

# Navigating the Landscape of Empathetic Dialogue Systems: **Current Innovations and Future Developments**



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# Outline

- ❖ Background
- ❖ Empathetic Dialogue Systems
- ❖ Empathetic Dialogue Systems for Social Good
- ❖ Conclusion and Future Directions



# Dialogue Systems: An 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.

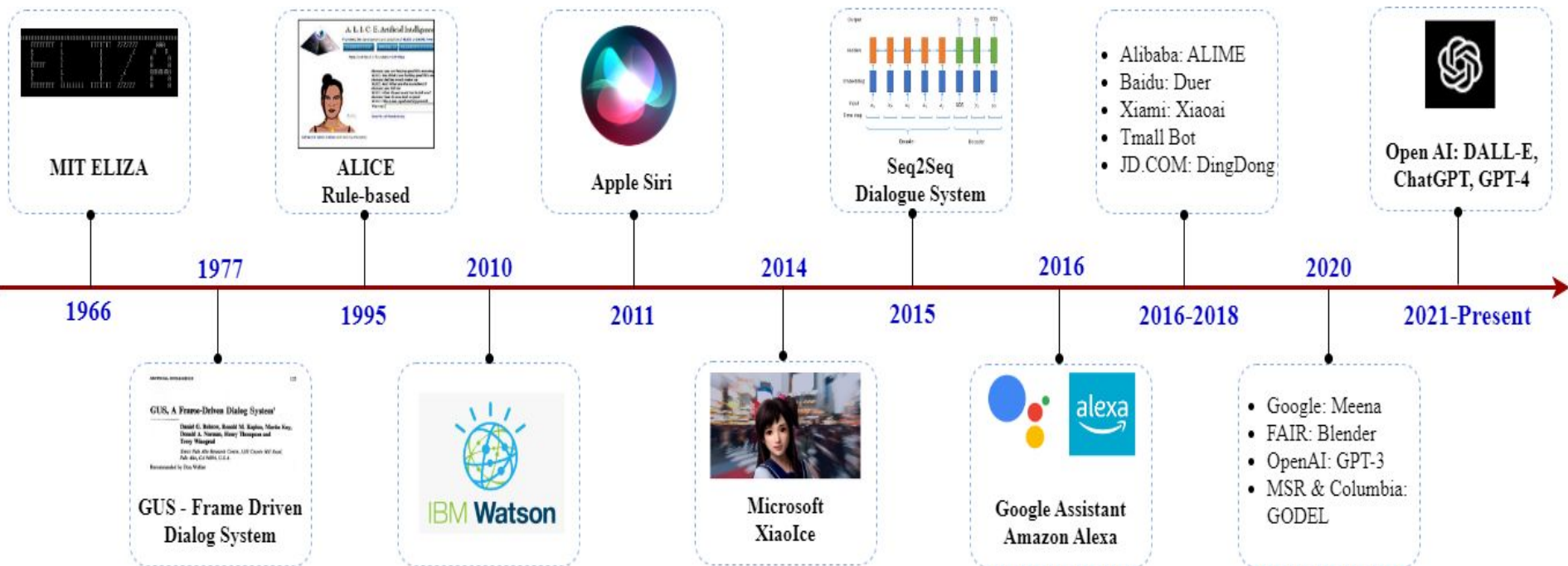
## Examples: Conversational AI Systems

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

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- **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 Xiaolce*

- **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



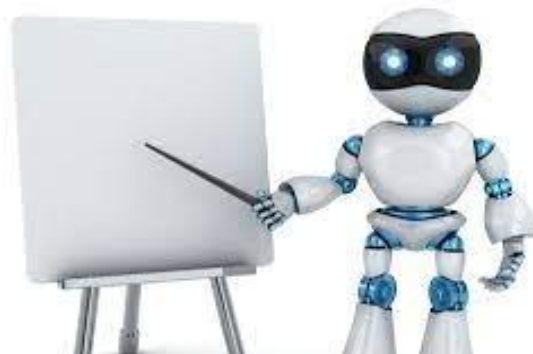
Product Recommender



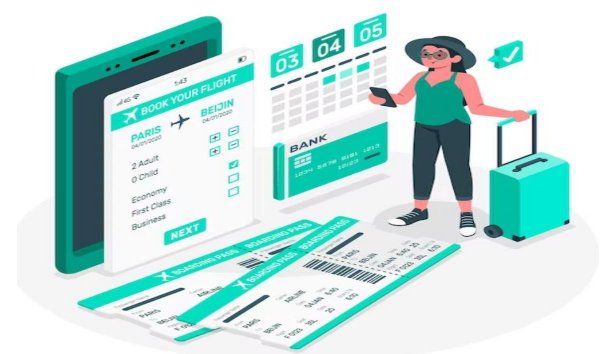
In-car Assistant



Medical Diagnosis

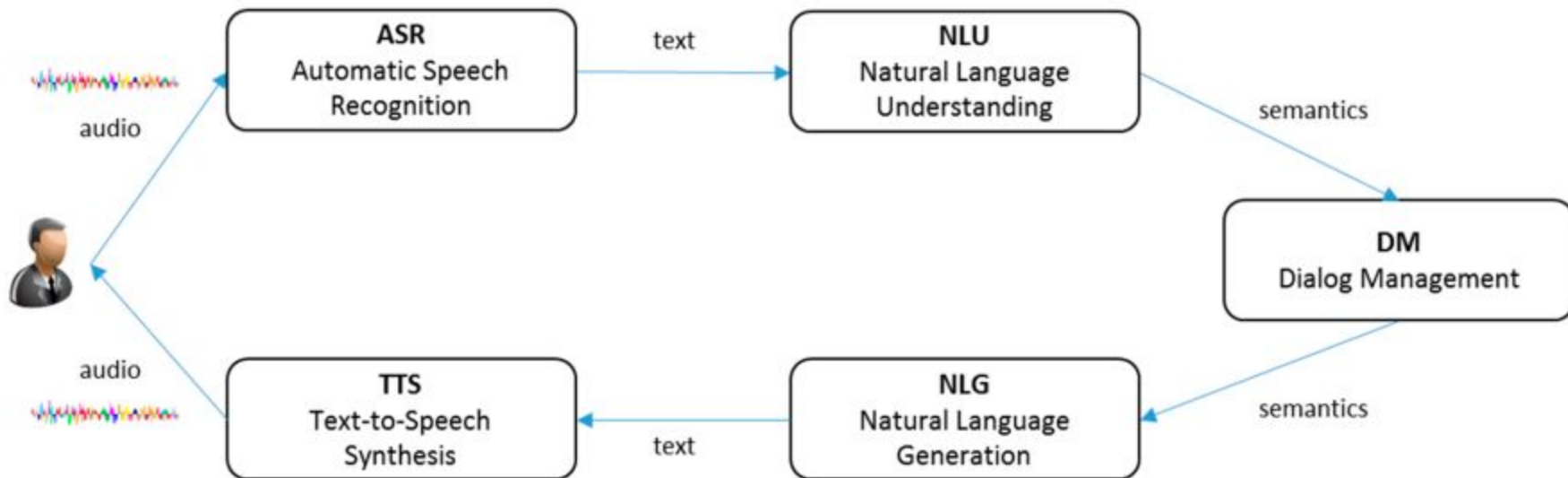


Intelligent Tutor

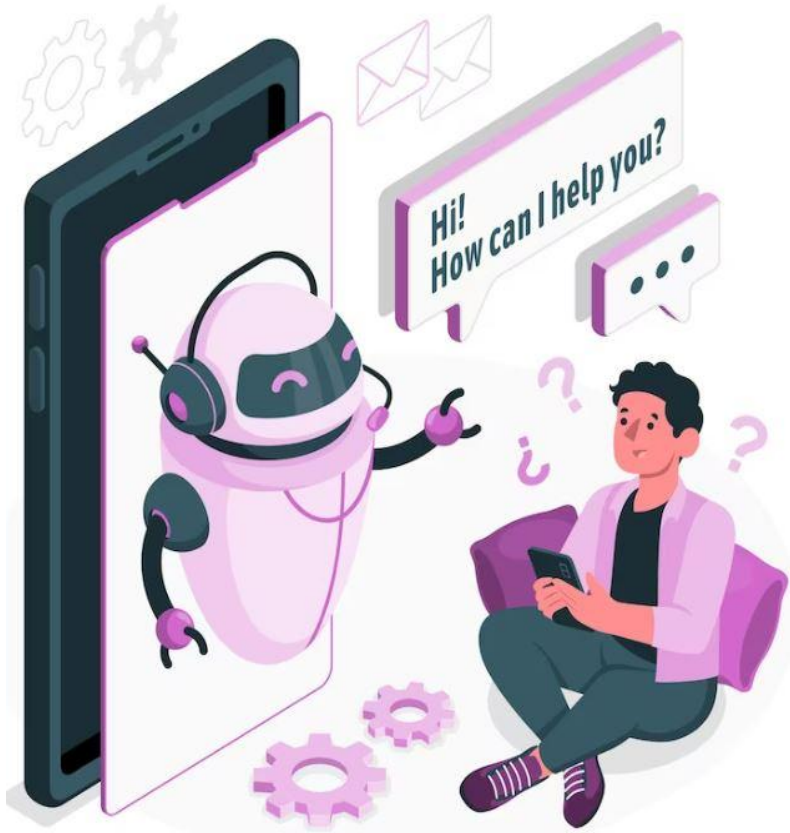


Travel Agent

# Modules in a Task-Oriented Conversational System







*The most simplest form of  
Conversational System: Chatbot*

# Chatbot: Impact

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- 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)

