please tell what are you looking for?	*Greet*
हमने सभी जानकारी प्रदान की है। (We have provided all the information.)	हमारी सेवाओं का उपयोग करने के लिए धन्यवाद, हमने सभी जानकारी प्रदान की है। (Thanks for using our services, we have provided all the information.)	*Appreciation*

Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

Resource Creation: Data Source and Description

- Use CYCCD dataset in English [10]
- Prepared Hindi Conversational Data
  - Source the requisite Twitter data from the dataset made available on Kaggle in Hindi
  - Segment the tweet into sentences
    - Purely courteous (and non-informative) sentences must be removed
    - Purely informative sentences must be retained
    - Informative sentences with courteous expressions must be transformed (to remove only the courteous part from the sentence)

Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

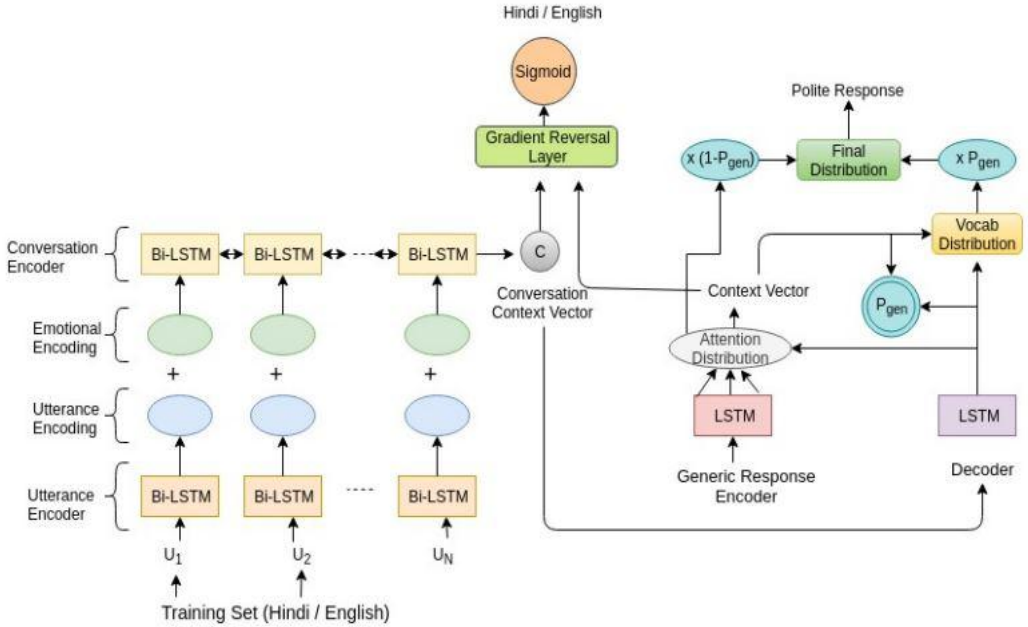
Resource Creation: Scaling up for large data creation

- **Clustering**
  - The vector-semantic representations of sentences are obtained using the sentence encoder trained on the SNLI corpus.
  - Use the K-Means clustering(k = 300) to cluster these sentences.
- **Annotations**
  - purely courteous,
  - purely informative,
  - hybrid
- **Preparing generic responses**
  - Obtain the generic response by removing the courteous sentences, retaining the informative sentences, and replacing the hybrid sentences with the prepared generic equivalents

Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

Proposed Methodology

- Based on a reinforced pointer-generator model for the sequence to sequence task
- The model is also conditioned on a hierarchically encoded and emotionally aware conversational context
- Model is jointly training of Hindi and English
- Gradient reversal layer is used to learn language invariant features



Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

Automatic Evaluation

Model	Type	English					Hindi				
		BLEU	*ROUGE-L*	*PPL*	*EA*	*CP*	*BLEU*	*ROUGE-L*	*PPL*	*EA*	*CP*
Seq2Seq	*Without Joint Training*	56.80	64.52	58.21	82.43	68.34	48.67	53.61	62.47	70.33	59.41
Seq2Seq + P		66.11	66.40	42.91	81.98	77.67	54.33	56.22	55.11	69.86	64.75
Seq2Seq + P + EE		68.16	71.17	43.52	85.75	76.05	55.75	57.58	54.36	74.54	66.72
Seq2Seq + P + EE + RL		69.22	72.37	43.77	86.87	77.56	56.82	58.88	53.81	75.23	67.16
Seq2Seq	*With Joint Training*	57.18	65.75	57.48	82.56	69.43	51.16	54.26	60.54	72.45	61.52
Seq2Seq + P		68.38	69.25	41.66	82.21	78.52	56.03	57.82	48.67	71.32	66.71
Seq2Seq + P + EE		70.84	72.77	42.98	86.34	76.85	57.14	59.48	46.23	76.81	67.71
Seq2Seq + P + EE + RL		71.22	73.37	43.11	87.41	78.33	57.82	59.93	45.79	77.15	68.09
Our Model		**72.45**	**75.21**	**41.89**	**87.96**	**79.20**	**59.66**	**61.48**	**44.18**	**77.93**	**68.52**

Observations:

- From the results, it is evident that the joint training of both the languages has helped in improving the performance of both Hindi and English in comparison to the individual models (i.e., only Hindi or English).
- For English, there is a significant improvement of 1.9% in BLEU score while the model is jointly trained on both the languages. While there is an increased improvement of 1.33% (overall 3.23%) using our proposed model which incorporates adversarial training
- the emotional accuracy of our proposed model by jointly training both Hindi and English is 2.7% and 1.09% better than the individual models, respectively.

Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

Results: Manual Evaluation

Language	Model	F			CA			PC		
		0	*1*	*2*	*0*	*1*	*2*	*-1*	*0*	*1*
English	*Seq2Seq*	16.88	41.32	41.80	16.74	40.33	42.93	24.56	48.71	26.73
	Our Model	9.87	42.05	48.08	13.52	39.27	47.21	13.24	37.19	49.57
Hindi	*Seq2Seq*	15.42	40.54	44.04	17.23	41.63	41.14	25.84	50.66	23.50
	Our Model	10.56	41.28	48.16	14.11	38.77	47.12	14.62	38.39	46.99

All values are in percentages.

Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

Generated Examples

Conversational History	Generic Response	Polite Response
Somebody please help me, I'm having the worst luck with your customer service	How can we help?	Help has arrived! We are sorry to see that you are having trouble, how can we help?
मेरा फोन एक मिनट पहले पूरी तरह से काम कर रहा था और फिर अचानक काम करना बंद कर दिया। (My phone was perfectly working a minute back and then it stopped working suddenly.)	आपको क्या परेशानी हो रही है? (What trouble are you having?)	हम आपके साथ इस पर गौर करेंगे, कृपया हमें बताएं कि आपको क्या परेशानी हो रही है? (We'll look into this with you, please tell us what trouble are you having?)
Is the Radio X radio within the app branded station, or just a station called Radio X?	Can you send us a screenshot of what you're seeing?	No worries at all! Help's here! Please send us a screenshot of what you're seeing? We'd like to take a close look.
पिछले हफ्ते ही घर आया था और मुझे फिर से अपने इंटरनेट से समस्या हो रही है। (Just came home last week and I'm having problems with my internet again.)	आपके इंटरनेट के साथ क्या हो रहा है? (What is happening with your internet?)	अरे नहीं यह अच्छा नहीं है। मैं मदद कर सकता हूँ! कृपया बताएं कि आपके इंटरनेट में क्या समस्या है? (Oh no that's not good. I can help! Please tell whats the problem with your internet?)

Firdaus et al. Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In LREC 2020.

Highlight 3

PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. (Firdaus et al., COLING 2022)

Problem Definition

- Identify the sentiments from the user utterances, and
- Using the sentiment information to transform the generic customer care responses into polite responses which are contextually appropriate to the dialog history and the user sentiments.

Motivation

- The usage of the user feedback in the form of sentiments is crucial to get contextually correct polite responses
- If the user has a negative sentiment towards the customer care system
    - Possible polite response should be towards apology, assurance, and empathy rather than greet or appreciation.

Firdaus et al. PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. In COLING 2022

Examples of polite responses in accordance to the user sentiments

Dialog Context	User Sentiment	Generic Response	Polite Response	Polite Behaviour
Hey, i got food poisoning from your inflight meal on sunday	Negative	Send us a dm	That's disappointing to hear, we are sorry please send us a dm.	Apology
I need the software update urgently, the battery lasts literally half a day	Negative	How can we help?	Don't worry, we are here for you, please say how can we help?	Assurance
Dear this new update is awesome, got great new apps!	Positive	The update has many features.	Thank you very much, please checkout the exciting features in the update.	Appreciation
Order 2 zinger box meals n got free popcorn chicken, yayyyy	Positive	Enjoy your meal.	That's nice to hear, enjoy your meal.	Acknowledge
How do i go about getting a monthly ride pass ?	Neutral	We have send the link	Hello, good morning we have send the link.	Greet

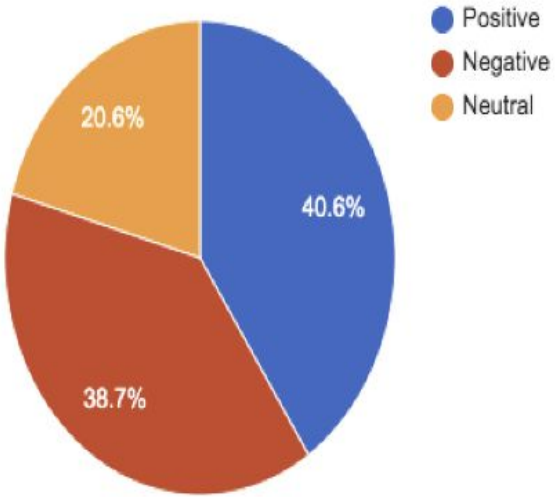
Firdaus et al. PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. In COLING 2022

Dataset

- Experimented on CYCCD dataset
- Annotated: CYCCD with sentiment labels
  - **Positive, Negative, Neutral**

	Train	*Valid*	*Test*
# Conversation	130898	19762	39665
# Utterances	168534	24724	49788

CYCCD Dataset Statistics

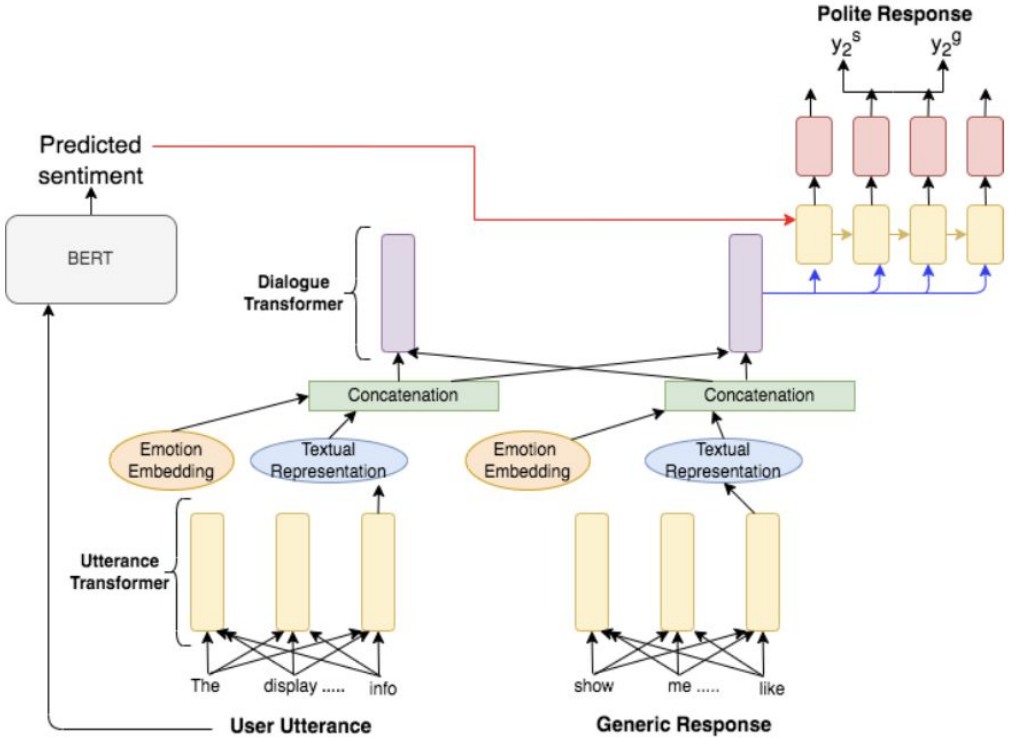


Sentiment distribution in the CYCCD dataset

Firdaus et al. PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. In COLING 2022

Proposed Approach

- Transformer Encoder-Decoder (TED) architecture
- Utilized a hierarchical transformer having two encoders
    - One is to encode the sentences named as sentence encoder
    - Another Transformer is used to encode the output of the sentence encoder to capture the dialog context



Firdaus et al. PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. In COLING 2022

Results: Automatic Evaluation

Model Description		PPL	BLEU-4	Rouge-L	PA
Existing Approaches	*Seq2Seq* (Sutskever et al., 2014)	1.112	0.145	0.278	0.38
	HRED (Serban et al., 2015)	1.085	0.198	0.308	0.45
	Polite-RL (Niu and Bansal, 2018)	1.028	0.224	0.321	0.69
	PT-TGA (Madaan et al., 2020)	1.032	0.251	0.332	0.68
	PG-RL (Golchha et al., 2019)	1.018	0.264	0.339	0.73
Proposed Approach	**HT + RL + SE (Joint Training)**	**1.004**	**0.275**	**0.352**	**0.77**
Ablation Study	*HT*	1.015	0.269	0.343	0.70
	HT + RL	1.008	0.272	0.349	0.74
	HT + RL + SE	1.006	0.273	0.350	0.75

Observations:

- Here PPL: Perplexity, PA: Politeness accuracy, HT: Hierarchical transformer, SE: Sentiment, RL: Reinforcement learning
- It is evident that the proposed network outperforms the Seq2Seq and HRED frameworks in terms of all the metrics.
- In the case of politeness, there is an enormous improvement in comparison to the Seq2Seq and HRED frameworks with more than 30% accuracy.
- By introducing sentiment information in our proposed framework, we see the growth in the performance compared to the PG-RL network establishing the importance of sentiment information for generating polite responses.

Results: Manual Evaluation

Model Description		F	R	PA
Existing Approaches	*Seq2Seq* (Sutskever et al., 2014)	3.82	3.73	48%
	HRED (Serban et al., 2015)	3.86	3.78	52%
	Polite-RL (Niu and Bansal, 2018)	3.91	3.79	61%
	PT-TGA (Madaan et al., 2020)	4.03	3.85	64%
	PG-RL (Golchha et al., 2019)	4.11	4.06	67%
Proposed Approach	**HT + RL + SE (Joint Training)**	**4.23**	**4.17**	**75%**
Ablation Study	*HT*	4.09	4.03	65%
	HT + RL	4.16	4.09	71%
	HT + RL + SE	4.19	4.12	73%

Observations:

- Here, PA: Politeness Appropriateness, HT: Hierarchical Transformer, SE: Sentiment, RL: Reinforcement Learning
- It is evident that the proposed method generates grammatically correct responses as the fluency score is the highest.
- The relevance score in the case of our proposed network is greater than all the existing and baseline approaches signifying that the generated responses are contextually correct according to the dialogue history

Generated Examples

Dialogue Context	Sentiment Information	Generic Response	Generated Polite Examples
My order doesnot have fries in it, that sucks!	Negative	we'll follow up with the store	**HT:** We will check **HT + RL:** Please, wait we'll follow up with the store. **HT + RL + SE:** Sorry, we'll follow the order with the store **Proposed:** Sorry for the inconvenience, please wait while we follow with the store.
The new iphone has awesome display	Positive	enjoy your new iphone!	**HT:** Ohh ur new phone, great **HT + RL:** That's nice about your iphone **HT + RL + SE:** Thanks and enjoy your phone. **Proposed:** Thanks for your kind words and enjoy your new phone!

Firdaus et al. PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. In COLING 2022

Highlight 4

Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In (Firdaus et al. , IEEE TCSS 2022)

Problem Definition

- Generate polite responses by varying the degree of politeness in dialogues while considering the user's persona information

Motivation

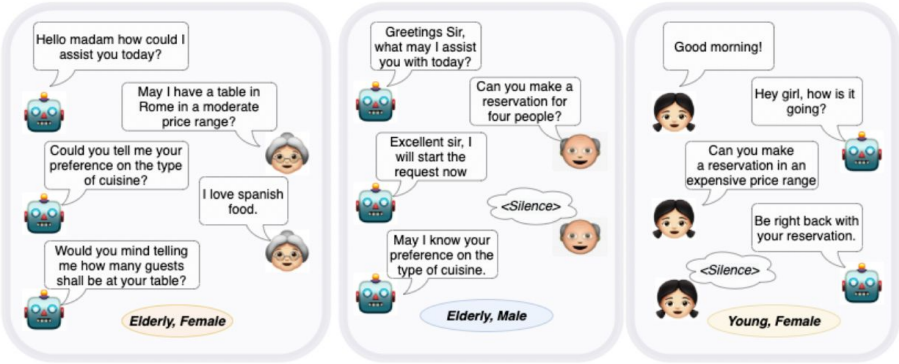
- Politeness in itself has different facets that is difficult to inculcate in a conversational agent
- Politeness varies among the different age groups. While communicating with elders, humans are found to be more polite than their conversations with younger people
- Also, the degree of communication and politeness vary when we communicate with people of different genders

Firdaus et al. Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In IEEE TCSS 2022.

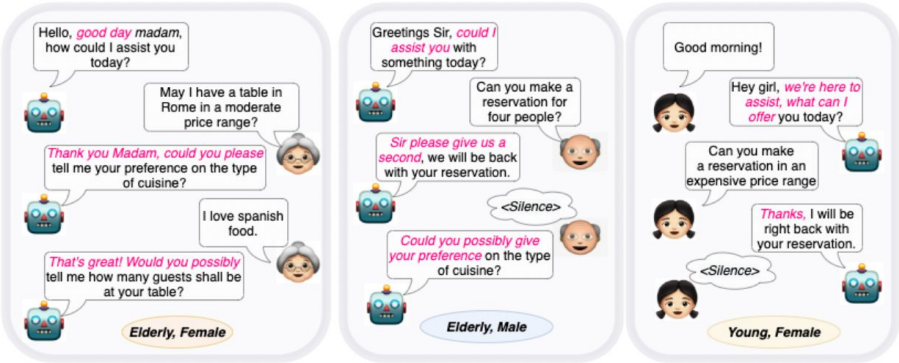
Example of Polite Personalized Conversation

The personalized dialogue conversation shows the difference in language styles with the change in users' information such as age and gender.

For example, communication with females tends to comprise more appreciation, making the conversation more polite than a male person.



Personalized Dialogue Conversations



Polite Personalized Dialogue Conversations

Firdaus et al. Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In IEEE TCSS 2022.

Dataset

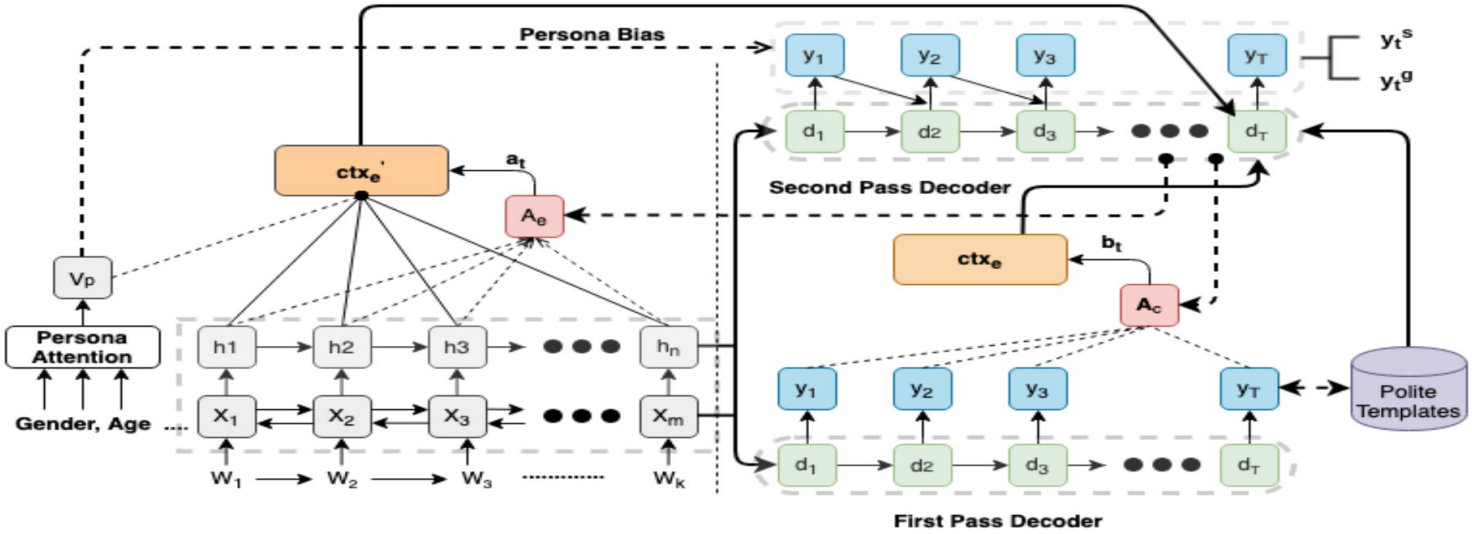
- bAbI dataset [9]
  - A multi-turn personalized dialogues
  - Use personalized features in the language style (such as Sir, Madam, etc.) to respond to the different users
- To provide politeness according to the user profiles, create polite templates in accordance with the dialogs

Female			Male		
Elderly	***Middle-Aged***	***Young***	***Elderly***	***Middle-Aged***	***Young***
Thank you madam I shall start the reservation now.	Maam please give me a second for processing the request.	We will be right back with your reservation please wait	We appreciate sir I will start the request now.	Sir have patience I'm processing the request.	Give me a second please, I'm on your request
Would you mind telling me your price range please?	Will you tell me the price range you are looking for	Please tell me what should the price be?	May i know your preferred price range	Which price range are you looking for please tell us.	What should the price be?
Thank you very much madam I shall provide you with options shortly.	We appreciate your choice maam i am finding some options for you	We will definitely find some options for you.	Great sir please give me a moment to provide you with options.	Please have patience Sir I'm looking for options.	We are looking best options for you.
I shall modify your reservation, please let us know is there is any other change	We are here to help, is there any other thing to modify	Awesome is there any other update	I will modify your request is there anything else to change please tell us	Sir may I know if anything else needs to be changed?	Hey anything else you want to update
Thank you for your time, we are glad to help I shall finish your reservation	Thank you let me complete the reservation	We are happy to help, your reservation is done	Excellent sir, we enjoyed helping! I will finalize your request	Great I'll finalize the request	Cool! it's done.

Firdaus et al. Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In IEEE TCSS 2022.

Polite Personalized Dialogue Generation Framework

- Encode the given persona information (i.e., the age, gender, etc.) and the polite templates for inducing politeness in accordance with the persona information
- Use attention over the persona information to selectively pass only those information that is important to generate polite responses for a given dialogue



Firdaus et al. Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In IEEE TCSS 2022.

Results: Automatic Evaluation

Model Description		PI	PT	PPL	BLEU-4	Rouge-L	PA
Existing Approach	*Polite-RL*	-	-	1.027	0.219	0.322	0.53
Baseline Approaches	*HRED*	-	-	1.032	0.212	0.318	0.38
	HRED + Copy	-	-	1.028	0.224	0.321	0.39
		√	-	1.024	0.239	0.334	0.40
		√	√	1.025	0.238	0.335	0.54
	HRED + DD	-	-	1.018	0.258	0.339	0.46
		√	-	1.015	0.261	0.342	0.49
		√	√	1.011	0.262	0.344	0.67
Proposed Approach	*PoPe-DG*	√	√	**1.004**	**0.275**	**0.352**	**0.73**
Ablation Study	*PoPe-DG - PB*	√	√	1.006	0.269	0.349	0.70
	PoPe-DG - RL	√	√	1.009	0.264	0.345	0.68

1. To evaluate the model at the relevance and grammatical level, we report the results using the standard metrics like Perplexity [56], Rouge-L [57], and BLEU-4 [58].
2. We also report the Politeness Accuracy as a metric to measure the degree of politeness in the responses.
3. We compute politeness score using a pre-trained classifier AlBERT [59]2 for measuring the degree of politeness in the generated responses similar to [38]. The classifier takes as input the generated response and predicts a probability value giving us the politeness accuracy of the generated response.

Results: Manual Evaluation

Model Description		Fluency	Relevance	Politeness Appropriateness
Existing Approach	*Polite-RL*	3.91	3.79	61%
Baseline Approaches	*HRED*	3.82	3.73	48%
	HRED + Copy	3.86	3.78	52%
	HRED + DD	3.93	3.82	55%
Proposed Approach	*PoPe-DG*	**4.11**	**3.96**	**69%**
Ablation Study	*PoPe-DG - PB*	4.07	3.92	63%
	PoPe-DG - RL	3.98	3.85	57%

Firdaus et al. Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In IEEE TCSS 2022.

Generated Examples

Dialogue Context	Persona Information	Ground Truth	Generated Example
U1: I'd like to book a table with Indian food. **U2:** I'm on your request.	Male, Young	Where should it be?	**HRED:** Where is it? **HRED + Copy:** Please, where is the location? **HRED + DD:** May I know the location? **PoPe-DG:** May I know where it should be located.
U1: Which price range are you looking for? **U2:** In a moderate price range please.	Female, Middle-aged	Sure ma'am, I'm finding some options for you.	**HRED:** I am finding for you. **HRED + Copy:** Please ma'am I will find options for you. **HRED + DD:** Thanks ma'am I will find options for you. **PoPe-DG:** Thank you ma'am please have patience, I'm finding some options for you.
U1: I'd like to book a table with Spanish food. **U2:** Excellent sir, I will start the request now.	Male, Elderly	May I know your preferred price range.	**HRED:** Tell us the price range. **HRED + Copy:** May I know your price range? **HRED + DD:** Please may I know the price range? **PoPe-DG:** Thank you sir, could you please tell us the price range?
U1: I will modify your request is there anything else to change. **U2:** Actually I would prefer in a cheap price range.	Female, Elderly	I shall modify your reservation is there any other change.	**HRED:** I will change the reservation. **HRED + Copy:** I will modify your reservation now. **HRED + DD:** I will modify, is there more changes? **PoPe-DG:** We appreciate the choice and will modify, is there any other change?
U1: I'll finalize the request. **U2:** You rock.	Male, Middle-aged	Is there anything I can help you with?	**HRED:** Do you need help? **HRED + Copy:** Is there anything you need please? **HRED + DD:** Could I assist you with anything? **PoPe-DG:** It's nice to help, could I assist you with something else?
U1: I'd like to book a table with French food. **U2:** Be right back with your reservation?	Female, Young	How many are you?	**HRED:** How many guests? **HRED + Copy:** How many of you? **HRED + DD:** Please can you say how many? **PoPe-DG:** Hey please tell us the number of guests?

Firdaus et al. Being Polite: Modeling Politeness Variation in a Personalized Dialogue Agent. In IEEE TCSS 2022.

Highlight 5

Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. (Mishra et al., Neurocomputing 2022)

Problem Definition

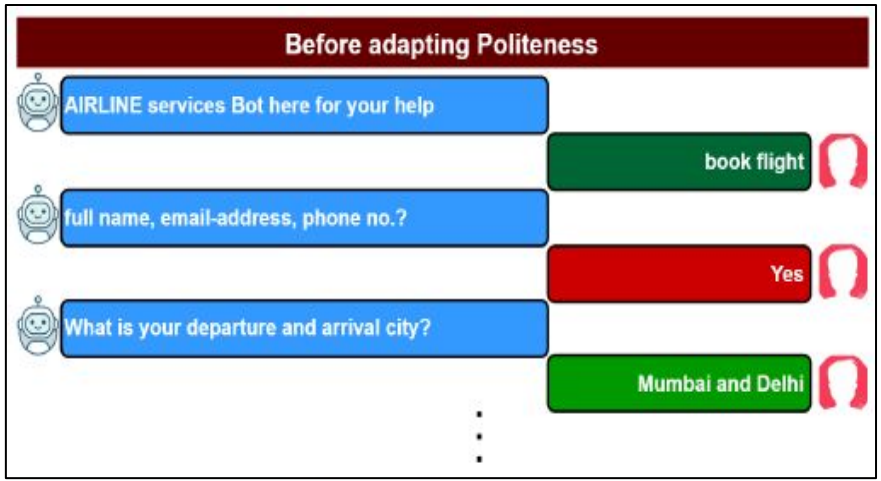
- Incorporate politeness in an end-to-end learning framework based on the agent's last action and the user's current response politeness feedbacks
- Four reinforcement learning based rewards have been designed to ensure that the conversation adapts to the different degrees of politeness

Motivation

- Lacking the ability to learn from user interactions to improve and adapt to the demands of the user
- The agent requires to pacify the aggrieved users for products in a polite manner
- Reinforcement learning ability to focus on long-term rewards have enhanced the performance of dialogue agents

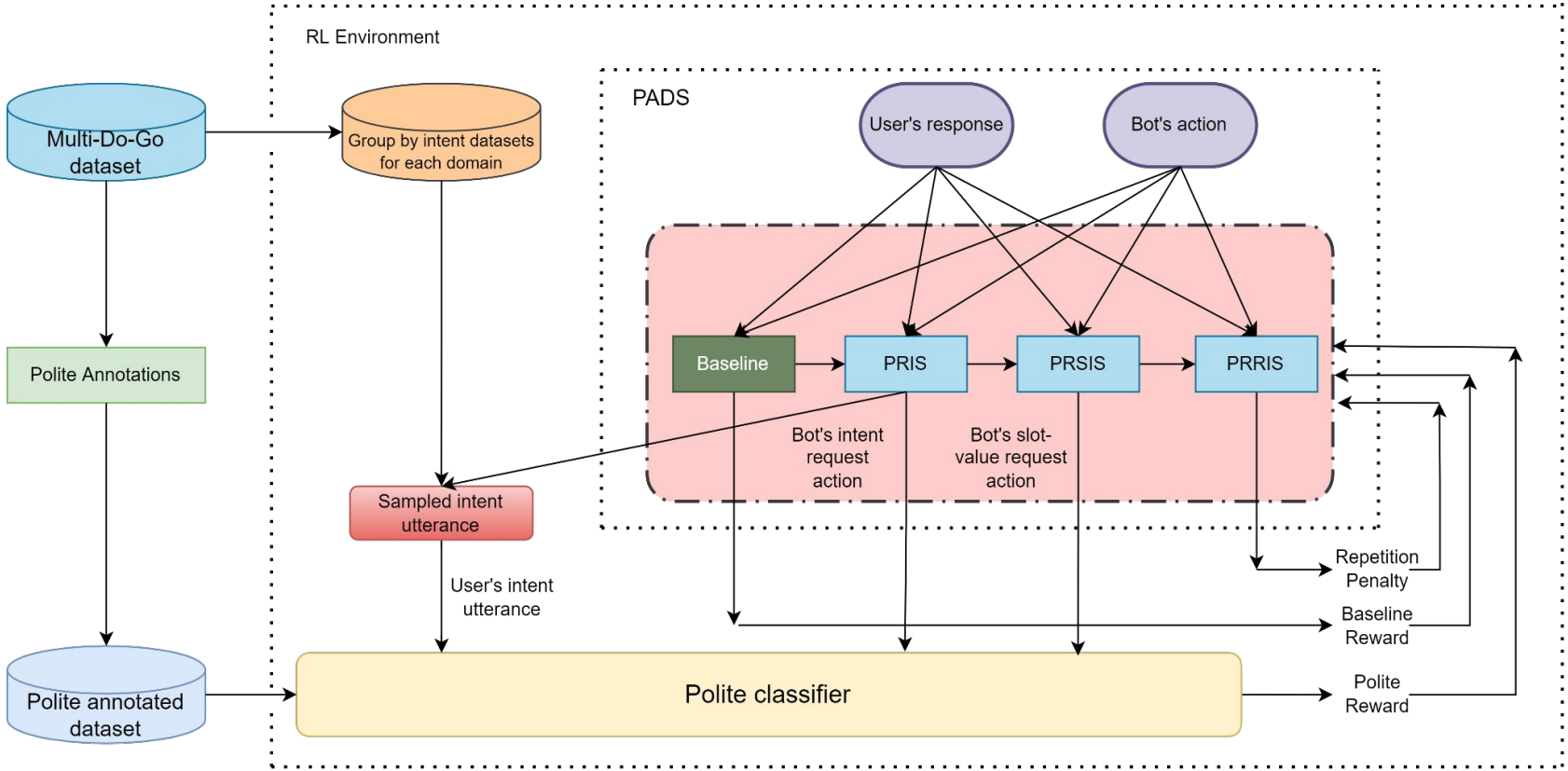
Mishra et al. Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. In Neurocomputing 2022.

An Example Conversation



Mishra et al. Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. In Neurocomputing 2022.

Politeness-adaptive Dialogue System (PADS)



Mishra et al. Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. In Neurocomputing 2022.

Dataset

- Annotated MultiDoGo [4] dataset with politeness labels
- **Domain**
  - *airline, fast food, finance, insurance, media, and software*
- **Politeness Labels**
  - *polite, somewhat_polite, somewhat_impolite, impolite*
- **Politeness Annotation**
  - ***Phase 1:*** The politeness score of each utterance of the MultiDoGo dataset is obtained via Stanford Politeness Classifier [5]
  - ***Phase 2:*** Every utterance is assigned one of the four fine-grained politeness classes

Mishra et al. Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. In Neurocomputing 2022.

Results: Automatic Evaluation

Domain	PPL	BLEU	MET	F1	APL
airline	1.598	0.051	0.340	0.212	0.772
fastfood	1.973	0.010	0.265	0.151	0.748
finance	1.907	0.045	0.265	0.161	0.787
insurance	2.031	0.041	0.331	0.205	0.790
media	1.576	0.038	0.326	0.189	0.752
software	1.929	0.038	0.332	0.181	0.746

Mishra et al. Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. In Neurocomputing 2022.

Results: Manual Evaluation

Model	*PA*	*TCR*
Baseline	0.35	0.41
PRIS	0.38	0.45
PRSIS	0.43	0.49
PRRIS	**0.47**	**0.53**

Mishra et al. Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations. In Neurocomputing 2022.

Highlight 6

GenPADS: Reinforcing Politeness in an End-to-End Dialogue System. (Mishra et al., PLOS ONE 2023)

Problem Definition

- Develop a generative politeness adaptive dialogue system
- Incorporate all three aspects, *viz.* informativeness, politeness and diversity in an end-to-end RL based learning framework

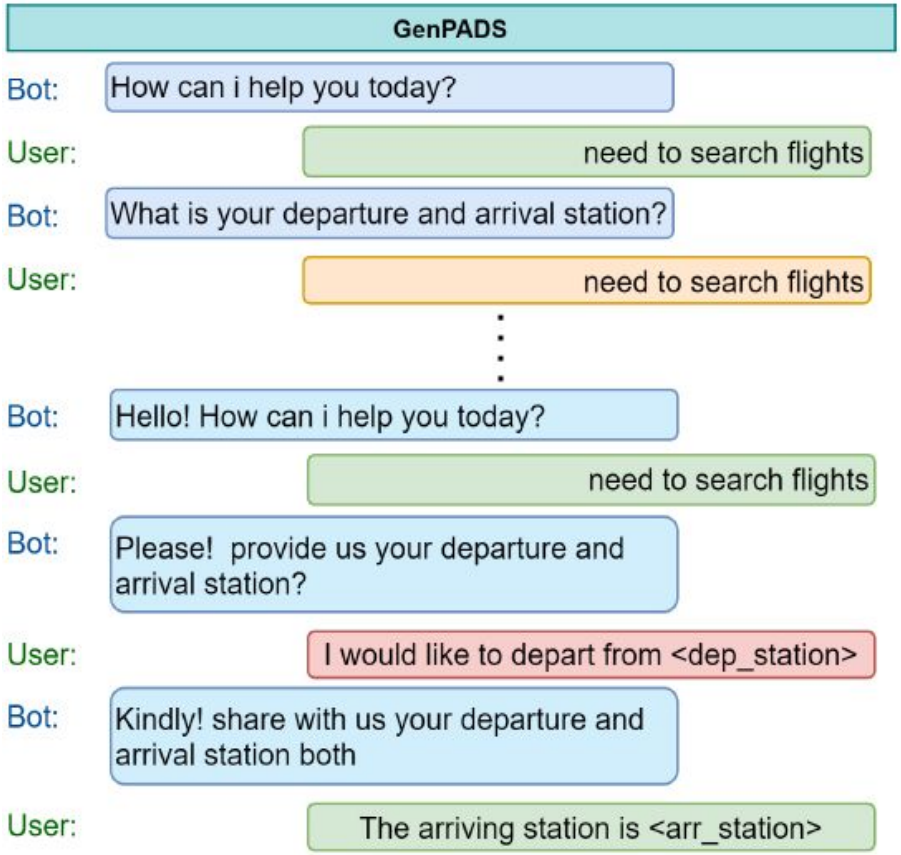
Motivation

- Address the problem of non-informative conversations or conversation drop-off in task-oriented dialogue settings
- Build a dialogue model that can learn the user's behavior online and generate polite, diverse, and interactive responses to improve the quality of the conversation
- Design the system to reinforce politeness in its dialogue generation and adapt to changes in the user's mood and demands during an ongoing conversation

Mishra et al. GenPADS: Reinforcing Politeness in an End-to-End Dialogue System. In PLOS ONE 2023.

An Example Conversation

- GenPADS in action for a flight domain scenario
- The user expresses dissatisfaction with the ongoing dialogue through impolite or noisy utterances (depicted by light orange boxes) or partial information (depicted by light red boxes).
- GenPADS adapts to this feedback and generates polite and diverse responses that are tailored to the user's and agent's politeness feedback



Mishra et al. GenPADS: Reinforcing Politeness in an End-to-End Dialogue System. In PLOS ONE 2023.

Dataset

- **Taskmaster**
  - Domains: *flights, food ordering, hotels, movies, music, restaurant search, and sports*
- **Dialogue Generation Dataset (DG-Dataset)**
  - Topics: *news, weather, and sports*
- **Politeness Labels**
  - *polite, somewhat_polite, somewhat_impolite, impolite*
- **Politeness Annotation**
  - Employed crowd-workers from Amazon Mechanical Turk (AMT) that labels every utterance with the provided set of polite labels

Mishra et al. GenPADS: Reinforcing Politeness in an End-to-End Dialogue System. In PLOS ONE 2023.

Generative politeness adaptive dialogue system (GenPADS)

- **Politeness Classifier (PC)**
  - The Politeness Classifier takes an input utterance and predicts its politeness level using a pre-trained model
  - The output of this component is used to determine the appropriate response generation strategy
- **Dialogue Generator (DG)**
  - The Dialogue Generator is a sequence-to-sequence model that generates responses given an input utterance.
  - It is trained on human-human dialogues from the DG-Dataset.
- **GenPADS Generation Module (G)**
  - Combines the outputs of the Politeness Classifier and Dialogue Generator to generate a polite and diverse response tailored to the user's and agent's politeness feedback
  - Uses a reinforcement learning approach to learn from user feedback during an ongoing dialogue

Mishra et al. GenPADS: Reinforcing Politeness in an End-to-End Dialogue System. In PLOS ONE 2023.

Results: Automatic Evaluation I

	PC	GenPADS Generation module G				
Domain	**F1**	**PP**	**BLEU**	**NIST**	**MET**	**R-2 F1**
Flights	0.92	1.912	0.052	0.186	0.641	0.472
Food-ordering	0.96	1.698	0.050	0.214	0.758	0.452
Hotels	0.94	1.972	0.065	0.207	0.664	0.504
Movies	0.95	2.137	0.039	0.1618	0.654	0.469
Music	0.93	2.367	0.037	0.133	0.555	0.379
Restaurant-search	0.95	2.156	0.047	0.162	0.669	0.494
Sports	0.92	1.762	0.018	0.069	0.739	0.585

Mishra et al. GenPADS: Reinforcing Politeness in an End-to-End Dialogue System. In PLOS ONE 2023.