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- 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

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- **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*)

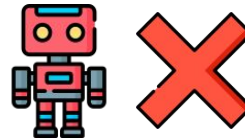
- **Consistency:** *to ensure that it generates appropriate response without missteps, such as contradictions*
- **Specificity:** *generating specific response*
- **Empathy: Affect-awareness (Sentiment-aware, Emotion-aware), Courteousness etc.**
- **Knowledgeability:** *should be able to take into account 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

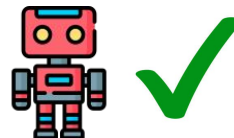


I finally got promoted today at work!!

Why would anyone promote you?



Congrats!! That's great!!



# Communication of Empathy



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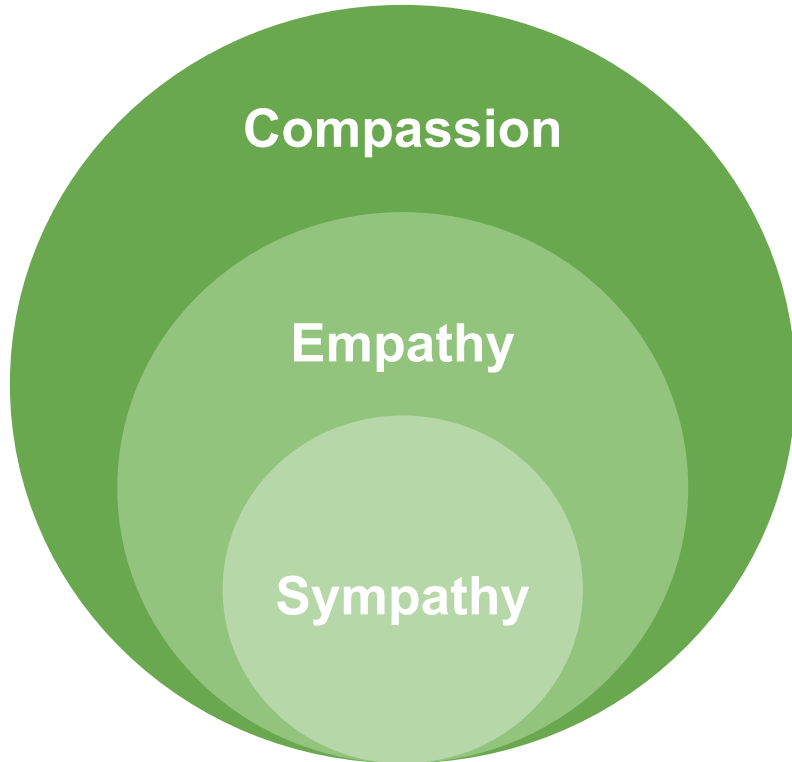
Wondering!!

What the **Empathy** is??





# Understanding Empathy



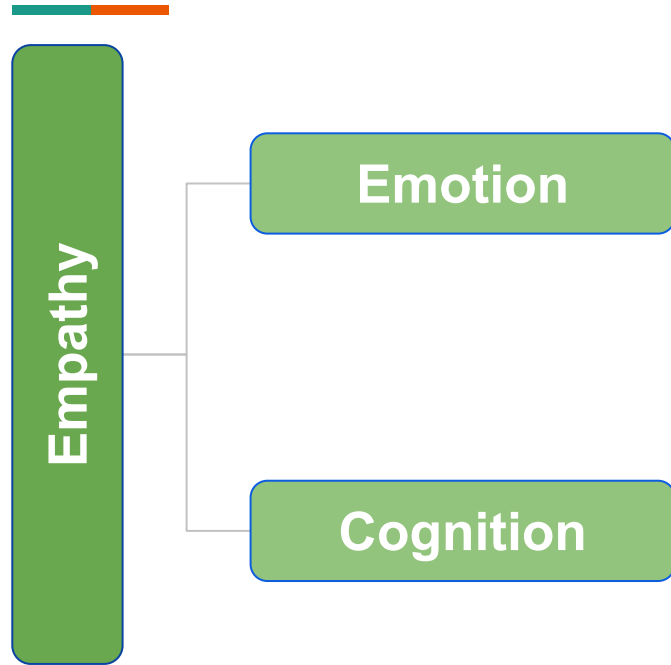
Seeing with the *eyes of another*, listening with the *ears of another* and feeling with the *heart of another*.

**Sympathy:** “I’m sorry that happened to you.”

**Empathy:** “I see your pain and I understand.”

**Compassion:** “How do you need me to help?”

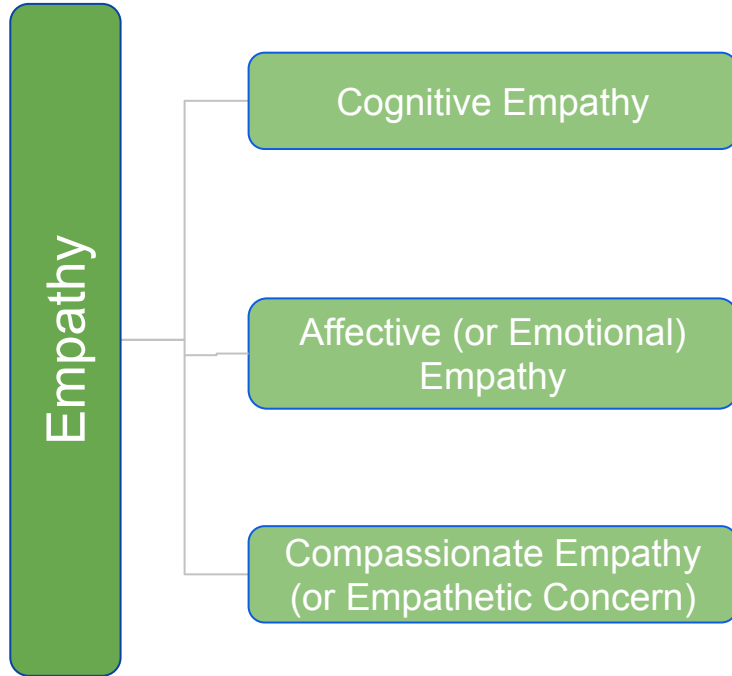
# Empathy as Two-dimensional Construct



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

# 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*")

# 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*



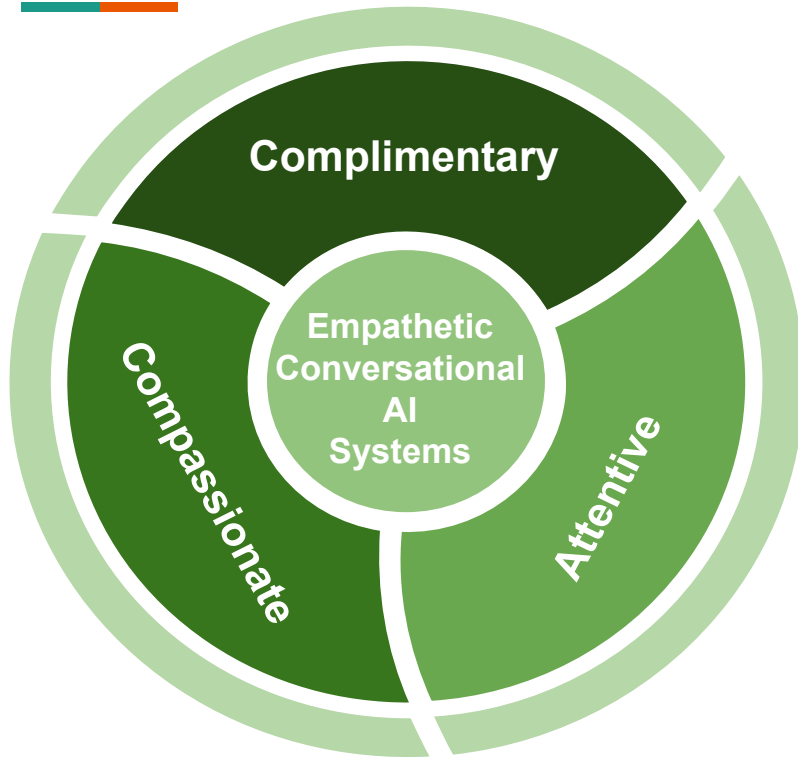
# Empathetic Dialogue Systems



# Why do we need Empathy in Dialogue Systems?



# Empathy in Conversational AI: Importance



Human-like systems (bridge human-machine gap)