Results: Automatic Evaluation II

		GenPADS					RetrievalPADS					Dialogue Generator				
Domain	**rew**	**DL**	**POL**	**MET**	**R-2 F1**	**SR**	**DL**	**POL**	**MET**	**R-2 F1**	**SR**	**PPL**	**BLEU**	**NIST**	**MET**	**R-2 F1**
Flights	BL	10.8	0.587	0.627	0.511	0.67	11.1	0.674	0.999	0.999	0.67	6.18	0.038	0.132	0.127	0.059
	PRRP	**10.7**	**0.851**	0.721	0.543	**0.79**	**10.3**	**0.842**	0.999	0.999	**0.77**					
Food-ordering	BL	13.8	0.656	0.668	0.506	0.69	12.9	0.597	0.999	0.999	0.686	3.05	0.027	0.172	0.387	0.345
	PRRP	**11.5**	**0.936**	0.642	0.444	**0.86**	**12.6**	**0.908**	0.999	0.999	**0.84**					
Hotels	BL	10.9	0.849	0.665	0.462	0.74	12.8	0.804	0.999	0.999	0.71	7.15	0.087	0.261	0.146	0.078
	PRRP	**9.9**	**0.893**	0.709	0.573	**0.82**	**10.3**	**0.864**	0.999	0.999	**0.82**					
Movies	BL	9.9	0.744	0.701	0.446	0.77	11.8	0.694	0.999	0.999	0.74	7.45	0.015	0.058	0.146	0.086
	PRRP	**9.5**	**0.888**	0.700	0.407	**0.84**	**9.7**	**0.865**	0.999	0.999	**0.83**					
Music	BL	9.7	0.910	0.525	0.330	0.71	9.6	0.881	0.999	0.999	0.71	11.4	0.007	0.33	0.231	0.156
	PRRP	**9.4**	**0.959**	0.440	0.237	**0.86**	**9.4**	**0.921**	0.999	0.999	**0.84**					
Restaurant-search	BL	9.5	0.418	0.739	0.446	0.79	11.7	0.381	0.999	0.999	0.75	8.46	0.046	0.153	0.165	0.089
	PRRP	**8.5**	**0.920**	0.709	0.467	**0.82**	**9.7**	**0.940**	0.999	0.999	**0.78**					
Sports	BL	11.3	0.806	0.541	0.328	0.64	13.6	0.795	0.999	0.999	0.64	5.14	0.007	0.032	0.270	0.163
	PRRP	**10.9**	**0.948**	0.657	0.418	**0.81**	**11.5**	**0.915**	0.999	0.999	**0.79**					

GenPADS and RetrievalPADS were tested for 10,000 dialogues. Performance of the superior model is highlighted in **bold**.

Results: Manual Evaluation

Domains	F	I	PA	D
Baseline	3.87	3.32	3.18	3.54
PRRP	**4.16**	**3.87**	**4.08**	**3.91**

Concept 6

Intent

Major Highlights

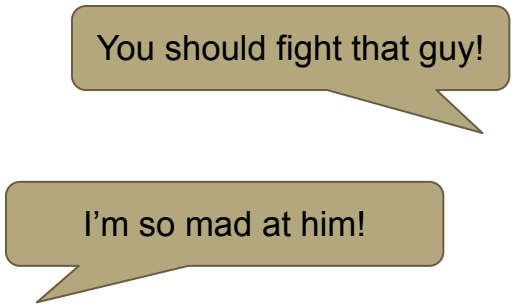
- Empathetic Dialog Generation with Fine-Grained Intents. (Xie et al., CoNLL 2021)

Highlight 1

Empathetic Dialog Generation with Fine-Grained Intents. (Xie et al., CoNLL 2021)

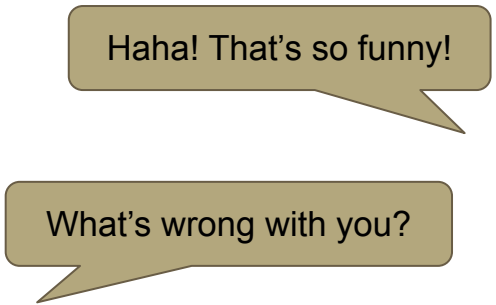
Empathy and Intents

Scenario 1



Simply following the speaker's emotion state

Scenario 2



Reversing the speaker's emotion state

Scenario 3

Responding with questioning

Leaves the speaker in angry state (or even escalates the situation)

Calms down the speaker and drives the conversation to a empathetic direction.

Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

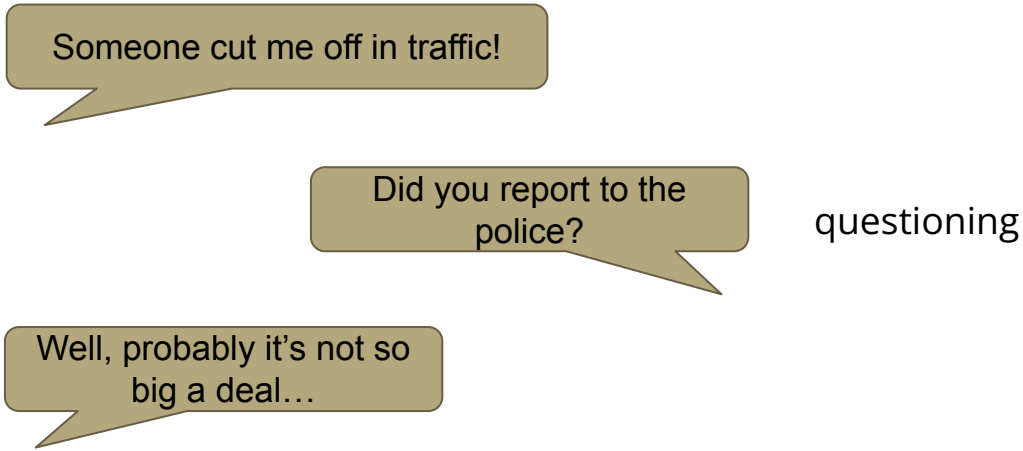
Current Situation

- Many require a pre-defined emotion label as input
- Psychology literature does not confirm deterministic rules
- Existing dialog datasets either do not have the neutral category or it is not sufficiently treated

Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Empathetic Intents

- Generate contextually coherent and emotionally appropriate responses
- Ensure a more precise learning of the emotional interactions revealed in the dialogue



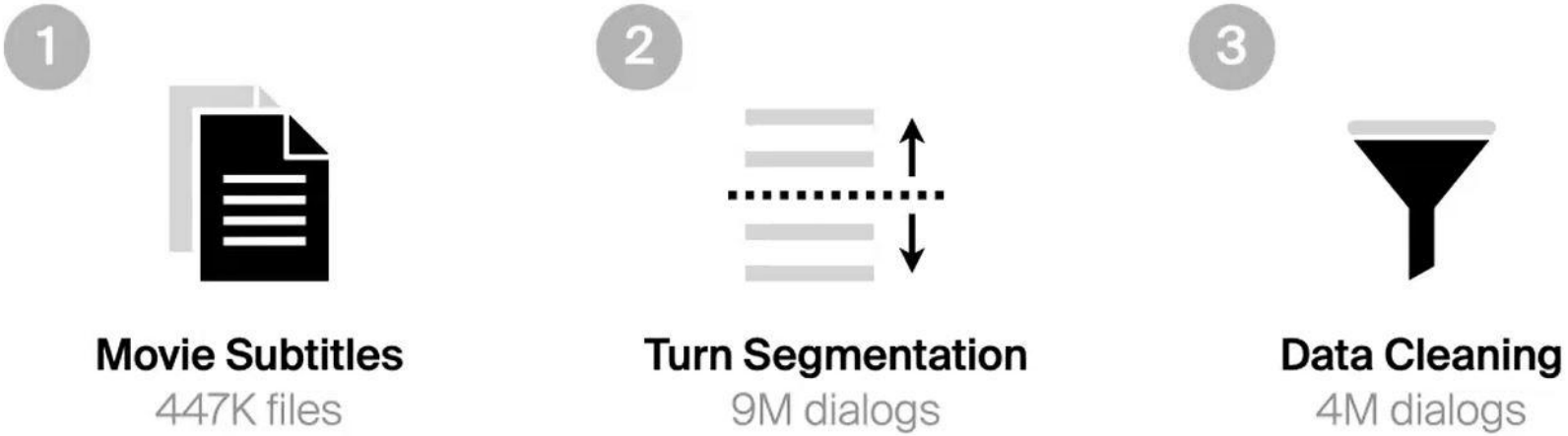
Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

8 Empathetic Response Intents

- Questioning
- Agreeing
- Acknowledging
- Sympathizing
- Encouraging
- Consoling
- Suggesting
- Wishing
- Neutral

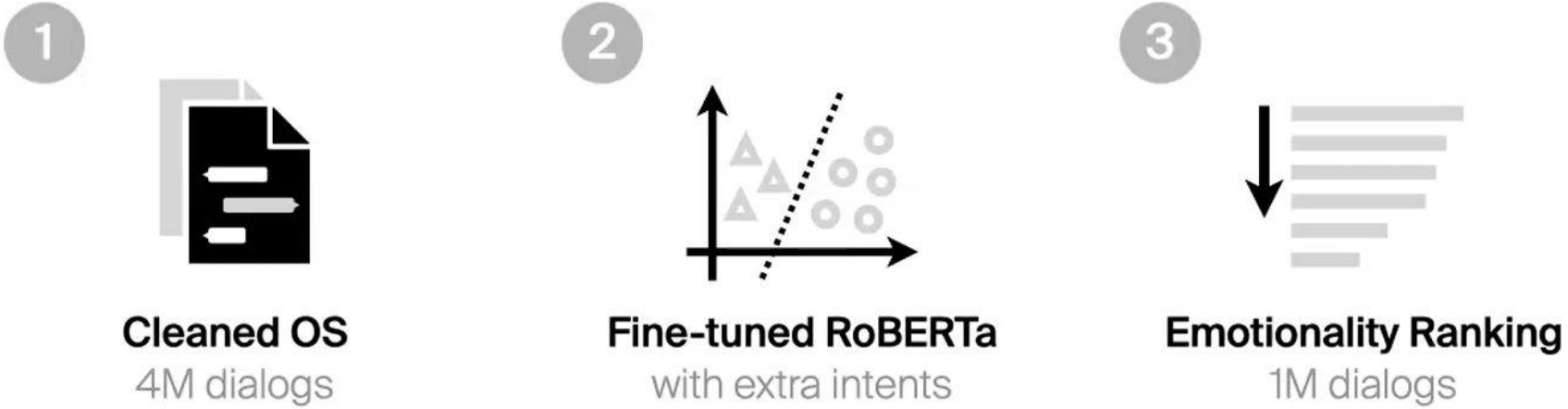
Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Data Curation (OpenSubtitles Dialogs)



Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

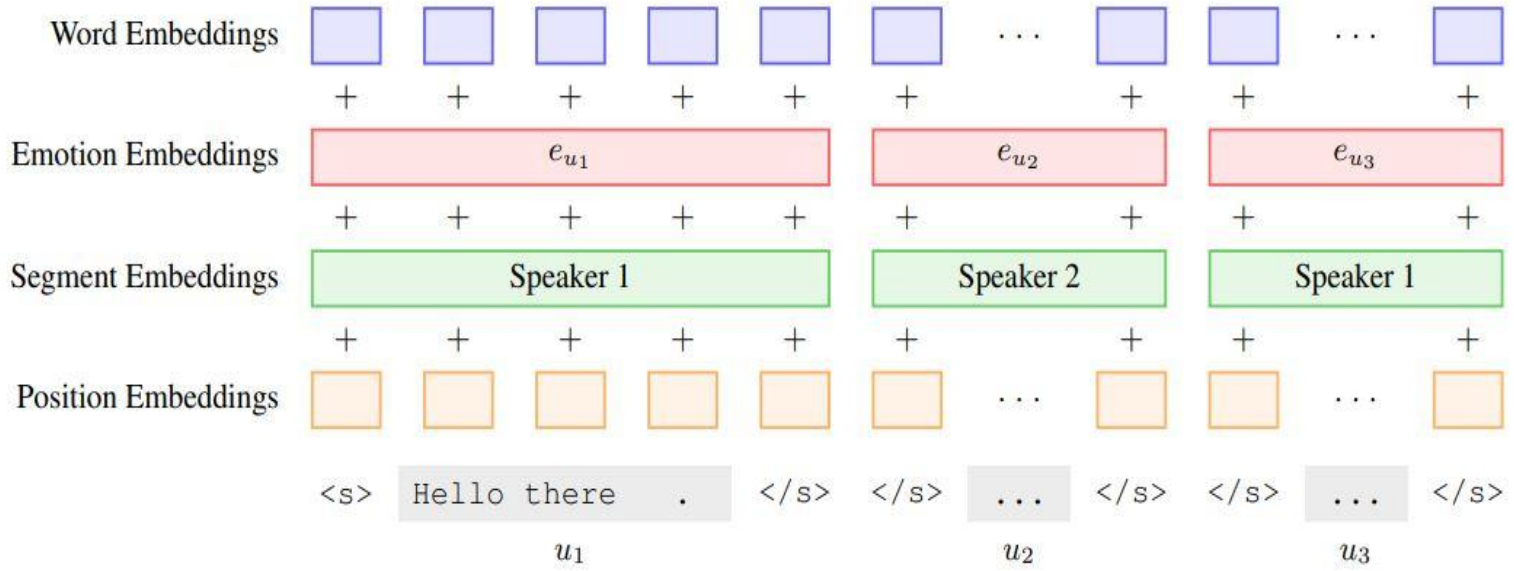
Data Curation (Emotional Dialogs in OpenSubtitles)



Empathetic intents: *questioning, agreeing, acknowledging, sympathizing, encouraging, consoling, suggesting, and wishing, neutral*

Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Proposed Method (Input Representation)



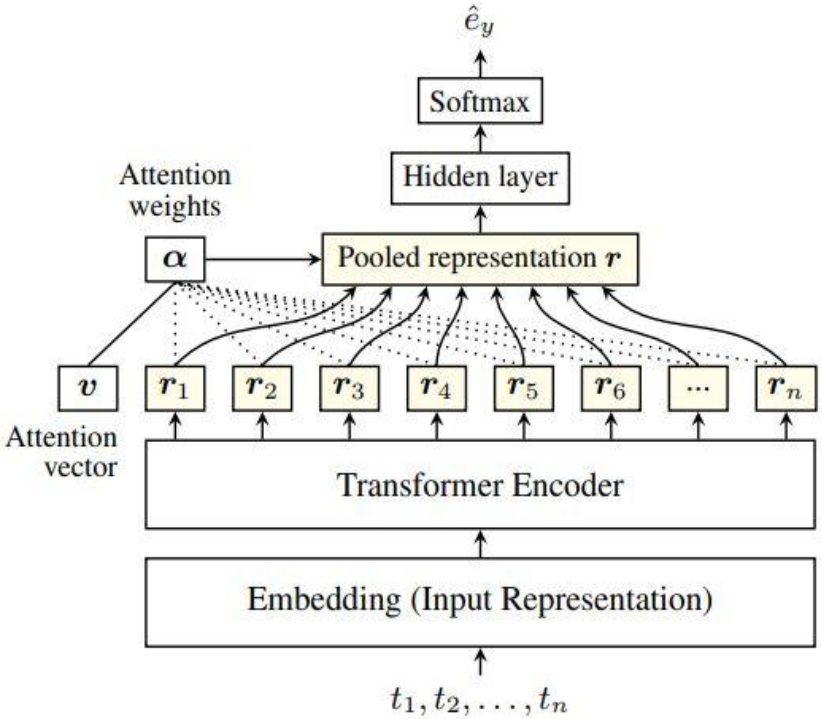
Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Proposed Method (Response Emotion/Intent Predictor)

- Transformer encoder to get context-depende representations
- Pool using attention (Dotted lines in Figure):

$$\boldsymbol{\alpha}_i = \frac{\exp(\boldsymbol{v}^T \boldsymbol{r}_i)}{\sum_{j=1}^{N} \exp(\boldsymbol{v}^T \boldsymbol{r}_j)}$$

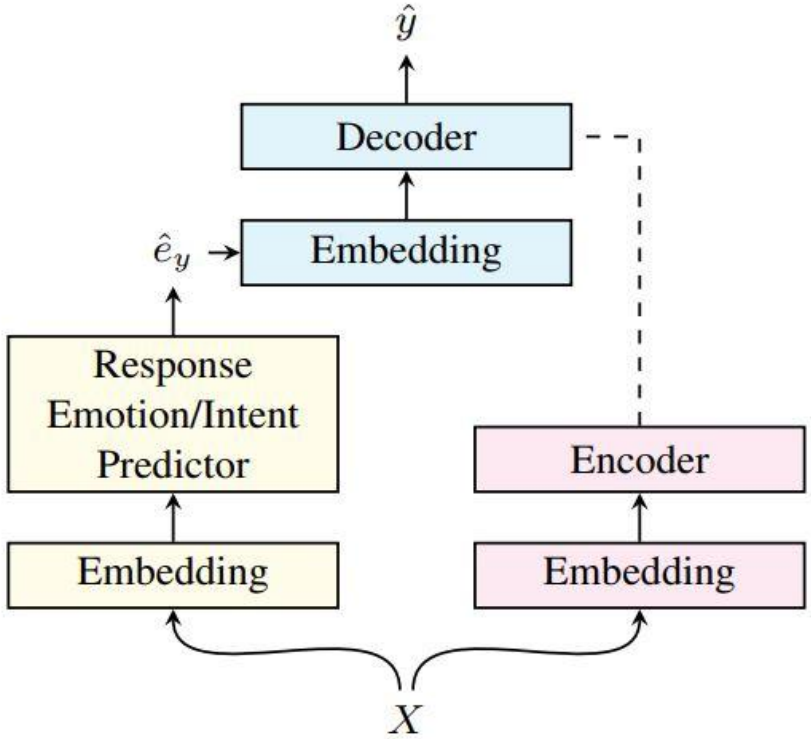
$$\boldsymbol{r} = \sum_{i=1}^{N} \boldsymbol{\alpha}_i \boldsymbol{r}_i$$



Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Proposed Method (Training)

- Trained separately
- Response emotion/intent Predictor
  - Cross-entropy loss between predicted and gold emotion/intent category
- Encoder-Decoder
  - Cross-entropy loss between predicted and gold response



Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Experiments

- **Datasets**
  - OpenSubtitles dialog (OS): 3M
  - Emotional dialog in OpenSubtitles (EDOS): 1M
  - EmpatheticDialogues (ED): 25K
- **Splitting**
  - 80%, 10%, 10% for training, validation and testing
  - 6,000 testing dialogs for human evaluation (2,000 from each dataset)

Results: Automatic Evaluation

	OS			EDOS			ED		
Model	**P**	**R**	**F-1**	**P**	**R**	**F-1**	**P**	**R**	**F-1**
Random	.1484	.0240	.0285	.0382	.0250	.0266	.0989	.0165	.0215
MEED2 (OS)	**.2210**	**.3960**	.2312	.0109	.1040	.0198	.0942	.3070	.1442
MEED2 (OS → EDOS)	.2012	.1480	.1537	**.1029**	**.1495**	**.0917**	.1288	.2630	.1674
MEED2 (OS → ED)	.2166	.3265	**.2502**	.0253	.0870	.0239	**.2660**	**.3530**	**.2864**

Weighted precision, recall and F-1 scores of the response emotion/intent predictor in our model on the three datasets. X→Y means pre-training on X and then fine-tuning on Y.

Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Results: Automatic Evaluation

	OS				EDOS				ED			
Model	**PPL**	**D1**	**D2**	**SES**	**PPL**	**D1**	**D2**	**SES**	**PPL**	**D1**	**D2**	**SES**
Pre-trained (OS)	24.8	.046	.159	.172	37.8	.046	.154	.126	564.6	.044	.167	.178
Fine-tuned (EDOS)	26.9	.044	.139	.162	32.3	.056	.165	.137	452.6	.031	.107	.176
Fine-tuned (ED)	88.9	.030	.109	**.174**	140.8	.028	.096	.130	19.3	.026	.091	**.316**
Raw (ED)	793.9	.009	.032	.144	1615.0	.008	.027	.098	35.8	.008	.029	.278
MEED2 (OS)	**22.0**	**.064**	**.210**	.168	31.9	.061	.197	.130	487.3	.046	.171	.174
MEED2 (OS → EDOS)	22.8	.057	.196	.168	**28.5**	**.070**	**.225**	**.171**	391.7	**.051**	**.199**	.207
MEED2 (OS → ED)	84.3	.038	.153	.165	125.7	.036	.138	.116	**17.2**	.036	.140	.299

PPL denotes perplexity, D1 and D2 denote Distinct-1 and -2, and SES denotes the sentence embedding similarity. X→Y means pre-training on X and then fine-tuning on Y.

Results: Manual Evaluation

Model	OS			EDOS			ED		
	Good	Okay	Bad	Good	Okay	Bad	Good	Okay	Bad
Pre-trained (OS)	.3097	.2878	.4025	.2975	.2933	.4091	.1799	.3037	.5164
MEED2 (OS)	.3166	.3158	.3676	.3073	.3288	.3639	.1863	.3088	.5049
MEED2 (OS → EDOS)	.3175	.3036	.3789	.2926	.3034	.4040	.2097	.2891	.5012
MEED2 (OS → ED)	**.3513**	.3125	.3362	**.3535**	.3093	.3372	**.4890**	.3033	.2077

Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Generated Examples

Context (from OS):
- Well, now, you know, most of your average people... won 't know a venomous reptile from a large garden worm.
Pre-trained (OS): I don 't know what you're talking about.
MEED2 (OS) (questioning): What do you mean, you won 't know?
MEED2 (OS → EDOS) (terrified): I'm not afraid of snakes.
MEED2 (OS → ED) (terrified): Oh my gosh, I hate snakes. What kind of snake was it?
Ground-truth (afraid): Oh, no. It has to be an absolute, authentic, poisonous snake... or he won 't work with it.

Context (from EDOS):
- Yes, it's been a long wait. The second half of King of Comedy will now begin!
- Hyo-jin. Yes. I'm excited to see what stars the second half will bring.
- Yes. Welcome our first contestants. Who are they?
Pre-trained (OS): The second half will bring the second half will be the second half.
MEED2 (OS) (questioning): Who are they? What do they look like?
MEED2 (OS → EDOS) (excited): Let's begin!
MEED2 (OS → ED) (excited): I can't wait to see who they are.
Ground-truth (wishing): Warriors. Welcome!

Context (from ED):
- Even though I could've gotten more money at another job, I've stayed with my current employer. It is a good place to work.
- well that's good to hear I guess. what do you do?
- I work in public relations. I create campaigns for companies.
Pre-trained (OS): what do you do?
MEED2 (OS) (questioning): what do they do in public relations?
MEED2 (OS → EDOS) (questioning): What are you doing in public affairs?
MEED2 (OS → ED) (acknowledging): that sounds like a great job.
Ground-truth (questioning): what's your most successful campaign so far?

Xie et al. Empathetic Dialog Generation with Fine-Grained Intents. In CoNLL 2021.

Concept 7

External Knowledge

External Knowledge and Empathy

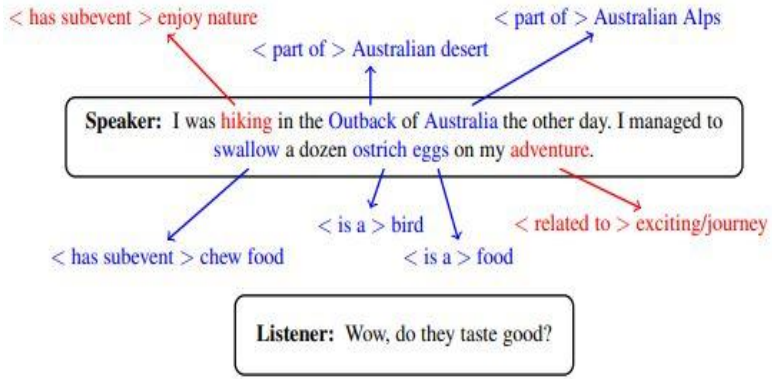
- External knowledge refers to the information and understanding that one acquires from sources outside of their personal experiences and beliefs. This can include facts, theories, cultural understanding, historical context, and so on
- External knowledge is helpful for generating more informative and relevant responses
- Having external knowledge can enhance empathy
    - Provides with a broader understanding of various situations, cultures, and circumstances

When we have a better understanding of different perspectives and experiences, we are more likely to be empathetic towards others.

Empathetic Conversational AI using External Knowledge

Commonsense and emotion lexicon knowledge bases queried with the words from user messages

Entities and the relations between the entities extracted from preexisting knowledge stored in external knowledge bases like ConceptNet



Helps with making meaningful inferences about the user's emotional state

Liu et al. Empathetic Dialogue Generation with Pre-trained RoBERTa-GPT2 and External Knowledge. In IWSDS 2021
Li et al.Knowledge bridging for empathetic dialogue generation. In AAAI 2022.

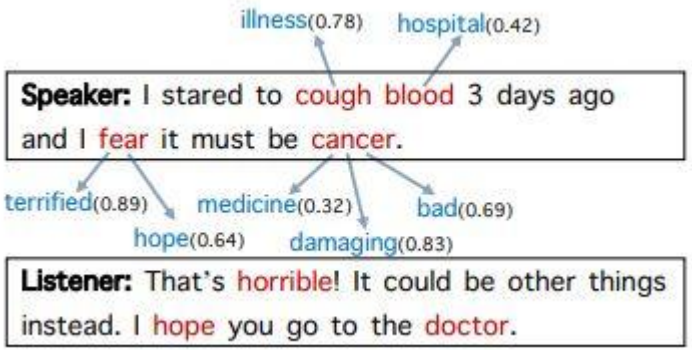
Major Highlights

- Knowledge Bridging for Empathetic Dialogue Generation (Li et al., AAAI 2022)

Highlight 1

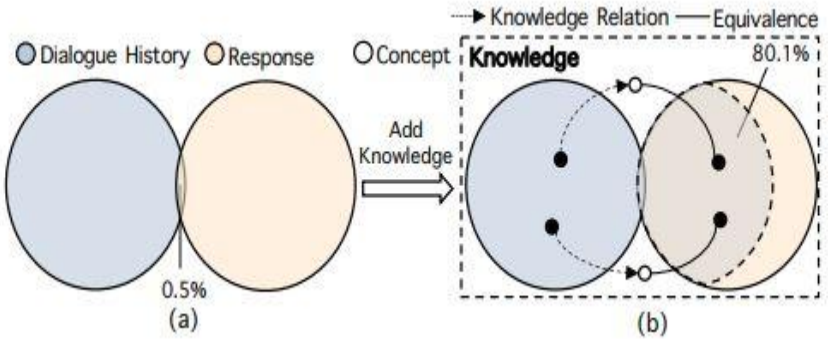
Knowledge Bridging for Empathetic Dialogue Generation (Li et al., AAAI 2022)

Dialogue History, Responses, and External Knowledge in Empathetic Dialogue Generation



An example of empathetic dialogues with external knowledge from EMPATHETICDIALOGUES.

(1)

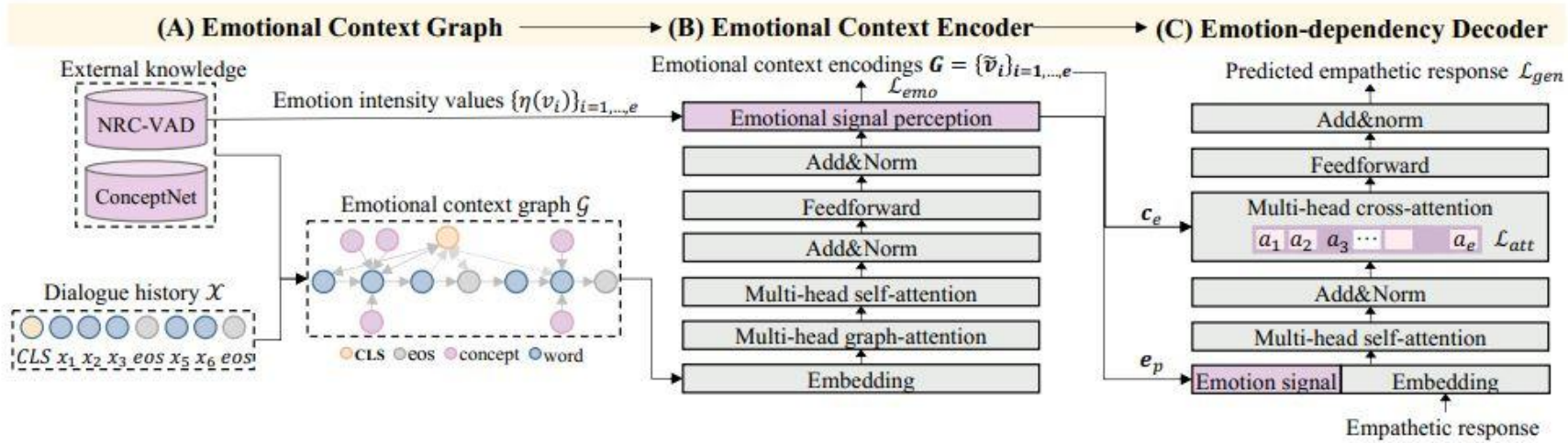


Relationships among dialogue history, responses and external knowledge.

(2)

Li et al. Knowledge Bridging for Empathetic Dialogue Generation In AAAI 2022.

Knowledge-aware EMPathetic dialogue generation (KEMP)



(A) Constructed via integrating the dialogue history with external knowledge

(B) Employs the graph-aware transformer to learn the graph embeddings, and propose an emotional signal perception procedure to perceive context emotions that lead the response generation

(C) Conditioned on the knowledge-enriched context graph, it particularly models emotion dependencies to generate empathetic response

Li et al. Knowledge Bridging for Empathetic Dialogue Generation In AAAI 2022.

Results: Automatic Evaluation

Models	Accuracy	Perplexity	Distinct-1	Distinct-2	Empathy	Relevance	Fluency
Transformer (Vaswani et al. 2017)	-	37.73	0.47	2.04	3.11	3.47	3.66
EmoPrepend-1 (Rashkin et al. 2019)	33.28	38.30	0.46	2.08	3.23	3.51	3.67
MoEL (Lin et al. 2019)	32.00	38.04	0.44	2.10	3.37	3.78	3.64
MIME (Majumder et al. 2020)	34.24	37.09	0.47	1.91	3.38	3.66	3.63
EmpDG (Li et al. 2020)	34.31	37.29	0.46	2.02	3.45	3.88	**3.67**
KEMP	**39.31**	**36.89**	**0.55**	**2.29**	**3.49**	**3.92**	3.65

Li et al. Knowledge Bridging for Empathetic Dialogue Generation In AAAI 2022.

Results: Manual Evaluation

Models	Win	Loss	Tie
KEMP vs Transformer	43.8%	17.5%	38.7%
KEMP vs EmoP	40.6%	18.5%	40.9%
KEMP vs MoEL	38.3%	18.0%	43.7%
KEMP vs MIME	36.6%	20.6%	42.8%
KEMP vs EmpDG	35.5%	21.3%	43.2%

Li et al. Knowledge Bridging for Empathetic Dialogue Generation In AAAI 2022.

Generated Examples

Emotion	**Terrified**
History	X_1: Do you know how crazy it is to skydive? X_2: I have a fear of falling from high places. X_3: It gave me the biggest rush that is for sure.
Gold	**I think I would pass out from fear lol.**
Transfmr	I am sure it was.
EmoP	I am sure it was a lot of fun.
MoEL	I am sure you will do it!
MIME	That is a good thing to do.
EmpDG	I think it is an amazing feeling.
Know.	danger, pain, travel, scared, excited, furious
KEMP	I would have been so scared.

Emotion	**Surprised**
History	X_1: I realized yesterday I was pregnant, I was in shock!
Gold	**Woah, that is huge news. How are you handling the news.**
Transfmr	Oh no! I am so sorry to hear that.
EmoP	Oh no! Did you get a job?
MoEL	That is so awesome! I am glad to hear that.
MIME	That is great.
EmpDG	Oh wow! what happened?
Know.	experience, surprise, mother, pain, feeling
KEMP	Oh wow! That is a great feeling.

Li et al. Knowledge Bridging for Empathetic Dialogue Generation In AAAI 2022.

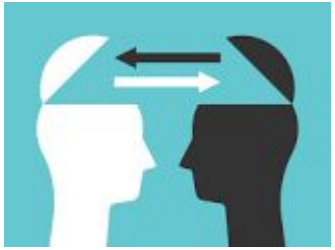
03

Empathetic Conversational AI for Social Good: Applications in Persuasion and Therapy

Concept 1

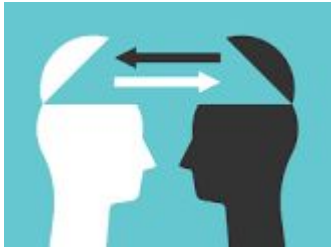
Relevance of Empathy in Persuasion

Persuasion



- The process of influencing someone's beliefs, attitudes, behaviors, or decisions through communication and argumentation.
- It involves presenting information, arguments, or appeals in a way that convinces or motivates someone to adopt a particular viewpoint, take a specific action, or make a particular choice.
- Persuasion can occur in various contexts, including interpersonal conversations, advertising, marketing, politics, public speaking, and more.

Persuasion



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- Persuasion can occur in various contexts, including interpersonal conversations, advertising, marketing, politics, public speaking, and more.

Empathy for Persuasive Conversational AI

- Shows genuine care about the other person's opinions and experiences
    - Helps build trust, create a sense of connection, and make the other person more receptive to your ideas or suggestions.
- Enables to anticipate and address potential objections or barriers to persuasion
    - Understanding the other person's concerns can help adjust the approach and provide relevant solutions or counterarguments that are more likely to resonate with them

Empathy helps foster a more open and respectful dialogue, increasing the chances of successfully persuading and influencing others

Major Highlights

- Persuasion for good: Towards a personalized persuasive dialogue system for social good (Wang et. al., ACL 2019)

- Empathetic persuasion: reinforcing empathy and persuasiveness in dialogue systems (Samad et. al., Findings NAACL 2022)

- PEPDS: A polite and empathetic persuasive dialogue system for charity donation (Mishra et. al., COLING 2022)

Highlight 1

Persuasion for good: Towards a personalized persuasive dialogue system for social good (Wang et. al., ACL 2019)

Personalized Persuasion

- Persuasive conversations employ intricate organization of strategic disclosures and appeals
- Personalized persuasion combines both strategies and user information related to the outcome of interest to achieve better persuasion results
    - User information: demographic and psychological backgrounds including personality, morality, value systems
- Personalized Persuasion aims to produce desired changes by making the information personally relevant and appealing

Personalized Persuasion for Charity Donation

- This work lays down the foundation for building automatic personalized persuasive conversational system
- Collected persuasive conversations for charity donation task
- Identified various persuasive strategies
- Analyzed the relations among participants' demographic backgrounds, personality traits, value systems, and their donation behaviors
- Analyzed what types of persuasion strategies worked more effectively for what types of personal backgrounds.

Persuasive Strategies

- Logical appeal
- Emotion appeal
- Credibility appeal
- Foot-in-the-door
- Self-modeling
- Personal story
- Donation information
- Source-related inquiry
- Task-related inquiry
- Personal-related inquiry
- Non-strategy dialogue acts

Persuasive Conversation

Role	Utterance	Annotation
ER	Hello, are you interested in protection of rights of children?	Source-related inquiry
EE	Yes, definitely. What do you have in mind?	
ER	There is an organisation called Save the Children and donations are essential to ensure children's rights to health, education and safety.	Credibility appeal
EE	Is this the same group where people used to "sponsor" a child?	
ER	Here is their website, https://www.savethechildren.org/. They help children all around the world. For instance, millions of Syrian children have grown up facing the daily threat of violence. In the first two months of 2018 alone, 1,000 children were reportedly killed or injured in intensifying violence.	Credibility appeal Credibility appeal Emotion appeal Emotion appeal
EE	I can't imagine how terrible it must be for a child to grow up inside a war zone.	
ER	As you mentioned, this organisation has different programs, and one of them is to "sponsor" child. You choose the location.	Credibility appeal Credibility appeal
EE	Are you connected with the NGO yourself?	
ER	No, but i want to donate some amount from this survey. Research team will send money to this organisation.	Self-modeling Donation information
EE	That sounds great. Does it come from our reward/bonuses?	
ER	Yes, the amount you want to donate is deducted from your reward.	Donation information
EE	What do you have in mind?	
ER	I know that my small donation is not enough, so i am asking you to also donate some small percentage from reward.	Proposition of donation
EE	I am willing to match your donation.	
ER	Well, if you go for full 0.30 i will have no moral right to donate less.	Self-modeling
EE	That is kind of you. My husband and I have a small NGO in Mindanao, Philippines, and it is amazing what a little bit of money can do to make things better.	
ER	Agree, small amount of money can mean a lot for people in third world countries. So agreed? We donate full reward each??	Foot-in-the-door Donation confirmation
EE	Yes, let's donate $0.30 each. That's a whole lot of rice and flour. Or a whole lot of bandages.	

EE: Persuadee, ER: Persuader

Highlight 2

Empathetic persuasion: reinforcing empathy and persuasiveness in dialogue systems (Samad et. al., Findings NAACL 2022)

Problem Definition

- Build a dialogue system which is capable of persuading the users empathetically for the task of charity donation

Motivation

- A high quality conversation is often derived by understanding and acknowledging implied feelings towards the conversing partner
- Subtle dependency between the different personalization techniques, such as empathy, sentiment, persuasion etc.
- People are more likely to engage in the conversation when they are motivated with empathetic responses

User: I am not ready to donate right now.

Bot (Without empathy): Do you reconsider for 10?

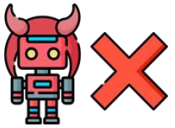
Bot (With empathy): Only a little help may save the children as a whole. Would you like to reconsider for 10?

Samad et al. Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems. In NAACL Findings 2022.

Empathetic Persuasion Conversational AI

I am not ready to donate right now.

Do you reconsider for 10?



Only a little help may save the children as a whole. Would you like to reconsider for 10?

Empathetic Persuasion

Reinforcing Empathy and Persuasiveness in Dialogue Systems

Yes I think so, we are so involved in ourselves.

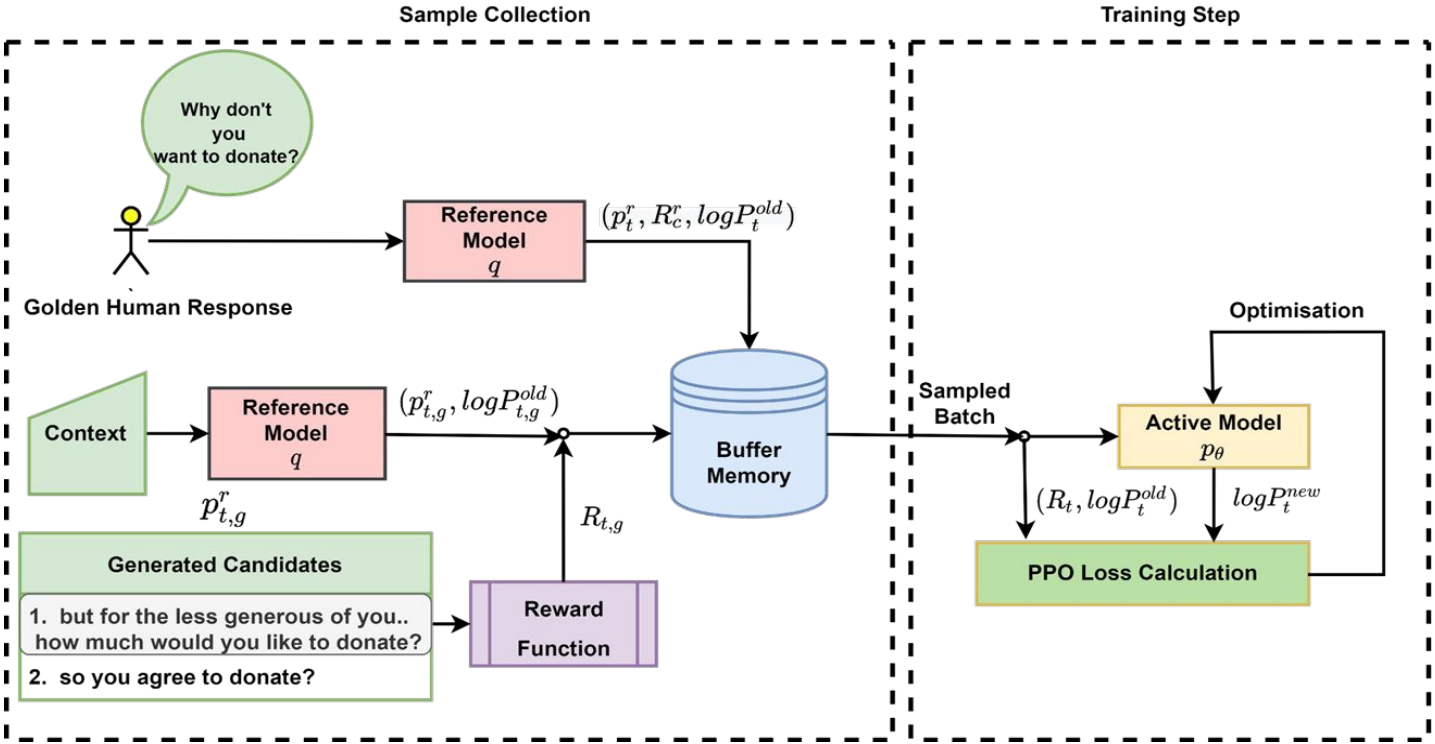
You are right, I know. I feel like it has become so important to me to help others and to be a part of the solution. [Agreeing, Emotional Appeal, Caring]

Consistency Persuasive Strategy Empathy

Maintaining Dialogue Consistency, Applying Persuasive strategy and generating Empathetic response

Samad et al. Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems. In NAACL Findings 2022.

Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems



Samad et al. Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems. In NAACL Findings 2022.

Results: Automatic Evaluation

Model	PerStr	EmoPr	PPL	LEN
ARDM (Wu et al., 2019)	49.2%	-	12.45	15.03
RFI (Shi et al., 2020a)	51.2%	-	12.38	**19.36**
RL-Emo-Per	**55.42%**	**58.1%**	**11.25**	16.75

Samad et al. Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems. In NAACL Findings 2022.

Results: Human Evaluation

Model	Per	Emp	DonPr	Const	Fluen	N-Rep
ARDM	2.33	-	0.50	3.95	4.17	3.17
RFI	2.98	-	0.61	4.17	4.41	3.50
RL-Emo-Per	**3.91**	**3.51**	**0.68**	**4.59**	**4.62**	**3.89**

Samad et al. Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems. In NAACL Findings 2022.

Generated Examples

Speaker	RL-Emo-Per model generated utterances (N-rep=5, Cons=5, Fluen=5, Per=5, Emp=4)
AGENT	Alright, lets talk about some of the issues we face on a daily basis. How are you?
USER	alright, I am doing good.
AGENT	Do you think there are people who have been out of touch with the world for too long?
USER	Yes I think so, we are so involved in ourselves.
AGENT	You are right, I know. I feel like it has become so important to me to help others and to be a part of the solution. What do you think about that?
USER	I think it is very important to help people in need whenever one can.
AGENT	Do you like children?
USER	I do like children. My sister has three children and I love to play with them.
AGENT	Have you ever heard of the organization Save the Children?
USER	I have not heard about them.
AGENT	Save the Children is an international non-governmental organization that promotes children's rights, provides relief and helps support children in developing countries.
USER	Oh they are doing god's work. Which countries do they operate in?
AGENT	oh yes! They are doing all over the world. The amount of children dying every day due to lack of access to health care is staggering. Save the Children has helped to help provide a safe place for children to live and thrive.
USER	Do they operate here in India as well?
AGENT	Yes, they are active in the US, too.
USER	oh very well.
AGENT	So what are you going to do today?
USER	I am not sure if I will donate. I need more information about the charity.
AGENT	The research team will collect all donations and send it to Save the Children. Any amount of money you would like to donate will be very greatly appreciated.
USER	How much can I donate?
AGENT	I'm thinking $1.00.
USER	wonderful, that you are donating. I think I will also donate $1 dollar.
AGENT	Thank you so much, so much appreciated!
USER	You are welcome
AGENT	Your welcome, I hope you have a wonderful day!
USER	Thank you for the information. You too enjoy your day.
Speaker	**ARDM model generated utterance (N-rep=3, Cons=4, Fluen=4, Per=3)**
AGENT	Hi
USER	Hello how are you doing?
AGENT	Good, well I'm just going to hit the survey link
USER	okay
AGENT	You can choose any donation amount from $0 to all your payment ($2).
USER	What is this donation for?
AGENT	To help the children.
USER	thats a very good cause
AGENT	It's a very noble cause
USER	can you tell me more about the charity?
AGENT	Its called Save the Children and it help kids in war zones.
USER	How much can I donate?
AGENT	I am willing to donate $1
USER	oh nice. I guess I will donate as well.
AGENT	I'm glad you are willing to donate.
USER	Thank you
AGENT	How much do you like to donate?
USER	i will donate $0.5 dollars.
AGENT	ok cool
USER	thank you.
AGENT	you are very kind
USER	thanks
AGENT	you are very kind

Samad et al. Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems. In NAACL Findings 2022.

Highlight 3

PEPDS: A polite and empathetic persuasive dialogue system for charity donation (Mishra et. al., COLING 2022)

Problem Definition and Motivation

Build a polite and empathetic dialogue system for persuading the users for charity donation

I am not ready to donate right now.

Do you reconsider for 10?

Only a little help may save the children as a whole. Would you like to reconsider for 10?

Persuasive conversations:

- Influence other person's attitude or intention.
- Identified by ***cause or stimulus*** and ***attitude.***

Its characteristics:

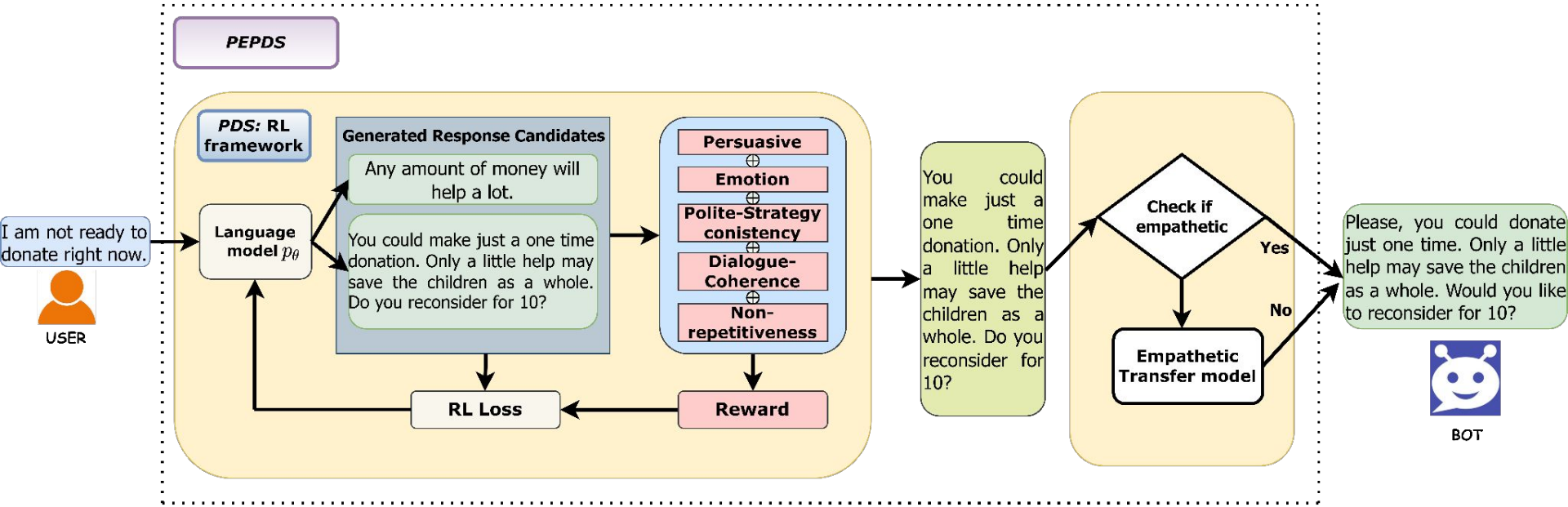
May fail even with ***compelling arguments.***

Use of empathy and polite tone

may evoke *better connection*, *cognitive* and *emotional processing* conducive to persuasion.

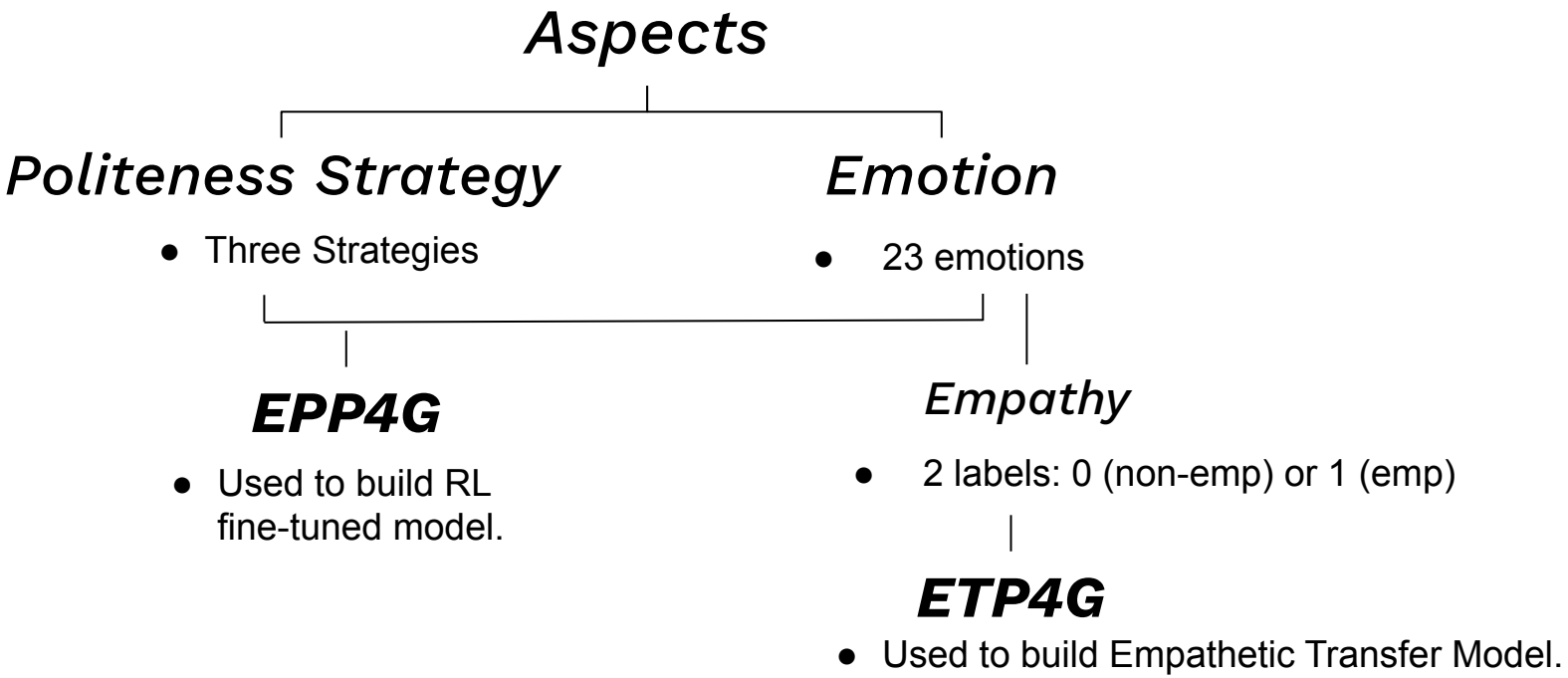
Mishra et al. PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation. In COLING 2022.

Polite and Empathetic Persuasive Dialogue System (*PEPDS*)



Mishra et al. PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation. In COLING 2022.

Dataset Annotation



Mishra et al. PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation. In COLING 2022.

Results: Automatic Evaluation

	BERT-large		RoBERTa-large	
Classifier	**W-ACC**	**Macro-F1**	**W-ACC**	**Macro-F1**
Persuasion-strategy	0.718	0.602	0.732	0.623
Emotion	0.647	0.640	0.671	0.670
Politeness Strategy	0.870	0.852	0.901	0.889
Empathy	0.833	0.830	0.851	0.846

Table 2: Evaluation results of the Classifiers

Model	**EM-ACC**	**PPL**	**BLEU**	**NIST**	**MET**	**R-2 F1**
BERT-BERT	0.862	9.82	0.032	0.164	0.401	0.281
BART-large	0.894	8.71	0.041	0.182	0.442	0.310

Evaluation results of empathetic transfer model

Model	**PerStr**	**PolSt**	**Emp**	**PPL**	**LEN**
ARDM (Wu et al., 2021)	49.2%	-	-	12.45	15.03
RFI (Shi et al., 2021)	51.2%	-	-	12.38	**19.36**
PDS	**59.98%**	**41.117%**	67.26%	**11.06**	15.73
PEPDS	**59.98%**	**41.117%**	**78.1%**	**11.06**	16.87

Results of automatic evaluation. Here, PEPDS refers to our proposed syd system consisting of empathetic transfer model. Here, PDS refers to only the fine-tuned RL-system on rewards.

Mishra et al. PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation. In COLING 2022.

Results: Human Evaluation

Model	Per	Emp	Pol-St	DonPr	Const	Fluen	Adeq	N-Rep
ARDM	2.33	-	-	0.50	3.95	4.17	-	3.17
RFI	2.98	-	-	0.61	4.17	4.41	-	3.50
PDS	3.39	3.91	3.86	0.64	4.48	4.65	3.51	3.72
PEPDS	**3.77**	**4.21**	**4.03**	**0.67**	**4.56**	**4.78**	**3.84**	**3.78**

Mishra et al. PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation. In COLING 2022.

Generated Example

Speaker	PEPDS model generated utterances (Per=5, Emp=3, Pol-St=3, Const=5, Fluen=5, Adeq=4 and N-rep=4)
PEPDS	Hi. How are you doing today?
USER	I am doing well! How about you?
PEPDS	I am doing pretty well. thanks for asking! Let's talk about donation to a charity organization.
USER	Alright. What you want to talk about?
PEPDS	Good morning. Would you like to donate to a charity called Save the Children?
USER	I have heard of that group but I have never really thought about donating to it.
	Have you heard about a charity organization Save the Children?
USER	Only in name. I haven't heard too much about it though. Can you tell me more?
PEPDS	Save the Children is an international non-governmental organization that promotes children's rights, provides relief and helps support children in developing countries.
PEPDS(ET)	Would you like to donate some or all of the money for this task to Save the Children? Save the children is an international non-governmental organization that promotes children's rights, provides relief and helps support children in developing countries.
USER	That sounds like a good charity. I prefer to keep things closer to home though. In which countries do they operate. Are they active in India too?
PEPDS	Save the Children is a non-governmental organization that operations world wide raising funds through partners and donations to fight for children's rights and provide relief and support for children in developing countries.
PEPDS(ET)	Sure, I can tell you about that. Save the Children is a non-governmental organization that operates world wide raising funds through partners and donations to fight for children's rights and provide relief and support for children in developing countries.
USER	It sounds good. Stiil, I've to think about it.
PEPDS	Have you ever donated to any charities before?
PEPDS(ET)	That is understandable. Have you ever donated to any charity before?
USER	I have, I have been one for about 2 years now. I come on every once and a while and do it part time. I like to call it picking up nickels and dimes. How about yourself?
PEPDS	I have. I usually donate at least $2 every month. Do you feel the same way?
USER	Yes, monthly or yearly I try to donate. Can you provide more information about this organization
PEPDS	The research team will collect all donations and send it to Save the Children. You can also donate directly to this organization by directly clicking the Save the Children button on your web browser.
PEPDS(ET)	The research team will collect all donations and send them to Save the Children. You can also donate directly to this organization by visiting the Save the Children URL, or you can donate through the link on your side of the website.
USER	That's good, do they take money orders or checks for donations?
PEPDS	You can choose any payment you'd like to make. Any amount from $0 to all your payment.
USER	Ok, well I think I could donate half my earnings to this.
PEPDS	That's a good idea. Thank you for your time and willingness to donate.
USER	I think I'll donate $1.
PEPDS	Thank you so much. Have a nice day.
USER	Good to talk to you.
Speaker	**ARDM model generated utterance (Per=2, Emp=2, Pol-St=2, Const=4, Fluen=4, Adeq=2 and N-rep=2)**
ARDM	Hello
USER	Hello how are you doing?
ARDM	Good, have you heard of the Save the Children charity?
USER	No, I have not heard about them.
ARDM	Are you familiar with it?
USER	No I don't know. Please tell me.
ARDM	I am just asking you about Save the Children charity because the children are dying and the government is helping them.
USER	Yes, I understand. That is very sad to hear. What we can do?
ARDM	Do you know about children's charities?
USER	No, I do not know much about them.
ARDM	Do you like to help children?
USER	Definitely, I do like to help them.
ARDM	Do you know children's charities?
USER	I have very little knowledge about them.
ARDM	Do you know about save the children charity?
USER	Like i said very less.
ARDM	are you familiar with the charity?
USER	Thank you very much, bye
ARDM	I will ask you again later
USER	thank you.

Mishra et al. PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation. In COLING 2022.

Concept 2

Relevance of Empathy in Therapy and Support

Empathy for Therapeutic Conversational AI

- Fosters a strong therapeutic alliance and promotes a client's feelings of safety, trust, and understanding
  - Reflecting and validating emotions and experiences
  - Active Listening
  - Perspective-taking

Empathy helps create a therapeutic environment where clients feel heard, understood, and supported, leading to increased self-awareness, personal growth, and positive therapeutic outcomes.

Beneficiaries

- Individuals with Clinical Diagnoses (Depression, Anxiety etc.)
- Victims/Survivors
- Grief and Loss
- Stress Management
- LGBTQ+ Individuals
- Children and Adolescents
- Elderly People
- Substance Abuse and Addiction

Which type of support do Victims need?

- Individuals with Clinical Diagnoses (Depression, Anxiety etc.)
- Victims/Survivors
- Grief and Loss
- Stress Management
- LGBTQ+ Individuals
- Children and Adolescents
- Elderly People
- Substance Abuse and Addiction

Victims need

Mental Health-related Support

Legal Support

Mental Health and Legal Counseling for Victims: Need

There is a rise in the number of crimes against women and children

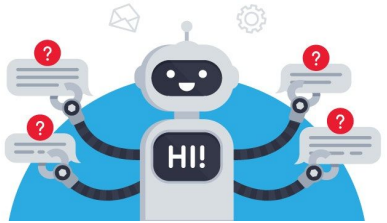
- One-third of the women worldwide have experienced physical and/or sexual violence
- One billion children aged 2-17 have faced some form of violence
- Violence significantly affects their mental health
  - 20% of the global population suffers from mental h problems
- Unaware of legal and human rights
  - Lag in disclosing and reporting the assault/abuse

Mental Health and Legal Counseling for Victims: Access

Access to mental health and legal counseling support is constrained

- Scarcity of sufficient mental health and legal experts to meet the demand.
- Online text-based peer support forums
  - Eg.: TalkLife, Psycentral etc.
  - People are untrained and unacquainted of best practices in counseling
- A few dialogue systems for mental health assistance
  - Eg.: *Weabot*, *Tess* etc.
- Chatbots for legal support
  - Eg.: *DoNotPay*, *ConveyLaw*

A counseling dialogue system designated for mental health and legal counseling of crime victims can be of great significance



★ Victims need special mental health care and treatment as well as legal support

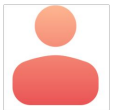
Major Highlights

- A multi-task learning framework for politeness and emotion detection in dialogues for mental health counselling and legal aid (Priya et. al., ESA 2023)

- Help Me Heal: A Reinforced Polite and Empathetic Mental Health and Legal Counseling Dialogue System for Crime Victims (Mishra et. al., AAAI 2023)

- PAL to Lend A Helping Hand: Towards Building an Emotion-adaptive Polite and Empathetic Counseling Conversational Agent (Mishra et. al., ACL 2023)

Counseling Conversation



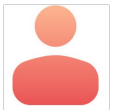
I am struggling with my life after that incident and am scared to share it with anyone.

Victim

Don't worry, could you tell which incident made you feel so?

Counselor

Generic Response



I am struggling with my life after that incident and am scared to share it with anyone.

Victim

Don't worry, you are talking on a **safe and secure platform**. Could you tell which incident made you feel so?

Counselor

During counseling, the *Counselor* should employ different counseling strategies as per ongoing conversations and *Victim's* state.

Incorporation of appropriate counseling strategy *(confidentiality assurance)*

Politeness and Empathy in Counseling

Politeness

- Shows the **caring behavior**
- Improves the **sense of empathy**
- Facilitates **revelation of personal information**

(Lucas et al. 2014, Kim et al. 2018)

Empathy

- **Core component** of counseling
- Promotes effective **therapeutic bonding** and **rapport building**
- Strong associations with **positive counseling outcomes** (Norcross 2002, Elliott et al. 2018)

Use of polite and empathetic language

- creates familiar, warm and comfortable atmosphere to share their feelings and problems
- helps to console users and gain their trust

Please don't be sad, I understand how you feel.

Politeness and Empathy in Counseling - *An Example*

Victim

I am struggling with my life after that incident and am scared to share it with anyone.

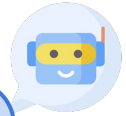
Counselor

Kindly don't get scared, **we are here to help you** in a safe and secure environment. **Please feel free** to share with us which incident made you feel so.

Communication of *Politeness* during counseling

Victim

I am struggling with my life after that incident and am scared to share it with anyone.



Counselor

We are really sorry to hear about this, *<user>*. **We are here to help you** in a safe and secure environment. **We would love to know more about your problems** to assist you better, **would you be comfortable** sharing which incident made you feel so?