Better and more meaningful user engagement




Enhances emotional bond with users



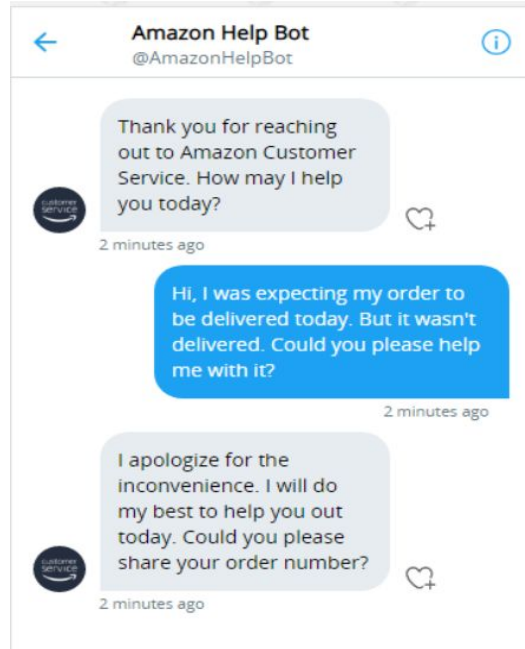
Perceived as social actors by users



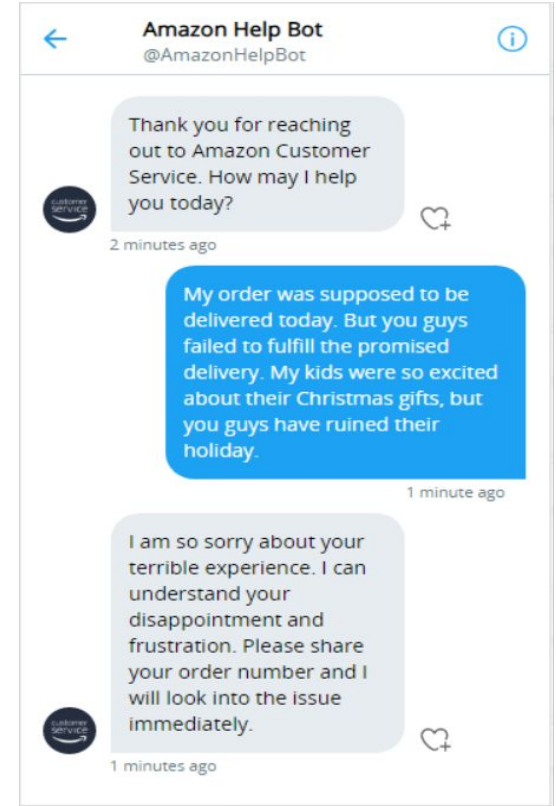
Leads to positive user experience and effective communication



# Amazon Help Bot



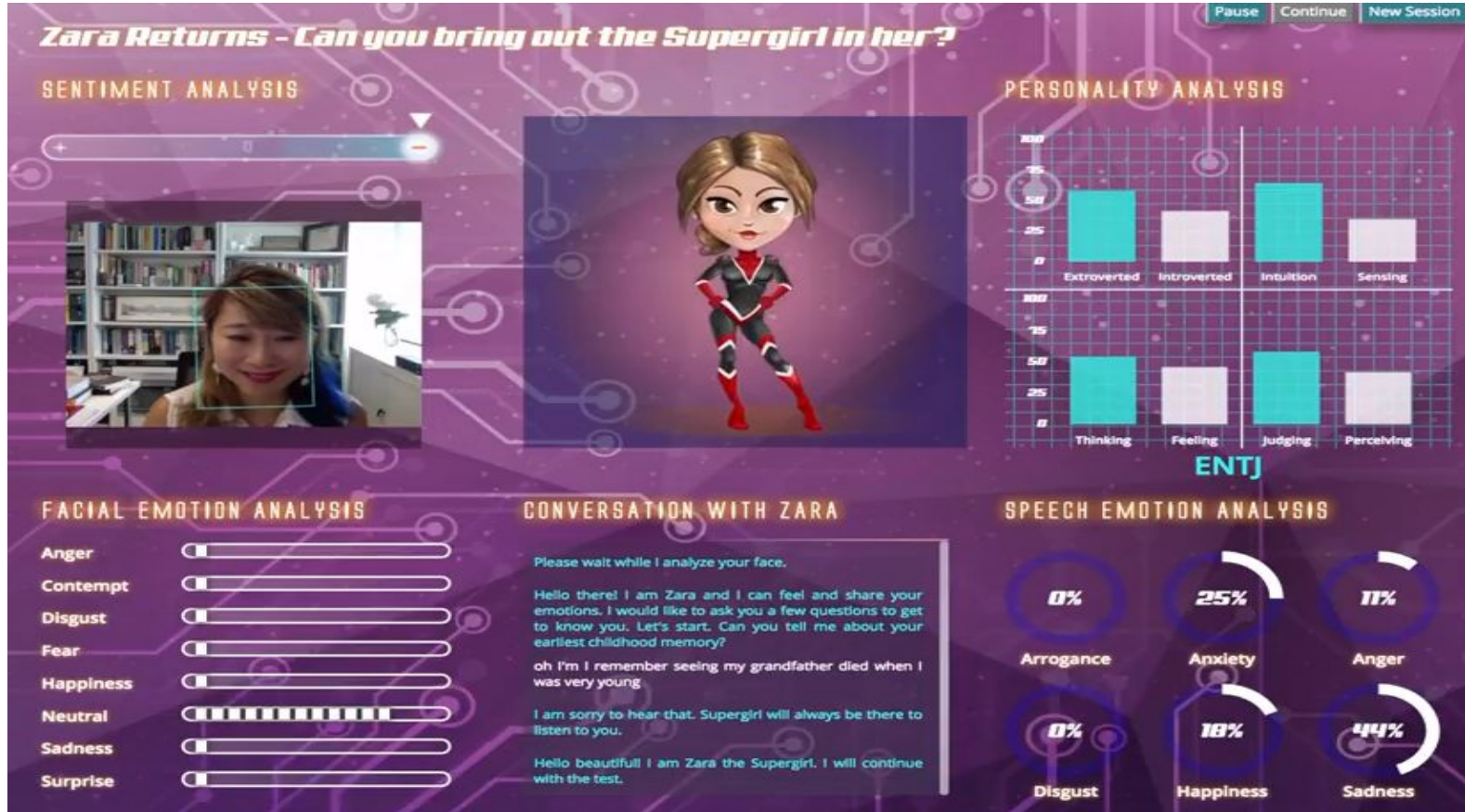
Scenario 1



Scenario 2



# Zara- The SuperGirl



# Nora- *the Empathetic Psychologist*

The interface is divided into three main sections:

- Avatar and Video Feed:** On the left, there is a stylized avatar of a woman with brown hair and a dark turtleneck. Below it is a video feed showing a man with glasses and an orange shirt. A control bar between them contains a video toggle and a refresh icon.
- Chat Window (1st Session):** A central chat window shows the following interaction:
  - System (14:11): "I'm sorry to hear you're feeling sad."
  - User (14:11): "Over the past two weeks, has your mood been rather unstable?"
  - System (14:11): "I am very unstable because I'm quite emotional"
  - System (14:12): "I'm sorry to hear you've been feeling anxious."
  - User (14:12): "What about your daily life, what is your current occupation?"
- Dashboard:** On the right, a dashboard displays three metrics:
  - Stress Level:** A horizontal bar chart with a value of approximately 55.
  - Sentiment:** A horizontal bar chart with a value of approximately 20.
  - Emotion:** A bar chart showing the following values: anger (low), anxiety (medium), criticism (low), happiness (medium), loneliness (high), and sadness (medium).