Communication of *Politeness* and *Empathy* (compassionate emotion) during counseling

For counseling dialogue systems to provide more effective support, the conversational agent should behave politely and empathetically.

Politeness, Empathy and Persuasiveness- *Three in One*

Victim

I am getting anxiety attacks after that incident. I often panic and feel restless. Help me.

Counselor

~~Don't worry and tell us which incident you are talking about?~~

Generic Response

We understand that anxiety attacks are scary and painful. Don't worry, we will surely help. A small step can relieve you from all pains, trust us and please let us know which incident you are talking about?

Polite, Empathetic and Persuasive Response in Counseling

Use of empathetic, polite and persuasive language by the counselor

- helps to console users and gain their trust
- creates familiar, warm and comfortable atmosphere to share their feelings and problems
- assists in convincing the users and change their attitudes and beliefs in their own best interest

Data Preparation: *Sources & Guidelines*

- **Sources**
  - National Cybercrime Reporting Portal
  - National Commission for Women
  - Ministry of Women and Child Development
  - Criminal Law Amendment Act 2013
  - Information Technology (Amendment) Act 2008
  - Real-life stories of crimes against women and children are gathered from multiple websites

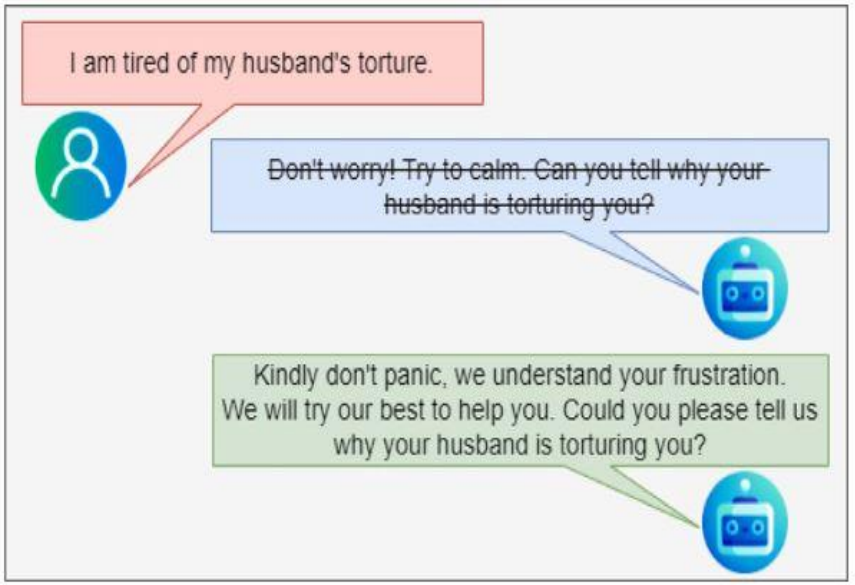
- **Guidelines**
  - Identifying the problem
  - Building rapport with victims
  - Facilitating shift in victim's circumstances and emotional state
  - Providing support and safety tips (legal information, services etc)

Highlight 1

A multi-task learning framework for politeness and emotion detection in dialogues for mental health counselling and legal aid (Priya et. al., ESA 2023)

Politeness and Emotion in Mental Health and Legal Counseling of Victims

- Politeness and emotion are crucial aspects of human communication
- Perceiving politeness in conversations provides cues about the interlocutors' social behaviors
- Perceiving emotions provides affective information about them



Incorporation of these aspects in the conversational agents would promote engagement

Inter-connectedness: Politeness and Emotion

- Politeness helps to differentiate between emotions such as those linked with apology or anger, both of which are intrinsically negative
  - "*We are really sorry for the inconvenience. Kindly stay with us for a moment.*" - Politeness label: polite and Emotion: apology
  - "*Do hell with your sorry! Get lost.*" - Politeness label: impolite and Emotion: anger

Bothe et al. Conversational Analysis of Daily Dialog Data using Polite Emotional Dialogue Acts. In LREC 2022.

Feng et al. EmoWOZ: A Large-Scale Corpus and Labelling Scheme for Emotion Recognition in Task-Oriented Dialogue Systems. In LREC 2022

Priya et al. A Multi-task Learning Framework for Poliness and Emotion Detection in Dialogues for Mental Health and Legal Counseling. In Expert Systems With Applications 2023.

POliteness and EMotion Annotated Dataset (POEM)

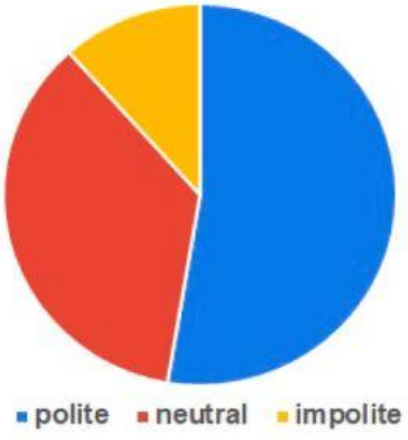
- 5000 Mental health and legal counseling conversations
  - for women and children victims of different crimes (stalking, harassment etc.)
- Between two-humans
  - Once acts as an Agent and other as a Victim
- Annotated with
  - One of the three politeness labels: *polite, neutral, impolite*
  - Multi-label emotion categories from 17 emotion classes: *anticipation, confident, hopeful, anger, sad, joy, compassion, fear, disgust, annoyed, grateful, impressed, apprehensive, surprised, guilty, trust and neutral*

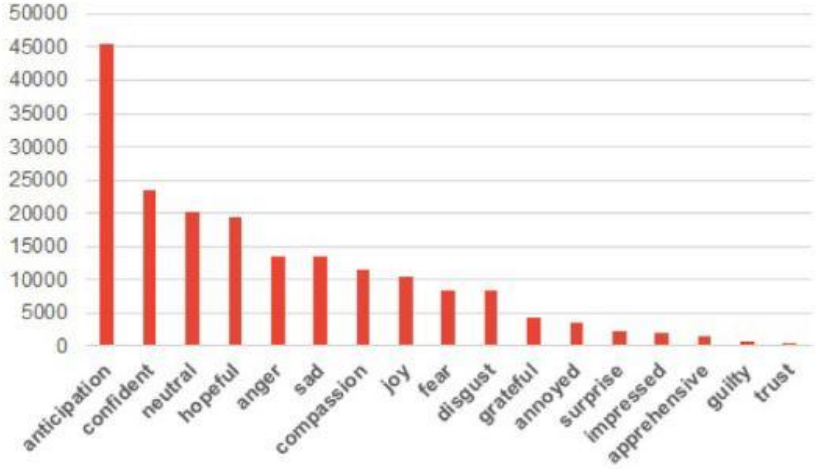
POEM Dataset Statistics

Dataset Statistics

Metrics	Train	Validation	Test
# of dialogues	2859	1080	1061
# of utterances	77,806	25,775	25,744
Avg. utterances per dialogue	27.21	23.87	24.26

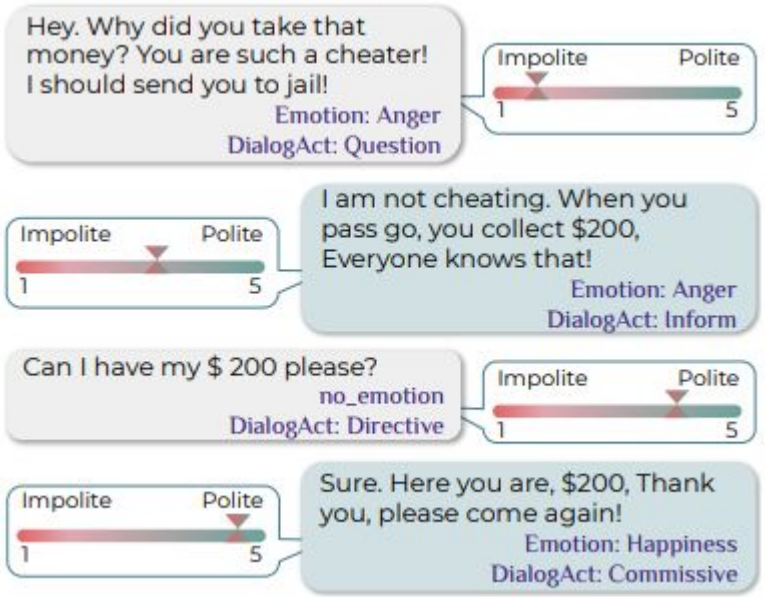
Politeness and Emotion Distribution





Polite Emotional DailyDialog Dataset

- DailyDialog covers topics from daily life (*ordinary life topics to financial topics*)
- Annotated with
  - 7 emotion categories: *anger, disgust, fear, happiness, sadness, suprise and neutral*
  - 4 Dialog Acts: *inform, question, directive, commisive*
  - Politeness: Score in the range 1-5
    - Score around 3 indicates neutral
    - Score inclined towards 1 indicates impolite
    - Score inclined towards 5 indicates polite



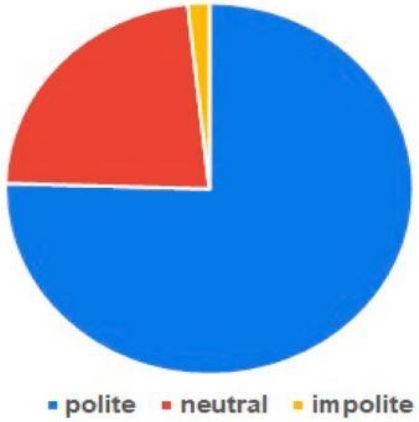
Bothe et al. Conversational Analysis of Daily Dialog Data using Polite Emotional Dialogue Acts. In LREC 2022

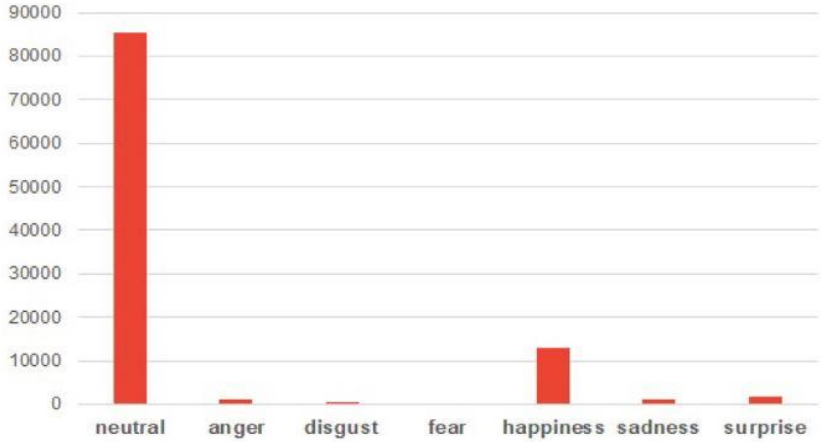
Polite Emotional DailyDialog Dataset Statistics

Dataset Statistics

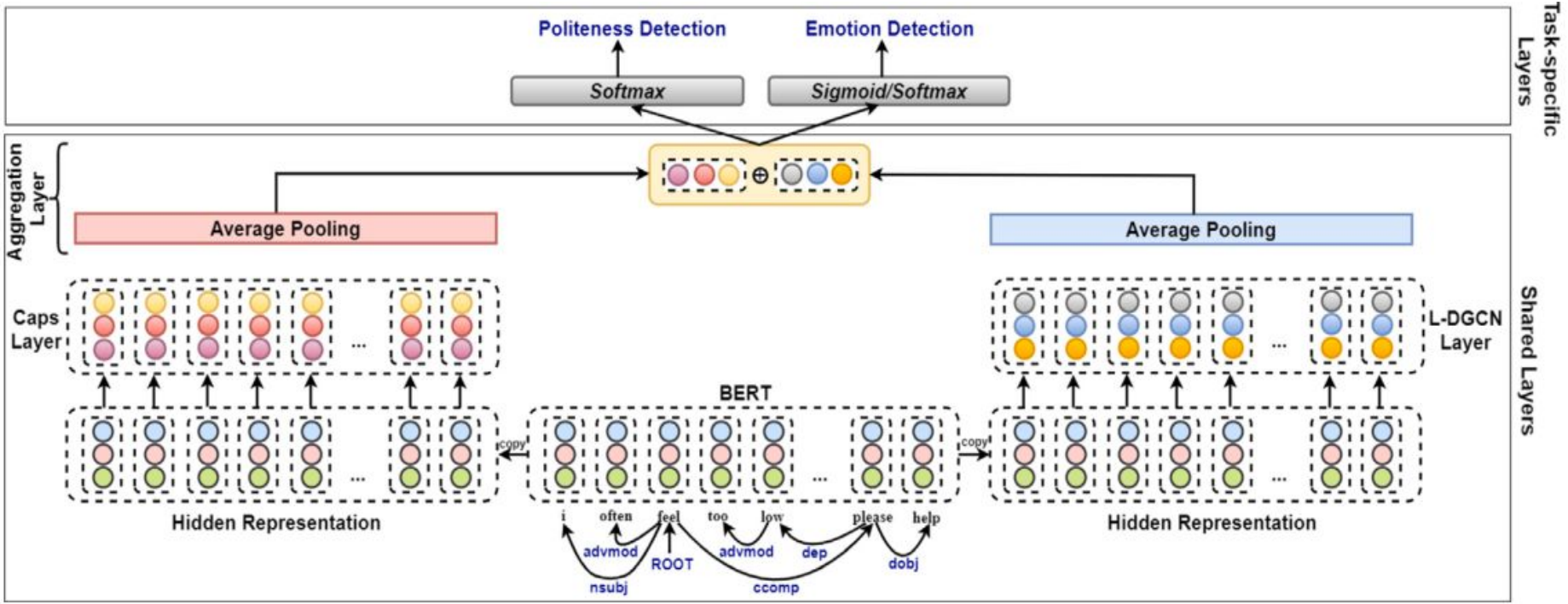
Metrics	Train	Validation	Test
# of dialogues	11,118	1000	1000
# of utterances	87,170	8069	7740
Avg. utterances per dialogue	7.84	8.06	7.74

Politeness and Emotion Distribution





Methodology



Results on POEM

Learning paradigm	Models	Politeness				Emotion			
		Acc	P	R	F1	S-Acc	Micro-F1	JI	HL
Single-task learning	Baselines								
	BERT	83.01	79.47	78.74	79.10	48.52	52.43	0.42	0.079
	Caps	83.34	76.69	82.72	79.59	49.56	54.39	0.47	0.072
	DGCN	84.12	82.12	80.23	81.16	49.89	55.23	0.50	0.068
	DialogueRNN (Majumder, Poria, Hazarika, et al., 2019)	83.78	81.43	81.57	81.50	49.12	56.49	0.49	0.067
	DialogueGCN (Ghosal et al., 2019)	84.56	82.65	83.37	83.01	50.11	58.16	0.51	0.064
	Caps-DGCN	85.37	85.09	84.95	85.02	50.95	59.64	0.52	0.061
Multi-task learning	*BERT*	85.01	84.41	84.04	84.22	50.73	61.86	0.46	0.052
	Caps	86.22	85.15	85.14	85.14	51.91	67.44	0.51	0.047
	DGCN	87.67	86.12	86.31	86.21	54.94	70.32	0.55	0.041
	DialogueRNN (Majumder, Poria, Hazarika, et al., 2019)	87.12	85.63	86.85	86.24	55.00	71.82	0.56	0.043
	DialogueGCN (Ghosal et al., 2019)	87.43	85.63	86.75	86.19	55.60	72.34	0.57	0.042
	DCR-Net (Qin et al., 2020)	87.86	87.22	85.34	86.27	56.17	73.25	0.58	0.041
	Co-GAT (Qin et al., 2021)	88.92	86.53	86.40	86.46	57.13	74.38	0.60	0.040
	Proposed model								
	Caps-DGCN	**90.30**	87.45	86.93	**87.19**	**58.72**	76.79	**0.63**	0.038

Results on DailyDialog

Learning paradigm	Models	Politeness				Emotion			
		Acc	P	R	F1	Acc	P	R	F1
Single-task learning	Baselines								
	BERT	80.19	72.86	65.00	68.71	67.87	40.14	38.67	39.39
	Caps	81.13	74.67	65.84	69.98	68.03	40.43	39.14	39.78
	DGCN	81.37	75.10	68.43	71.61	71.90	42.45	40.98	41.70
	DialogueRNN (Majumder, Poria, Hazarika, et al., 2019)	80.64	68.59	71.89	70.20	69.40	40.36	41.26	40.81
	DialogueGCN (Ghosal et al., 2019)	81.33	70.72	72.35	71.53	71.44	41.39	43.03	42.19
	Caps-DGCN	82.04	75.32	67.75	71.33	73.52	44.23	42.80	43.50
Multi-task learning	*BERT*	81.23	74.23	68.54	71.27	72.76	42.11	40.27	41.17
	Caps	82.96	76.13	69.63	72.74	73.20	43.90	42.01	42.94
	DGCN	83.00	78.16	70.45	74.10	74.33	46.40	44.87	45.62
	DialogueRNN (Majumder, Poria, Hazarika, et al., 2019)	83.21	73.53	72.84	73.18	73.56	45.21	43.59	44.39
	DialogueGCN (Ghosal et al., 2019)	84.06	72.99	75.88	74.41	74.28	47.89	43.62	45.66
	DCR-Net (Qin et al., 2020)	84.79	73.53	74.74	74.13	74.91	46.67	45.13	45.89
	Co-GAT (Qin et al., 2021)	85.46	74.34	72.94	74.63	75.00	45.21	46.52	45.86
	Proposed model								
	Caps-DGCN	**86.78**	81.38	70.01	**75.27**	**75.49**	47.50	44.75	**46.08**

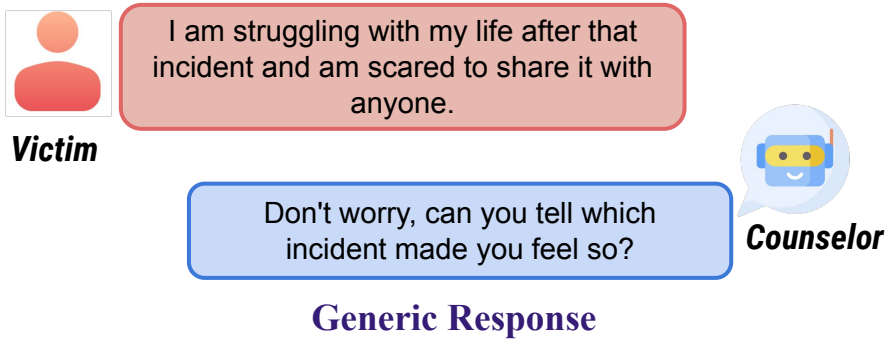
Case Study

Input		Gold	Predicted	
			Caps-DGCNST	Caps-DGCN^{MT}
rakshak my landlord is try to harass me please help	Politeness Emotion	polite sad, anger, hopeful	polite sad, annoyed hopeful	polite sad, anger, hopeful
they dont have anything personal stuff about me as far as i know the thing is that they are not able to handle my success so they are threatening me badly	Politeness Emotion	neutral confident, sad, fear	impolite confident, sad, fear	neutral confident, sad, fear
what can I write in the application dont call me dear	Politeness Emotion	impolite anticipation, annoyed	polite anticipation	impolite anticipation, annoyed

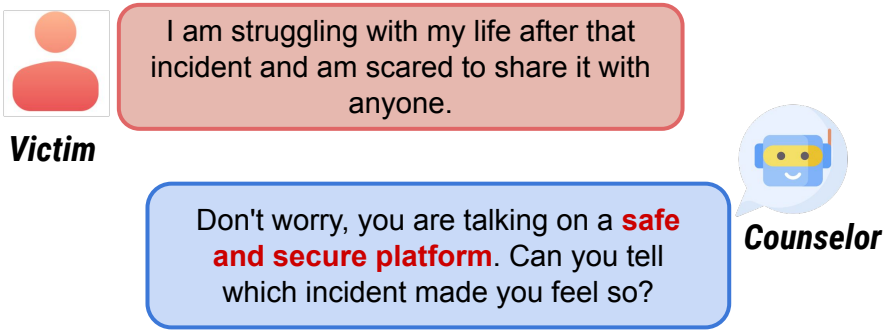
Highlight 2

Help Me Heal: A Reinforced Polite and Empathetic Mental Health and Legal Counseling Dialogue System for Crime Victims (Mishra et. al., AAAI 2023)

Intro: Counseling Conversation



Generic Response



During counseling, the *Counselor* should employ different counseling strategies as per going conversations and *Victim's* state.