At the bottom of the chat window, it shows "Server responded", "Mic: Listening", "Dialogue state: IQ-3", and "Intent: answer IQ-2".

# Empathy and related aspects



- Emotion/Sentiment
- Emotion Cause
- Persona
- Politeness
- Multimodal Information

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# Concept 1

## Emotion/Sentiment and Empathy

# 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.

# 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)



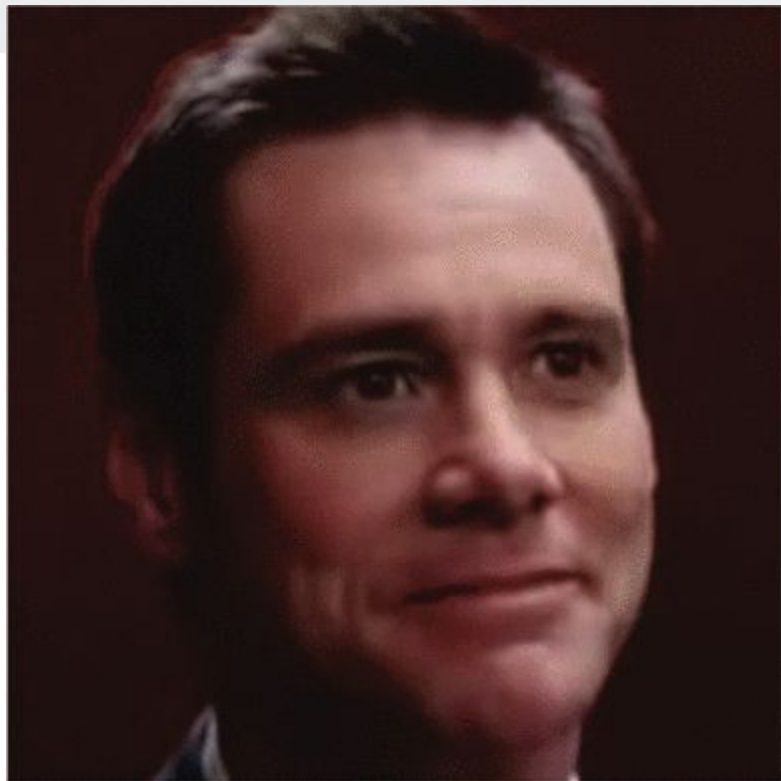
That's a great job, as I play guitar and do welding for a career. (Positive)

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



# 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.



# Major Highlights



- COMMA-DEER: COmmon-sense aware Multimodal Multitask Approach for Detection of Emotion and Emotional Reasoning in Conversations



## Highlight 1

**COMMA-DEER: COMmon-sense aware Multimodal Multitask Approach for Detection of Emotion and Emotional Reasoning in Conversations**

# Introduction

- Emphasis on accelerating suicide prevention efforts by World Health Organization
  - fulfill the United Nations' Sustainable Development Goal (SDG) objective of 2030.
- Emotional information can function as an authoritative inner voice among people suffering from mental illness
- Emotions often interfere with thought processes and drives to having distorted views of the world, situations, relationships, etc.
- **Emotional reasoning** - how you feel defines your reality OR the inability to distinguish between emotions and thoughts.
- **Motivation:**
  - The lack of suitable annotated data in the public domain is a serious impediment to mental health research utilising NLP methods.
  - Certain nuances in mental health conversations makes them challenging to be addressed using the existent automated systems.
  - Identifying Emotion Reasoning utterances is challenging since existing automated system lacks commonsense reasoning ability.

# Contributions of this study

- **Primary Contributions:**

- Introduce a novel problem of joint detection of emotional reasoning and emotion in conversations exploiting the correlatedness between the two tasks.
- Presents the first multimodal mental health conversational corpus, DEER
  - Manually annotated with emotion and presence of emotional reasoning
  - Marked with speaker information, start and end timestamps at the utterance level.
- Propose COMMA-DEER, a commonsense aware multimodal multitask system for detection of emotion and emotional reasoning utterances in a conversational setting.

# Why and how multimodality may help?

- **Visual cues for present textual utterances may lie at past time steps** which are not captured if only textual modality is considered

D: And what was it that you knew at that moment?

P: That erm... that they worked for MI5.

...

...

...

...

D: Now I've noticed a couple of times, while we've been talking, that you've sort of looked round you, into the room as if you're checking for something.

D: Could I ask you what's happening at those times?



Figure 1: Demonstrating how multimodality may capture various nuances in dialogues.

# Why and how multimodality may help?

- Patient's movements may help in identifying emotional reasoning utterances as well as correct emotion for a particular utterance

P: Her partner's recording everything from every room even the cafeteria. (ER)

D: How can they do that?

P: I don't know, if they have all the electric wires outside. (ER)

P: I don't know how it is done.



P: The way everything carries on every day since I came to the hospital, I realize it was done in every convent I went to live. (ER)

(ER)



P: Either like this and like this so no matter any place on the body wherever they may get at you (ER)



Figure 2: Sample instances showing Emotional Reasoning utterances and demonstrating how multimodality may capture various nuances in dialogues.

# Methodology

- **Task Definition:** Given a dyadic interaction between two speakers, a doctor and a patient, in which utterances are exchanged asynchronously, identify emotion and the existence of emotional reasoning in the utterances.
  - $U_t^m = (u_{1}^m, u_{2}^m, \dots, u_{n}^m)$  denote a conversation; m denotes dialogue and n: total utterances
  - $E_t^m = (e_{1}^m, e_{2}^m, \dots, e_{n}^m)$  : emotion labels for each utterance in the conversation
  - $ER_n^m = (er_{1}^m, er_{2}^m, \dots, er_{n}^m)$  : presence or absence (0 or 1) of ER at the utterance level.
  - The proposed method maximizes the value of the following function:
$$\underset{\theta}{argmax}(\prod_{i=0}^m \prod_{j=0}^n P(e_j^i, er_j^i | u_j^i, u_{j-1}^i, \dots, u_1^i; \theta))$$
  - where  $u_{j-1}^i, \dots, u_1^i$  represents the previous set of utterances ordered temporally
  - $u_j^i$  is the current (target) utterance whose emotion label ( $e_j^i$ ) and presence of emotional reasoning ( $er_j^i$ ) is to be predicted.
  - P is the log likelihood function and  $\theta$  denotes the model parameters to be optimized.

# Model Architecture

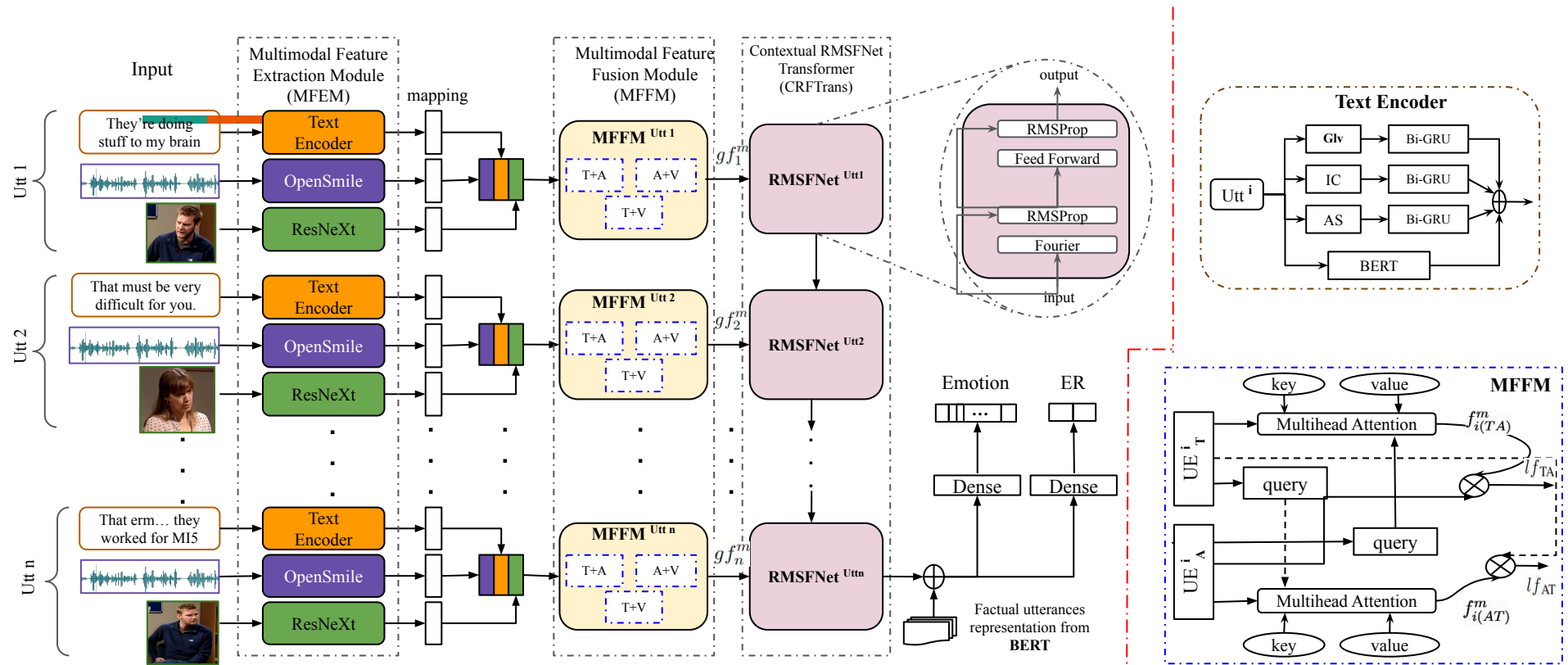


Figure 3: Architecture of the **Temporal and Emotion-assisted Multitask Framework (TEMF)**. PE: positional encodings; TE: transformer encoder.



# Dataset Description

- We collected 30 doctor and patient interviews from YouTube (Real: 20; Enacted: 10)
- Transcripts are manually generated for each video
  - marked with speaker information (Doctor or Patient) at utterance-level
  - start and end timestamps for each utterance.
- Annotations for the ER and emotion classes are performed at the utterance level by three annotators.
- Utterances were labeled as ER if they were detected as an obvious result of emotional reactions that directly contradicted any objective and/or perceptual realities.
- Each utterance is marked with one of Ekman's [1] six basic emotions: *anger*, *disgust*, *fear*, *joy*, *sadness*, and *surprise*.
- The Emotion and ER tasks yielded scores of 0.75 and 0.83, respectively.

# Dataset Distribution

Classes	Instances	$k$
Anger	171	0.71
Disgust	69	0.65
Fear	163	0.74
Joy	124	0.90
Sadness	494	0.82
Surprise	174	0.58
Others	2558	0.86

Table 1: Emotion Distribution

	Doctor	Patient	Total
Emotion	217 [5]	978 [351]	1195 [356]
Others	1250 [42]	1308 [345]	2558 [387]
<b>Total</b>	1467 [47]	2286 [696]	3753 [743]

Table 2: Distribution of Emotion utterances and ER for doctor and patients. Values in the brackets indicate the ER counts.

# Dataset Sample

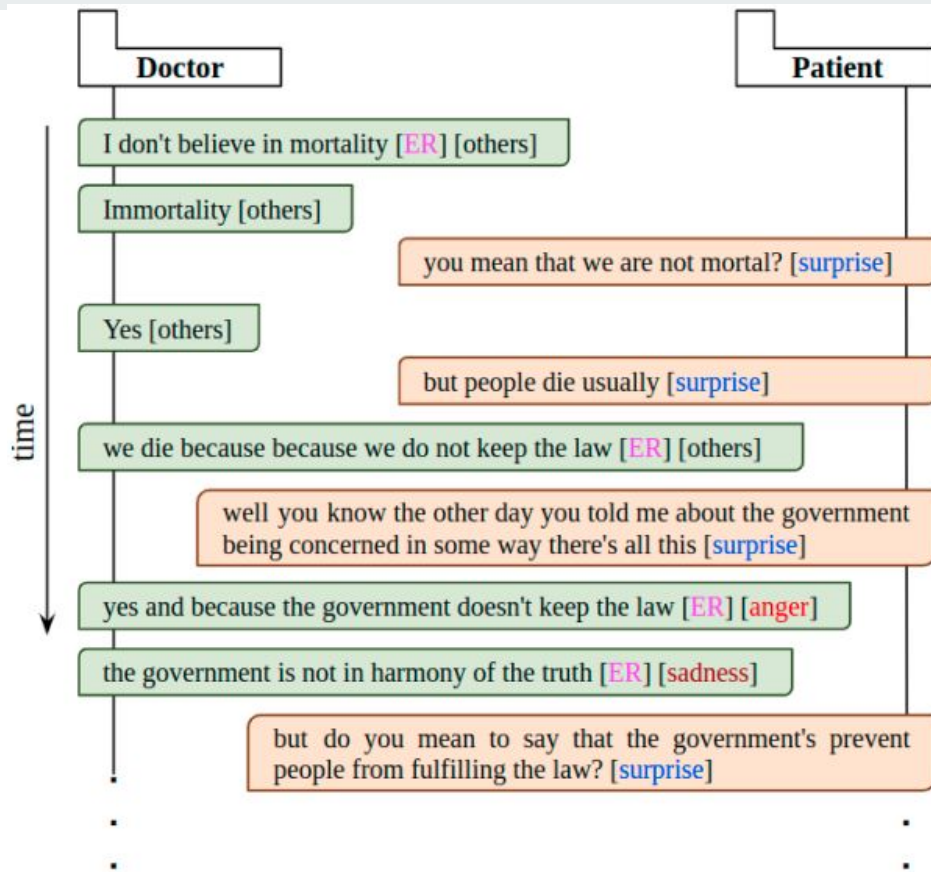


Figure 4: Sample conversation excerpt from the annotated DEER dataset.

# Results-I

<b>Modality</b>	<i>Single-task</i>		<i>Multi-task</i>	
	<b>F1<sup>ER</sup></b>	<b>F1<sup>EMO</sup></b>	<b>F1<sup>ER</sup></b>	<b>F1<sup>EMO</sup></b>
T	62.78	56.11	64.79	60.78
A	57.76	54.98	60.43	57.91
V	52.16	51.51	54.11	53.67
T+V	64.97	61.11	66.79	64.55
T+A	66.18	62.41	68.91	65.72
A+V	61.66	58.54	63.94	62.59
T+V+A	69.28	63.17	71.82	66.91
<b>[T+V+A]<sub>+CS</sub></b>	<b>72.14</b>	<b>66.33</b>	<b>73.44</b>	<b>70.14</b>

Table 3: Results of the proposed COMMA-DEER method on various modalities. CS: common-sense.

# Results-II

<del>Models</del>	Emotion		ER	
	F1 (%)	ACC. (%)	F1 (%)	ACC. (%)
<i>Single-task Baselines</i>				
bc-LSTM [3]	58.41	59.63	60.15	60.87
CMN [2]	62.64	64.52	68.17	69.31
DialogueRNN [4]	63.92	64.16	68.67	70.13
<i>Multi-task Baselines</i>				
MTL-BERT [5]	62.33	63.51	65.61	65.91
CMSEKI [6]	64.14	66.31	69.88	71.31
<i>Proposed</i>				
<b>COMMA-DEER</b>	<b>70.14</b>	<b>70.93</b>	<b>73.44</b>	<b>74.62</b>

Table 4: Results of the proposed COMMA-DEER method on various modalities. CS: common-sense.

Setup	F1 <sup>EMO</sup> (%)	F1 <sup>ER</sup> (%)
<b>COMMA-DEER</b>	<b>70.14</b>	<b>73.44</b>
[T+V+A] <sub>-RMS</sub>	67.11 (-3.03)	70.24 (-3.20)
[T+V+A] <sub>-MFFM</sub>	65.78 (-4.36)	68.83 (-4.61)

Table 5: Ablation experiment's results. % fall in scores are shown in brackets.

# Results on varying context length



Figure 5: Graphical depiction of results of COMMADEER on varying context length.