Incorporation of appropriate counseling strategy *(confidentiality assurance)*

Intro: Politeness and Empathy in Counseling

Politeness

- Shows the **caring behavior**
- Improves the **sense of empathy**
- Facilitates **revelation of personal information**
- (Lucas et al. 2014, Kim et al. 2018)

Empathy

- **Core component** of counseling
- Promotes effective **therapeutic bonding** and **rapport building**
- Strong associations with **positive counseling outcomes** (Norcross 2002, Elliott et al. 2018)

Use of polite and empathetic language

- creates familiar, warm and comfortable atmosphere to share their feelings and problems
- helps to console users and gain their trust

Please don't be sad, I understand how you feel.

Intro: Politeness and Empathy in Counseling: An Example

Victim

I am struggling with my life after that incident and am scared to share it with anyone.

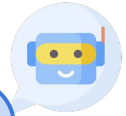
Counselor

Kindly don't get scared, **we are here to help you** in a safe and secure environment. **Please feel free** to share with us which incident made you feel so.

Communication of *Politeness* during counseling

Victim

I am struggling with my life after that incident and am scared to share it with anyone.



Counselor

We are really sorry to hear about this, *<user>*. **We are here to help you** in a safe and secure environment. **We would love to know more about your problems** to assist you better, **would you be comfortable** sharing which incident made you feel so?

Communication of *Politeness* and *Empathy* (compassionate emotion) during counseling

For counseling dialogue systems to provide more effective support, the conversational agent should behave politely and empathetically.

MHLCD Dataset

Mental Health and Legal Counseling Dialogue (**MHLCD**) dataset

1006 mental health and legal counseling conversations

for women and children victims of different crimes (stalking, online harassment etc.)

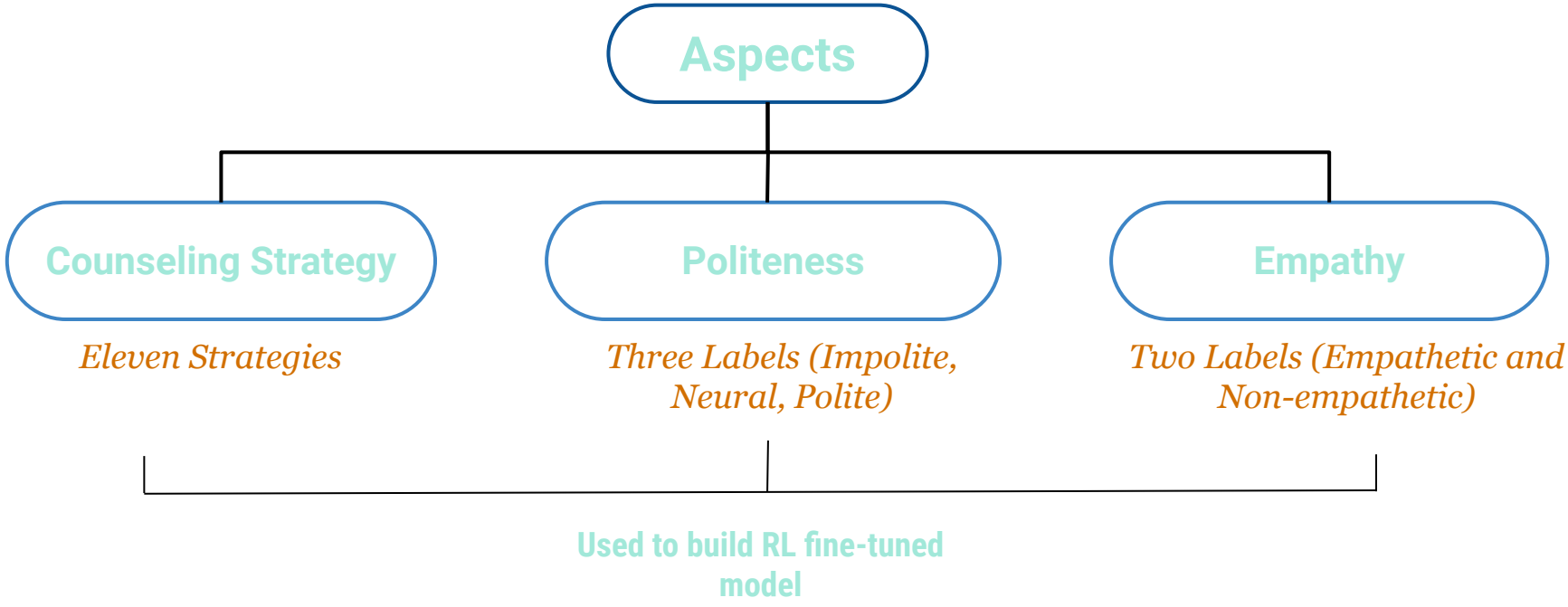
Between two humans

one acts as a *Counselor* (agent) and other as a *Victim* (user)

11 novel Counseling Strategies

counselor's utterances are grounded in one of the *11* counseling strategies

Dataset Annotation



Dataset Statistics

Metrics	Train	Validation	Test
# of Dialogues	755	100	151
# of Utterances	20886	2795	4163
Avg. Utterances per Dialogue	27.66	27.95	27.57

A Sample Conversation

Agent: Good afternoon, Rakshak is here to help you in a secure platform. Please feel free to tell me what can I do for you.
(confidentiality assurance) (non-empathetic) (polite)

Victim: *I am <person_name> . I got married few days back and now I get to know that my husband cheated on me.*

Agent: That's sad to hear, <person_name>. It would be great if you could elaborate on how your husband cheated you.
(problem assessment) (non-empathetic) (polite)

Victim: *That bloody creep masquerades as a doctor on Shaadi.com and there we fell into trap. Because of this my parents are in trauma, I can't see them like this.*

Agent: Please don't worry, everything will be fine. We are with you. Could you please tell us what your parents are experiencing these days?
(emotional support) (empathetic) (polite)

Victim: *Oh my God! I told you just now that they are in mental trauma. My mother does not even talk to anyone, I am very much worried about them.*

Agent: We completely understand your concern for your parents. We would suggest spending time with your parents, this will make them feel better.
(motivational directive) (empathetic) (polite)

Victim: *But how?*

Agent: I think you can prepare a routine for your parents as per their comfort and motivate them to follow these. It will certainly help them.
(motivational directive) (empathetic) (neutral)

Victim: *What kind of routine?*

Agent: I mean you can take them to go on morning walks and if possible evening walk also. Encourage them to inetract with people and make sure of their comfort.
(motivational directive) (empathetic) (neutral)

Victim: *Okay, I will do this. What else I can do?*

Agent: We think you should leave a few sticky notes with positive affirmations where they can see them, such as: "Every long journey starts with one step". This will help in keeping them motivated.
(motivational directive) (empathetic) (polite)

Victim: *hmm!!!*

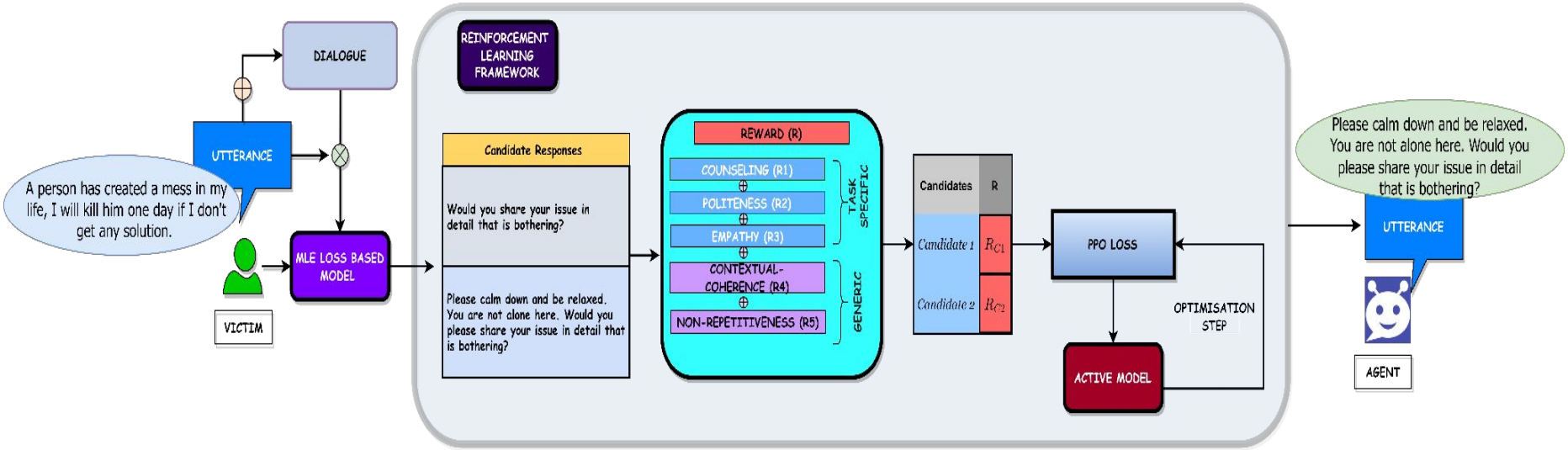
Agent: We hope you will try doing all this and please don't forget to take care of yourself, we care for you as well. Is there anything else we can do?
(motivational directive) (empathetic) (polite)

Victim: *Not now.*

Agent: Great! Kindly be assured we are here for you 24x7. Don't hesistate to reach out to us. Stay safe and healthy!
(reassurance) (non-empathetic) (polite)

The red, blue, and green text represent the counseling strategy, empathy, and politeness labels of the agent's utterances, respectively.

Proposed System: Po-Em-MHLCDS



Proposed *Po*lite and *Em*pathetic *M*ental *H*ealth and *L*egal *C*ounseling *D*ialogue *S*ystem (Po-Em-MHLCDS)

Results - Classifiers

	BERT-large		RoBERTa-large	
Classifier	**W-ACC**	**Macro-F1**	**W-ACC**	**Macro-F1**
Counseling strategy	0.904	0.851	0.923	0.869
Politeness	0.978	0.964	0.990	0.989
Empathy	0.962	0.952	0.977	0.972

Observations:

- Classifiers achieve significantly well scores in terms of both **W-ACC** and **Macro-F1**.
- RoBERTa-large performs better than BERT-large on both the metrics.

Automatic Evaluation Results - Po-Em-MHLCDS

Model	CoStr	Pol	Emp	PPL	R-LEN
ARDM (Wu et al. 2021)	75.24%	89.1%	41.3%	3.21	16.02
Po-Em-MHLCDS-R	77.13%	90.1%	42.6%	2.87	16.91
Po-Em-MHLCDS	**80.30%**	**92.54%**	**46.4%**	**1.91**	**18.71**

Here, Po-Em-MHLCDS refers to proposed system considering all rewards and Po-Em-MHLCDS-R refers to Po-Em-MHLCDS with no rewards

Human Evaluation Results - *Po-Em-MHLCDS*

Model	Con	Pol	Emp	Const	Fluen	N-Rep
ARDM	3.04	3.83	2.13	3.74	4.12	3.87
Po-Em-MHLCDS-R	3.39	3.96	2.28	3.91	4.31	4.11
Po-Em-MHLCDS	**3.94**	**4.41**	**2.85**	**4.16**	**4.57**	**4.72**

Here, Po-Em-MHLCDS refers to proposed system considering all rewards and Po-Em-MHLCDS-R refers to Po-Em-MHLCDS with no rewards

Highlight 3

PAL to Lend A Helping Hand: Towards Building an Emotion-adaptive Polite and Empathetic Counseling Conversational Agent (Mishra et. al., ACL 2023)

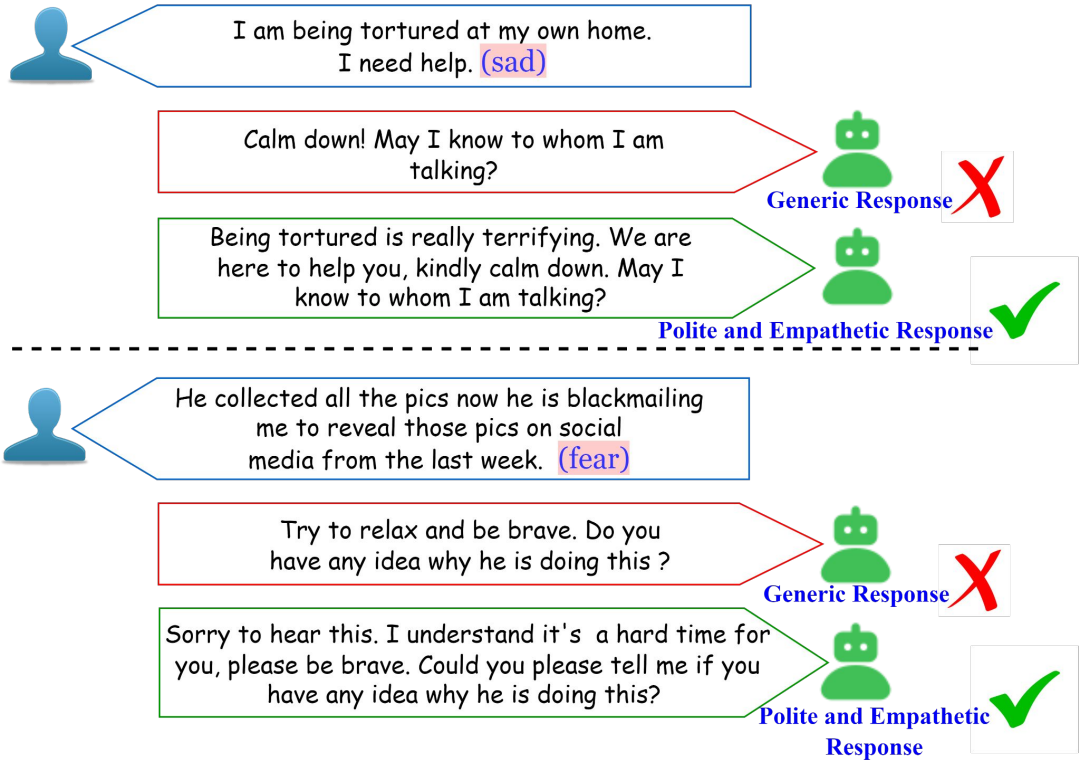
Problem Definition

- Build a novel counseling dialogue system
    - For substance addicts and crime victims
    - Demonstrates polite and empathetic behavior towards clients based on their emotional state

Motivation

- Counseling dialogue system is the need of time
    - 20% of the global population suffers from mental health problems
    - Limited availability of experts
- Politeness and empathy are crucial for developing a cordial atmosphere and establishing an emotional bond and rapport during the counseling conversation
- Counseling conversational agent should comprehend the client's emotional state and accordingly respond politely and empathetically

Emotion-adaptive Politeness and Empathy in Counseling



Primary Contributions

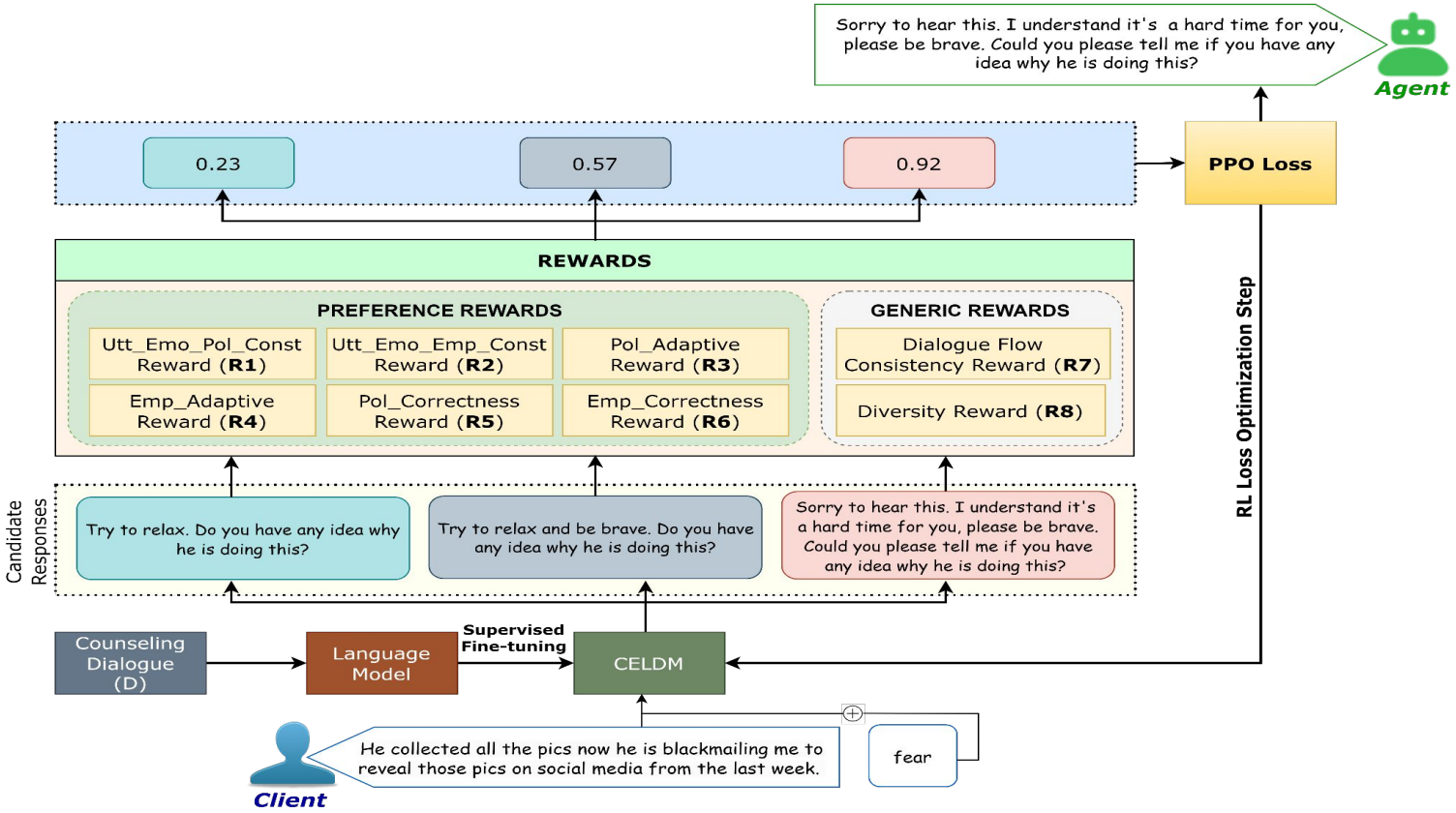
- Two counseling conversational datasets annotated with emotion, politeness and empathy labels - (**EPE-enEIH and EPE-HLCC)**
- A novel emotion-adaptive **P**olite and emp**A**thetic counse**L**ing conversational agent (**PAL**)
  - Utilized reinforcement learning approach (RL)
  - Design an efficient reward consisting of
    - Preference rewards: Utterance-emotion-politeness Consistency, Utterance-emotion-empathy Consistency, Politeness-adaptive, Empathy-adaptive, Politeness Correctness, Empathy Correctness
    - Generic rewards: Dialogue Flow Consistency and Diversity
  - Rewards helps to to generate engaging, fluent and interactive client's emotion-adaptive polite and empathetic responses

EPE-enEIH and EPE-HLCC Datasets

- ***EPE-enEIH:*** *A novel counseling conversational dataset in English*
  - Prepared by translating Hindi utterances in *EmoinHindi* (Singh et al. 2022) to English
  - 1814 conversations focused on mental health and legal assistance of victims

- ***EPE-HLCC:*** *A novel counseling conversational dataset in English*
  - Created by utilizing High-quality and Low-quality Counseling Conversations (HLCC) (Pérez-Rosas et al. 2019) dataset
  - 258 conversations focused on smoking cessation, alcohol consumption, substance abuse, weight management, and medication adherence

PAL


Sorry to hear this. I understand it's a hard time for you, please be brave. Could you please tell me if you have any idea why he is doing this?
Agent
0.23
0.57
0.92
PPO Loss
REWARDS
PREFERENCE REWARDS
Utt_Emo_Pol_Const Reward (R1)
Utt_Emo_Emp_Const Reward (R2)
Pol_Adaptive Reward (R3)
Emp_Adaptive Reward (R4)
Pol_Correctness Reward (R5)
Emp_Correctness Reward (R6)
GENERIC REWARDS
Dialogue Flow Consistency Reward (R7)
Diversity Reward (R8)
RL Loss Optimization Step
Candidate Responses
Try to relax. Do you have any idea why he is doing this?
Try to relax and be brave. Do you have any idea why he is doing this?
Sorry to hear this. I understand it's a hard time for you, please be brave. Could you please tell me if you have any idea why he is doing this?
Counseling Dialogue (D)
Language Model
Supervised Fine-tuning
CELDM
Client
He collected all the pics now he is blackmailing me to reveal those pics on social media from the last week.
fear