# Sample Predictions

Note Excerpts	COMMA-DEER	CMSEKI	DialogueRNN
<p>D: Right, ok. And have you seen much of your parents recently?</p> <p>P: Yeah. I thought about going back there but I, I don't want to drag them into this.</p> <p>D: Right.</p> <p><b>P: I don't want MI5 knowing about them.</b></p>	<p>Anger ER</p>	<p>Others Non-ER</p>	<p>Others Non-ER</p>
<p>P: Yes. But in the building? No, I don't think so. As long as I pay my rent, there shouldn't be any problems. I paid my rent on Friday.</p> <p><b>D: So what happened at work?</b></p>	<p>Others Non-ER</p>	<p>Sadness Non-ER</p>	<p>Anger ER</p>
<p>P: You know, jealous talk.</p> <p>D: But it was only in your apartment that you would hear these voices?</p> <p>P: Yes.</p> <p>D: Who was talking? What were they saying?</p> <p><b>P: If I was doing something, lets say if I was looking for something, they'd taunt me, "she can't see it". They'd know that I was looking for something.</b></p>	<p>Fear ER</p>	<p>Others ER</p>	<p>Others Non-ER</p>
<p>P: I wasn't hungry, and I wasn't eating, because it felt tight here.</p> <p>D: You also told me about some gas...</p> <p>P: Yes, there was a smell coming from the trash chute and the air vents, always at Night.</p> <p>D: What caused it?</p> <p><b>P: It was some sort of gas, but I'm not sure what.</b></p>	<p>Others Non-ER</p>	<p>Others Non-ER</p>	<p>Others ER</p>

Table 4: Sample predictions from the best performing baselines and the proposed COMMA-DEER approach. D: Doctor; P: Patient.

Labels highlighted in blue signifies correct predictions and that in red signifies mis-classifications.

# Analysis

- Existing systems finds difficulty when previous utterances taken as context do not entail the current utterance
- Common-sense knowledge aware systems such as the proposed COMMA-DEER and CMSEKI baseline produces strong results
- Existing baseline models suffers heavily from biasness due to data imbalance problem
- The proposed COMMA-DEER system provides commendable performances for skewed emotion classes
- Modelling inter-speaker dependencies may help improving performance of COMMA-DEER
- Predicted emotions in few cases are reasonable, but do not match with actual annotations
  - Demands for treating the problem as a multi-label task



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## Concept 2

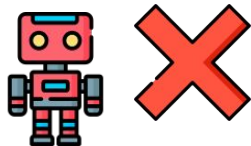
# Emotion Cause and Empathy

# Emotion Cause and Empathy



I'm upset.

Everything will be okay.

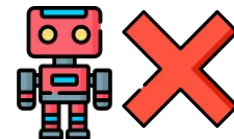


Non-empathetic response



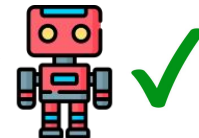
I'm upset

Sorry to hear that. What happened?



We broke up.

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



Empathetic Response

# Major Highlights



- DeCoDE: Detection of Cognitive Distortion and Emotion cause extraction in clinical conversations



## Highlight 1

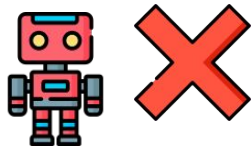
**DeCoDE: Detection of Cognitive Distortion and Emotion  
cause extraction in clinical conversations**

# Emotion Cause: Improves Empathy

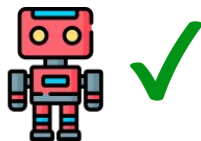


I had a severe headache.

Are you Okay?



It's just terrible, isn't it?

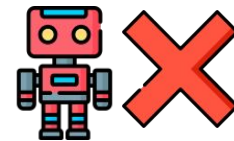


Weak Empathy - Generic expressions in response

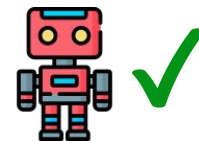


I had a severe headache.

How is your headache, any better?



You must be worried about your job interview.



Stronger Empathy - Reason behind the emotion

# Introduction and Motivation

- Cognitive distortion is a major contributor to the development of many mental illnesses.
- Early detection of Cognitive Distortion can play a vital role in the symptomatology of mental illnesses
- Emotion cause extraction (ECE) task can identify the possible causes behind a certain emotion expression in the text
- No conversational dataset exists related to mental health and multi-modal datasets for clinical conversation settings are scarce
- **Primary Contributions**
  - Proposing a novel task of **D**etection of **C**ognitive **D**istortion and **E**motion (DeCoDE) cause extraction in clinical conversations
  - Introducing the first **C**ognitive **D**istortion and **E**motion **C**ause (CoDEC) annotated multi-modal clinical conversation dataset with manual annotations
  - Developing an emotion-aware multi-modal multi-task framework for the proposed task
  - Hypothesizing that the performance can be enhanced by incorporating information from future time steps.

# Methodology

- **Task Definition:** For a target utterance  $u_t$ , the task objective is to detect whether the utterance is cognitive distortion or not (0 or 1) and extract all possible causal spans for the given emotion  $e_t$ .
  - $D = [u_1, \dots, u_i, \dots, u_p]$  denote a document
    - $p$  denotes the number of number of utterances in the document
    - $u$  denotes an utterance in the document
  - $u_i = [\text{word}_{i,1}, \dots, \text{word}_{i,j}, \dots, \text{word}_{i,q}]$ 
    - $q$  denotes the length of the word sequence contained in the utterance
  - $E = [e_1, \dots, e_i, \dots, e_p]$ : emotion labels for each utterance in the conversation

# Model Architecture

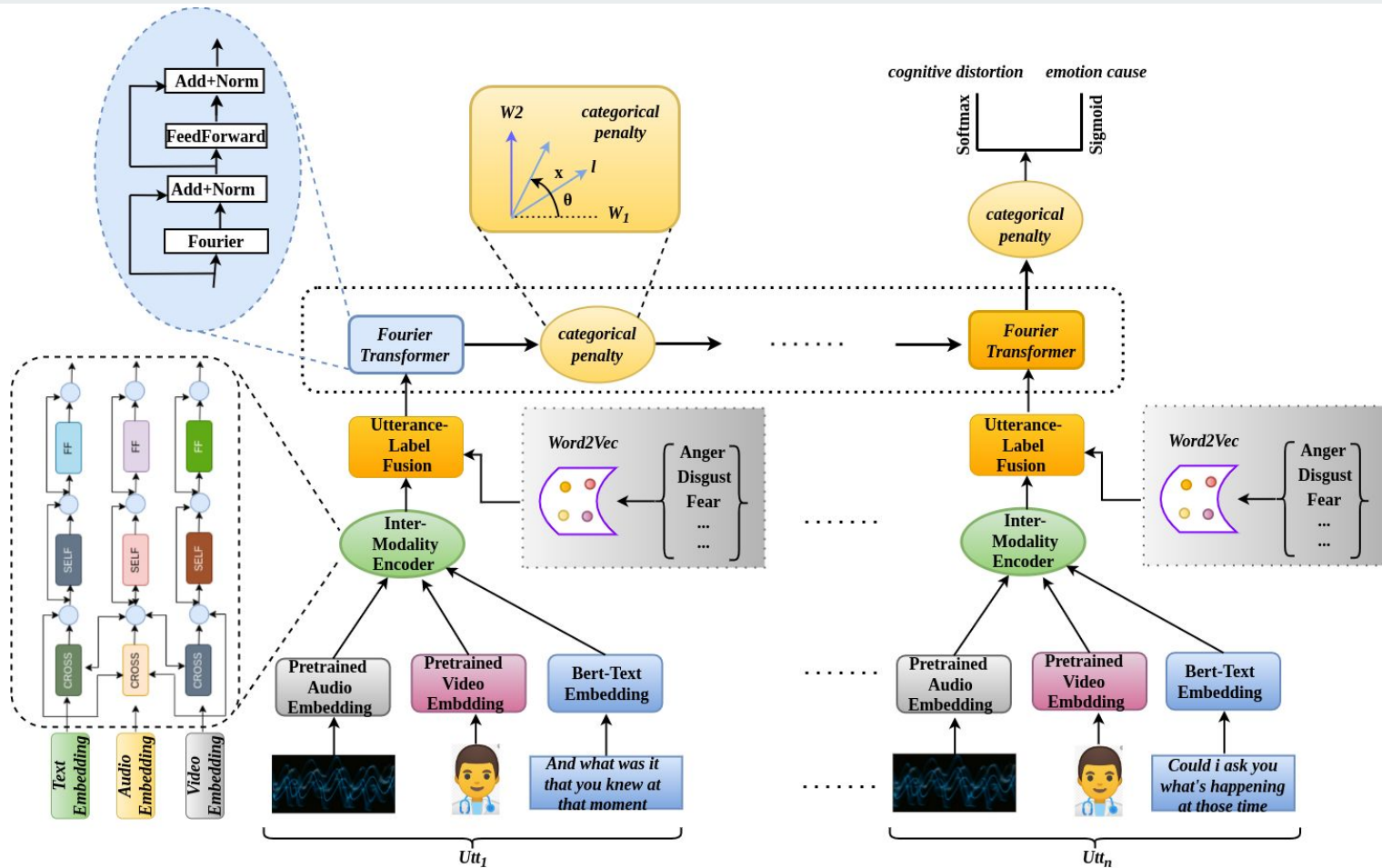



Figure 1: Architectural diagram of the proposed framework.