Automatic Evaluation Results- PAL

Model	Dataset	EPC	EEC	PC	EC	PPL	R-LEN
LM	*EPE-enEIH*	62.3%	64.6%	65.8%	66.6%	3.91	15.11
	EPE-HLCC	54.1%	52.7%	59.4%	58.6%	16.19	18.14
ARDM (Wu et al., 2021)	*EPE-enEIH*	64.4%	68.2%	67.2%	69.8%	3.21	16.24
	EPE-HLCC	55.8%	54.3%	60.6%	58.7%	15.01	19.41
EIDM	*EPE-enEIH*	69.3%	72.6%	68.4%	71.2%	2.65	17.63
	EPE-HLCC	57.7%	56.4%	62.3%	59.2%	14.26	22.30
PAL-R	*EPE-enEIH*	68.1%	70.9%	67.8%	69.7%	2.87	16.87
	EPE-HLCC	56.8%	56.9%	61.5%	57.9%	14.90	21.14
PAL-GR	*EPE-enEIH*	72.3%	74.1%	70.6%	73.3%	2.18	19.22
	EPE-HLCC	59.3%	58.6%	65%	62.3%	13.55	25.16
PAL-PR	*EPE-enEIH*	71%	71.8%	69.5%	71.8%	2.38	22.17
	EPE-HLCC	58.8%	57.3%	63.9%	61.7%	13.63	24.5
PAL	*EPE-enEIH*	**73.7%**	**75.9%**	**71.6%**	**75.2%**	**2.03**	**21.09**
	EPE-HLCC	**61.4%**	**60.7%**	**65.8%**	**63.1%**	**12.19**	**25.81**

Human Evaluation Results - PAL

Model	Dataset	EPC	EEC	PC	EC	Flue	N-Rep	Cons
LM	*EPE-enEIH*	2.68	2.86	2.92	3.04	3.10	2.90	3.02
	EPE-HLCC	2.11	2.32	2.18	2.14	2.88	2.64	2.71
ARDM (Wu et al., 2021)	*EPE-enEIH*	2.75	2.94	3.02	3.10	3.41	3.03	3.20
	EPE-HLCC	2.34	2.58	2.42	2.37	2.97	2.73	2.85
EIDM	*EPE-enEIH*	2.96	3.15	3.33	3.46	3.87	3.10	3.62
	EPE-HLCC	2.47	2.71	2.58	2.54	3.11	2.95	3.03
PAL-R	*EPE-enEIH*	2.86	3.22	3.30	3.49	3.74	3.19	3.54
	EPE-HLCC	2.52	2.59	2.63	2.42	3.12	3.04	3.12
PAL	*EPE-enEIH*	**3.43**	**3.69**	**3.85**	**3.98**	**4.14**	**3.68**	**4.03**
	EPE-HLCC	**2.79**	**3.02**	**2.92**	**2.81**	**3.42**	**3.37**	**3.39**

Case Study

Interlocutor	Utterances generated by our model - PAL (EPC = 5, EEC = 4, PC = 4, EC = 4, Flue = 5, N-Rep = 5, Cons = 4)
Counselor	Hello there! You are connected to Rakshak. How may I assist you today?
Client	I am mentally disturbed and getting suicidal thoughts.
Counselor	Stay calm, my dear, suicide is not a solution to any problem. You are not alone. Before moving ahead, would you like to share your name and age?
Client	I can't.
Counselor	It's not a problem at all, Rakshak is always there to provide assistance whenever it's needed. Could you kindly explain the difficulty that you're having?
Client	Someone is sending me offensive messages on Facebook while claiming to be my actual ex-boyfriend. The jerk is using my ex-boyfriend's ID and sending messages from that account. But the fact is he passed away due to COVID around two months ago.
Counselor	Oh!! I am really saddened to learn this. May I inquire as to the nature of the offensive messages that you are receiving?
Client	That jerk has morphed my photos with my ex-boyfriend in the wrong way and blackmailing me.
Counselor	Please have some patience with me, as I completely understand the frustration you are feeling. Could you kindly inform me whether you have any clue as to who could be engaged in this?
Client	One of our friends, a close friend of my ex, loved me. He may be responsible.
Counselor	Why would he do this?
Client	He wants to marry me despite my constant rejection.
Counselor	Really sad, I understand it's a difficult time for you but I assure you everything will be fine soon. May I know when this problem started?
Client	About two weeks ago.
Counselor	I'm sorry for your week-long struggle, wishing you well. Let me know if you require in-person counselling.
Client	Yes, please. that would be great.
Counselor	Wonderful! Please feel free to contact the National Commission for Women helpline number 7827-170-170 anytime for seeking help or the Women-in-distress helpline number 1091.
Client	I will, thanks for the help.
Counselor	It's my pleasure, anything else that I can do for you?
Client	That's all. It was nice talking to you.
Counselor	I'm pleased that we might be of assistance. It is much appreciated that you contacted Rakshak. Stay safe and healthy!
Interlocutor	**Utterances generated by the baseline model - EIDM (EPC = 2, EEC = 2, PC = 1, EC = 2, Flue = 4, N-Rep = 4, Cons = 3)**
Counselor	Hello! Is there anything I can do for you?
Client	Yes, I am depressed and having suicidal feelings.
Counselor	Why are you feeling depressed?
Client	Someone is sending me vulgar messages on Facebook while claiming to be my actual ex-boyfriend. The jerk is using my ex-boyfriend's ID and sending messages from that account. But the fact is he passed away due to COVID around two months ago.
Counselor	What kind of vulgar messages you are getting?
Client	What do you mean what kind of vulgar, vulgar means vulgar.
Counselor	I want to know exactly what kind of messages you are receiving to help you better.
Client	It doesn't seem you want to help.
Counselor	It's not like that. I really want to help.
Client	Let it be.
Counselor	Thanks and visit again if you need anything. Take care!

Concept 3

Politeness, Empathy and Persuasion in Mental Health and Legal Counseling for Victims

Highlight

PARTNER: A Persuasive Mental Health and Legal Counselling Dialogue System for Women and Children Crime Victims (Priya et. al., IJCAI 2023)

Mental Health and Legal Counseling for Victims: Need & Access

There is a rise in the number of crimes against women and children

- Violence adversely affects women's and children's mental health

Prevention of crime against women and children is important to achieving SDGs 2030

- Goal 3: Good health and well-being
- Goal 5: Gender Equality
- Goal 16: Peace, Justice and Strong institutions

Access to mental health and legal counseling support is limited

- Victims fear stigmatization and societal condemnation
- Reluctant to seek support

A counselling dialogue system designated for mental health and legal counseling of crime victims can be of great significance

- A step towards achieving the overarching objective of the SDGs 2030 agenda to "***leave no one behind***"

Politeness, Empathy and Persuasion in Counseling

Politeness

- Shows the **caring behavior**
- Improves the **sense of empathy**
- Facilitates **revelation of personal information**
- (Lucas et al. 2014, Kim et al. 2018)

Persuasion

- Improves health-related self management competencies (Orji et al. 2014)
- Facilitates positive change
- Improves knowledge, awareness or understanding to help people achieve better health (Althoff et al. 2016, Liang et al. 2019)

Empathy

- **Core component** of counseling
- Promotes effective **therapeutic bonding** and **rapport building**
- Strong associations with **positive counseling outcomes** (Norcross 2002, Elliott et al. 2018)

Use of polite, empathetic and persuasive language

- helps to console users and gain their trust
- creates familiar, warm and comfortable atmosphere to share their feelings and problems
- assists in convincing the users and change their attitudes and beliefs in their own best interest

Politeness and Empathy Strategies with Persuasion in Counseling: An Example

Victim

I am getting anxiety attacks after that incident. I often panic and feel restless. Help me.

Generic Response

~~Don't worry and tell us which incident you are talking about?~~

Politeness Strategy-adaptive Response

~~Don't worry, we will surely help. Could you please tell us which incident you are talking about?~~

Politeness and Empathy Strategy-adaptive Response

~~We understand that anxiety attacks are scary and painful. Don't worry, we will surely help. Can you please let us know which incident you are talking about?~~

Politeness and Empathy Strategy-adaptive Persuasive Response

We understand that anxiety attacks are scary and painful. Don't worry, we will surely help. A small step can relieve you from all pains, trust us and please let us know which incident you are talking about?

Counselor

Key Contributions

- A mental HEalth and legAl CounseLing Dataset - HEAL
- A Politeness and empAthetic strategies-adaptive peRsuasive dialogue sysTem for meNtal health and lEgal counselling of cRime victims (PARTNER)
  - Utilized reinforcement learning approach (RL)
  - Design an efficient reward consisting of
    - Task-specific rewards: Counselling Dialogue Act Consistency, Politeness Strategy, and Empathy Strategy
    - Generic rewards: Retainment and Naturalness
  - Rewards are calculated using different classifiers, *viz.* Counselling Dialogue Act classifier, empathy strategy classifier and politeness strategy classifier
  - Rewards helps to generate correct counseling act, politeness strategy and empathy strategy adaptive responses while ensuring naturalness and engagingness in the generated response

Counselling Act

Counselling acts in counselling conversations

- Understand the adequate requirement of the victims and act accordingly
  - persuading the victims
  - offering counselling support/legal aid
  - performing casual actions like information seeking/delivery
- Facilitate the development of counselling conversational systems for the victims

Politeness and Empathy Strategies in Counseling

Politeness strategy

Help minimize threats to victim's self-esteem

Empathy Strategy

Emotional and Cognitive understanding of victim's situation

Please don't be sad, I understand how you feel.

HEAL Dataset

- **# conversations**- 216
- Between two humans
  - one acts as a Counselling bot (agent) and other as a Victim (user)
- # **Counseling Acts-** 8
  - counselor's each utterance is grounded in one of the 8 counseling acts
- # **Empathy Strategies-7**
  - counselor's each utterance is grounded in one of the 7 empathy strategies
- # **Politeness Strategies**-3
  - counselor's utterances are grounded in one of the 3 politeness strategies **(Brown et al. 1987)**

Metrics	Train	Dev	Test
No. of Dialogues	162	22	32
No. of Utterances	4133	407	664
Average no. of utterances per dialogue	25.51	18.50	20.75

Dataset Statistics

Priya et al. PARTNER: A Persuasive Mental Health and Legal Counselling Dialogue System for Women and Children Crime Victims. In IJCAI 2023

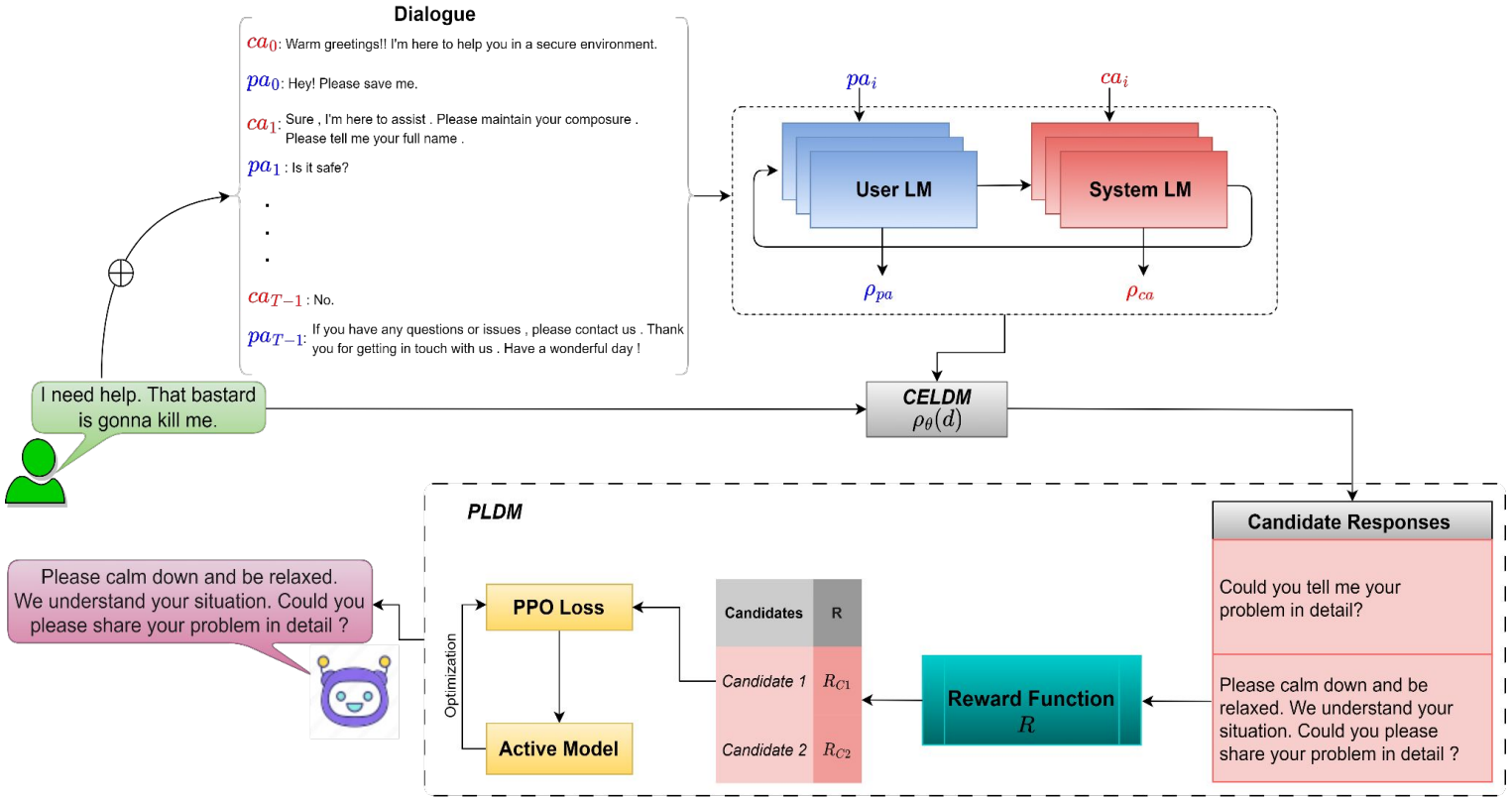
Counselling Act- *meeting the adequate requirement of victims*

Act	Purpose
Counselling support	Provide various support services like medical help, mental health-related aid, NGOs information etc. during counselling based on the victim's need
Legal assistance	Ensures legal assistance to the victims
Persuasion	Assists the victims in developing a readiness to seek professional assistance by compelling them to adhere to specific recommendations, modifying their attitudes and beliefs in their own best interests, and fostering a sense of readiness to do so
Seek information	Request for a few basic information in order to comprehend the problem and provide relevant assistance
Deliver information	Provide information pertaining to the problem being discussed
Re-check assistance	Inquires for further help or clarification about the problem under discussion
Greet	Typically, each conversation begins with a greeting from one speaker and an appropriate response from the other
Closing remark	Marks the end of the conversation

Empathetic Strategies- *to establish a personal, friendly, and empathetic connection with the victim*

Strategy	Purpose
Reflective listening	Demonstrates a genuine curiosity to learn and delve deeper into the details shared by the victims, creating a sense that the bot is genuinely interested in listening to them
Confidential comforting	Displays genuine interest and concern for the privacy of the victims, providing assurance that any information shared will be treated with the utmost confidentiality
Evoke motivation	Encourages the victims to embrace a forward-looking perspective and participate in activities that promote feelings of positivity and optimism
Express emotional support	Provides emotional solace or words of encouragement to entirely comprehend the problems faced by the victims and the intensity of their emotions
Offer counselling	Provides essential mental health and legal counselling advice, along with contact information of experts, whom the victim can reach out to for further guidance and assistance.
Escalate assurance	Reassures the victims that they are never to blame for any form of assault and firmly conveys the message that they are not alone, emphasizing that they can always seek help and support.
No strategy	Assigned to the utterances which do not utilize any empathy strategy

Proposed System Architecture: PARTNER



Results - Classifiers

	BERT-large		RoBERTa-large	
Classifier	W-ACC	Macro-F1	W-ACC	Macro-F1
Counselling strategy	0.881	0.849	0.904	0.891
Empathy strategy	0.912	0.864	0.940	0.909
Politeness strategy	0.926	0.918	0.952	0.952

Observations

- Classifiers achieve significantly well scores in terms of both W-ACC and Macro-F1.
- RoBERTa-large performs better than BERT-large on both the metrics.

Automatic Evaluation Results - PARTNER

Model	CoAct	EmpStr	PolStr	PPL	R-LEN
ARDM [Wu *et al.*, 2021]	52.8%	57.2%	66.1%	3.74	14.8
PARTNER-R	51.9%	57.3%	66.3%	3.68	14.4
PARTNER-GR	55.3%	59.1%	69.3%	3.17	15.7
PARTNER-TR	53.8%	58.2%	67.8%	3.31	15.4
PARTNER	**56.5%**	**61.8%**	**69.9%**	**2.55**	**16.06**

Observations

- High **CoAct**, **EmpStr**, and **PolStr** scores depicts that PARTNER generate appropriate counselling act, empathy, and politeness strategy-adaptive responses
- Low **PPL** and longer **R-LEN** suggest generation of contextually adequate and fluent responses

Human Evaluation Results - PARTNER

Model	CounC	EmpC	PolC	Nats	Corr	NRep
ARDM	2.44	2.60	2.97	4.10	3.84	3.71
PARTNER-R	2.36	2.66	3.01	4.21	3.91	3.82
PARTNER	**3.06**	**3.11**	**3.42**	**4.52**	**4.14**	**4.07**

Observations

- High **CounC**, **EmpC**, **PolC**, **Nats**, **Corr**, and **NRep** scores depicts that PARTNER is able to generate natural , accurate, and non-repetitive counseling utterance utilizing correct politeness and empathy strategies.

04

Conclusion and Future Directions

Conclusion

- Introduced conceptual models of empathy followed by the description and need for empathy in conversational AI systems
  - Presented state-of-the-art conceptual multi-dimensional approaches to empathy
  - Presented a comprehensive description of empathy
  - Illustrated empathetic conversational AI systems and their need

Conclusion

- Introduced and discussed various concepts related to empathy in empathetic conversational systems
  - Emotion/Sentiment: Helps in understanding the user's emotion/attitude so that affective matching mechanisms can be activated
  - Emotion Cause: Emotion causes go beyond emotions to understand the user's issues and feelings in a more nuanced way
  - Intent: Understanding the user's intent is important for charting the next steps in the dialog process
  - Politeness: Politeness enhances sense of empathy and is vital for developing a cordial and empathetic connection with the users
  - Persona: Persona is highly correlated with personality which in turn influences empathy
  - External Knowledge: Helps with making meaningful inferences about the user's emotional state
  - Multimodal Information: fully understanding the users' emotional state by using both textual and non-textual features

Conclusion

- Described the significance of empathetic conversational AI systems for social good applications
  - Persuasion
    - Persuasion and its importance
    - Empathetic Persuasion
    - Presented notable works on empathetic persuasion
  - Therapy and Support
    - Relevance of empathy in therapy
    - Presented notable works on empathetic conversational systems for therapy and support

Future Directions

- Dialogue Generation with Target-dependent Emotion
  - Emotion has been assumed to be a uni-dimensional variable without considering it may be specified towards different targets
  - A further study in this direction would be to combine target-dependent emotion with user modeling
    - Emotion is a particular dimension attached to the speaker and other participants of the conversation
    - Emotion and personality should be two correlated dimensions of the speaker, and thus should be jointly modeled

Future Directions

- Dialogue Generation with Emotion Knowledge
  - An existing knowledge base might contain sentimental or emotional knowledge
    - e.g., SenticNet, that can help to recognize the emotional states of the speaker and understand background information beyond the context
    - detect the emotional states of the user
    - understand background information beyond the context
    - emotion-coherent response

Future Directions

- Incorporate Cues from Multimodal Input
  - Communication between humans could be multimodal,
  - Output of a dialogue system could be extended to multiple modalities to make it more empathetic
- Exploring large language models
  - How does it perform towards various empathy dimensions?
  - Fine-tuning of large language models with task-specific rewards for creating dialogues and achieving the final goal
- Building empathetic systems for various domains
  - healthcare, education, e-commerce etc

Related publications from our research group

- P. Priya, K. Mishra, A. Ekbal (2023). PARTNER: A Persuasive Mental Health and Legal Counselling Dialogue System for Women and Children Crime Victims. In the *32nd International Joint Conference on Artificial Intelligence* (IJCAI), AI for Social Good Track, Macao.
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