# Dataset Description

- 30 doctor-patient conversation sessions were collected from YouTube.
- Patients suffered from some form of cognitive distortions.
- 20 interviews were genuine, while the remaining 10 were enacted with actors.
- Utterances were manually transcribed and marked with speaker information and start/end timestamps.
- Each utterance was annotated for cognitive distortion (CoD), emotion, fact, and response to cognitive distortion (ReCoD).
- Annotations for emotion and cognitive distortion were performed by three annotators and obtained by majority vote.
- The cognitive distortion task had a Fleiss-Kappa score of 0.83, while emotion cause had 0.77.

# Dataset Distribution



Attribute	Count
CoD	743
ReCoD	410
One Cause	410
Two Causes	179
Three Causes	36

Table 1: Frequency of utterances over various attributes.

Class	Count	Causes
Anger	184	One: 101; Two: 42; Three: 10
Disgust	77	One: 49; Two: 22; Three: 2
Fear	169	One: 96; Two: 32; Three: 6
Joy	128	One: 28; Two: 7; Three: 2
Sadness	503	One: 198; Two: 80; Three: 10
Surprise	176	One: 78; Two: 24; Three: 2
Neutral	2516	No Causal Spans Exists

Table 2: Distribution of Emotion utterances and ER for doctor and patients. Values in the brackets indicate the ER counts.

# Dataset Sample

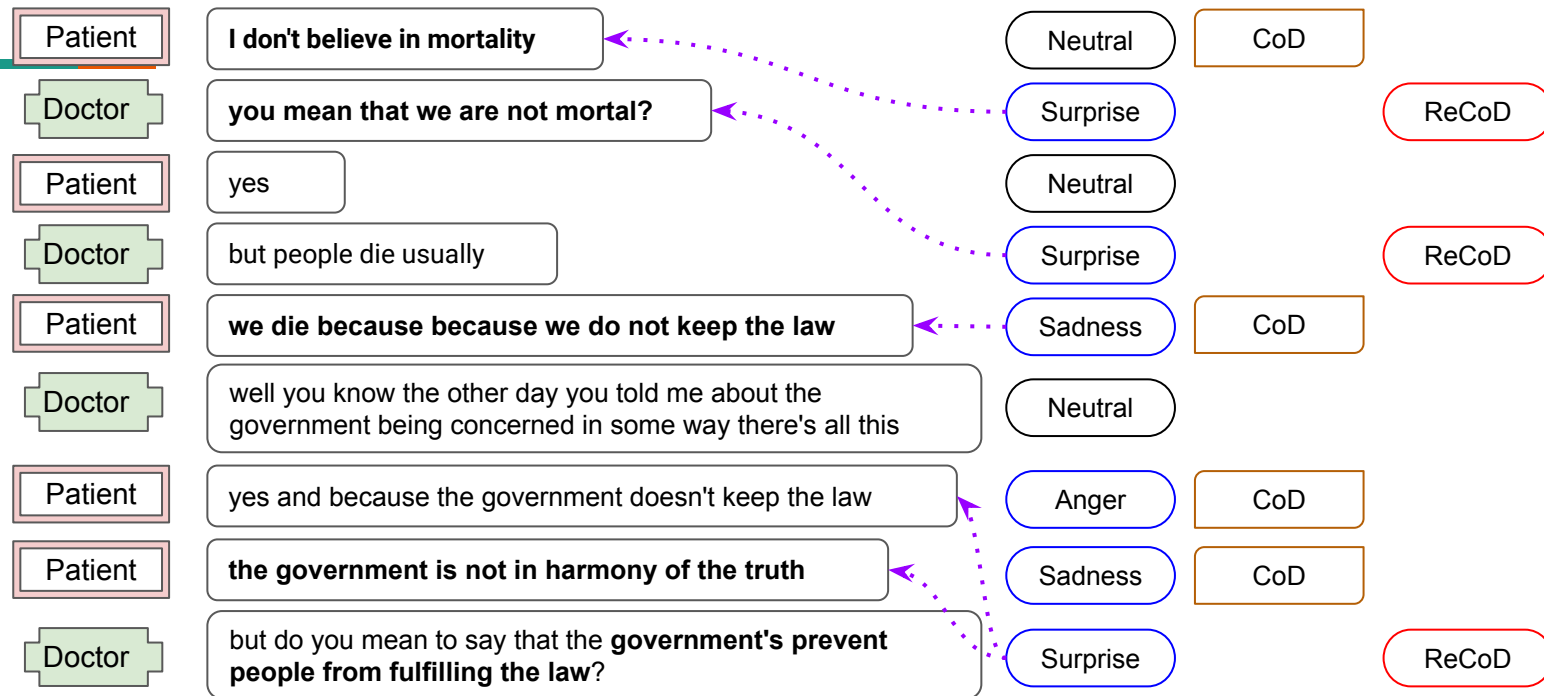


Figure 2: Sample snapshot of our CoDeC Dataset. The font highlighted in bold is the causal span

# Results-I

Modality	Cognitive Distortion		Emotion Cause				
	F1 (%)	Acc. (%)	FM	PM	HD	JF	ROS
T	66.68	68.71	21.98	28.31	0.45	0.58	0.69
A	62.69	64.11	20.74	24.46	0.41	0.53	0.68
V	55.96	52.13	18.29	19.31	0.37	0.48	0.61
T+V	68.31	69.59	25.19	29.78	0.49	0.61	0.71
T+A	69.74	71.11	27.31	31.91	0.51	0.63	0.72
A+V	66.22	67.63	24.33	27.58	0.47	0.59	0.70
T+V+A	<b>73.48</b>	<b>75.91</b>	<b>29.43</b>	<b>33.24</b>	<b>0.53</b>	<b>0.65</b>	<b>0.74</b>

Table 3: Experimental results of DeCoDE on various modalities.

# Results-II

	Models	Cognitive Distortion		Emotion Cause				
		F1 (%)	Acc. (%)	FM	PM	HD	JF	ROS
Baselines	RoBERTa [6]	67.16	69.24	25.73	25.51	0.46	0.59	0.69
	SpanBERT [2]	65.79	66.83	23.58	21.12	0.44	0.57	0.67
	MTL-BERT [7]	66.93	69.79	25.11	23.67	0.47	0.58	0.69
	CMSEKI [8]	70.31	71.47	27.11	28.59	0.50	0.62	0.71
Proposed	DeCoDE	73.48	75.91	29.43	33.24	0.53	0.65	0.74
Ablation Experiments	DeCoDE <sub>-[CP]</sub>	71.25	72.35	27.22	30.89	0.50	0.62	0.72
	DeCoDE <sub>-[EMO]</sub>	71.76	73.17	28.18	31.17	0.51	0.63	0.71
	DeCoDE <sub>-[EMO+CP]</sub>	69.47	70.85	25.91	29.33	0.49	0.60	0.69
	DeCoDE <sub>+ [ReCoD]</sub>	74.21	76.31	30.15	34.31	0.54	0.66	0.74

Table 4: Results from our proposed model and the various baselines. Values in bold are the maximum scores attained

# Results on varying context length

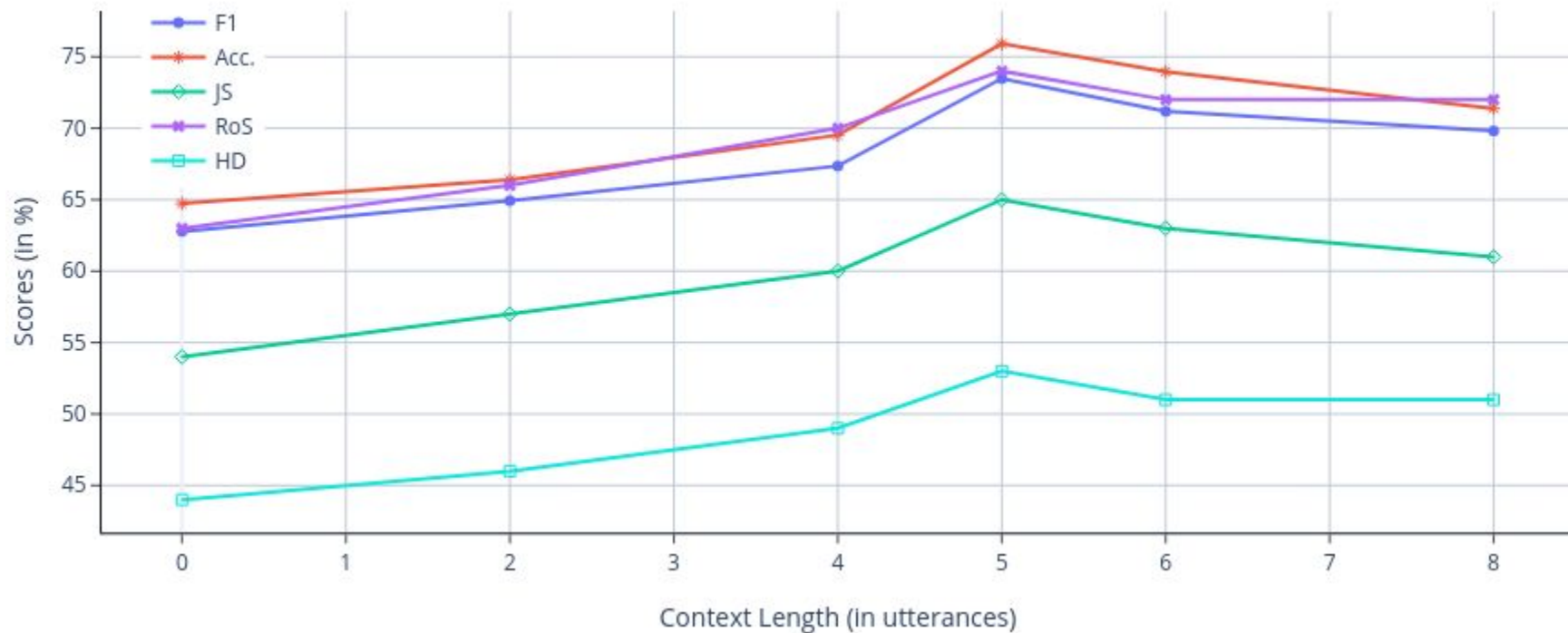


Figure 3: Graphical depiction of results on varying context length.

# Sample Predictions


DeCoDE	CMSEKI	MTL-BERT
 <b>Actual:</b> she might be reporting back to them [Y]		
she might be reporting back to them [Y]	might be reporting back to them [Y]	she might be reporting back to them [Y]
<b>Actual:</b> i am a lord god jehovah [Y]		
i am a lord god jenovah [Y]	No Cause [N]	a lord god jenovah [N]
<b>Actual:</b> try to ensure somehow that they are being raised properly, from a distance [N]		
you started carrying guns [N]	you started carrying guns [Y]	you started carrying guns [Y]
<b>Actual:</b> try to ensure somehow that they are being raised properly, from a distance [N]		
to ensure somehow that they are being raised properly [N]	try to ensure somehow that they are being raised properly [Y]	that they are being raised properly, from a distance [N]

Table 5: Sample predictions from the various systems. Color Coding: Blue- Correct, Red: Incorrect; Teal: Incomplete. [Y] and [N] indicate Yes and No predictions for the CoE task, respectively

# Conclusion

- Presented the first multi-modal, emotion-cause annotated clinical conversation dataset for mental health interviews.
- Developed a multi-modal, multi-task framework called DeCoDE for cognitive distortion and emotion cause extraction in clinical conversations.
- DeCoDE is the first task-specific system addressing emotion-cause extraction in conversations.
- Demonstrated the effectiveness of the proposed framework compared to state-of-the-art baselines.
- **Future work:**
  - Develop techniques to educate people about cognitive biases caused by cognitive distortions for new treatment approaches.
  - Explore how to properly capture the implicit aspects of complex causation.



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## Concept 3

# Multimodal Information and Empathy

# 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

# 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**

# 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)



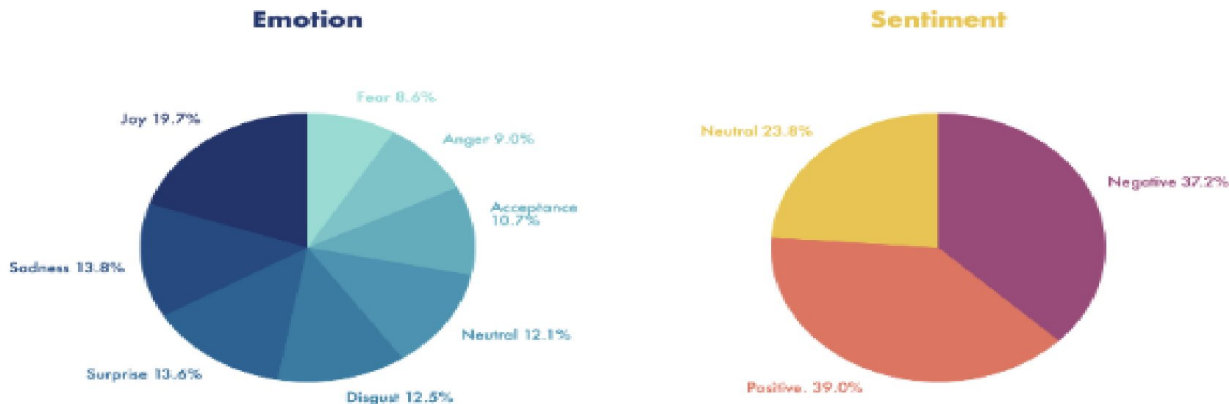
See, Yeah  
(Joy, Positive)



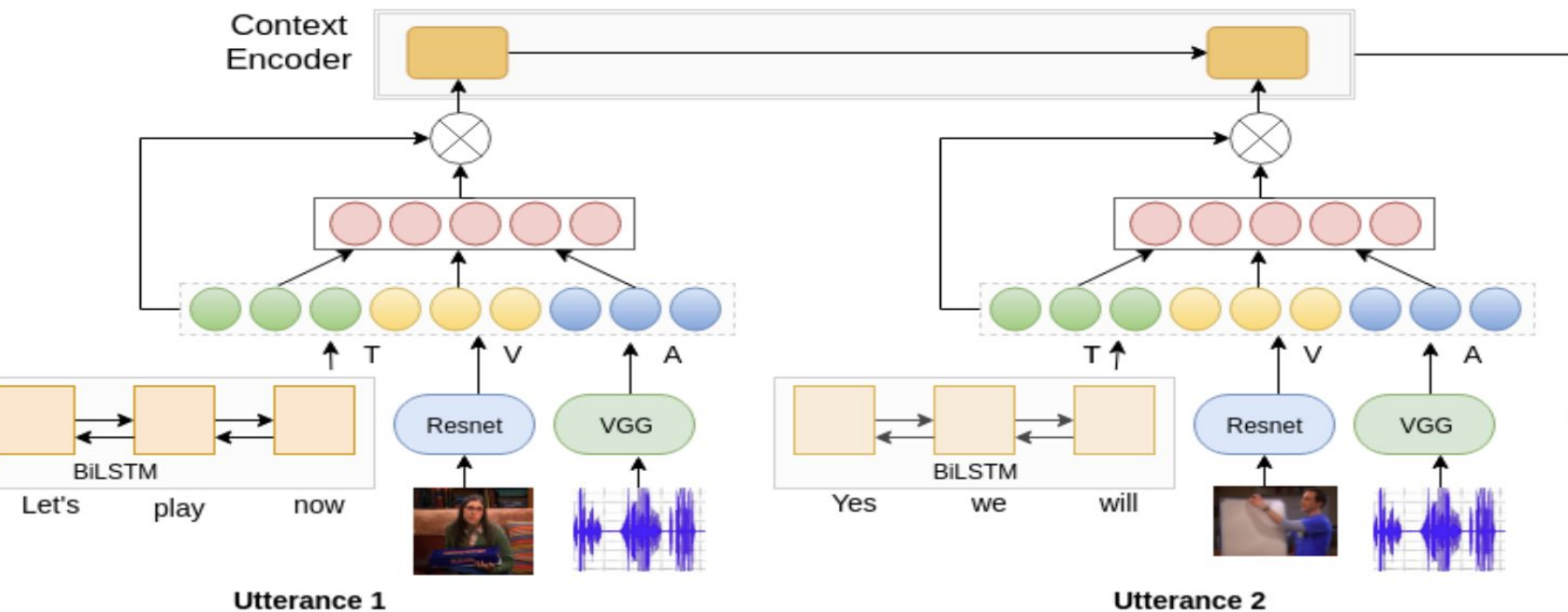
Really, you got all this rustic crap for free.  
(Anger, Negative)

# 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*).



# Multimodal Hierarchical encoder with Attention

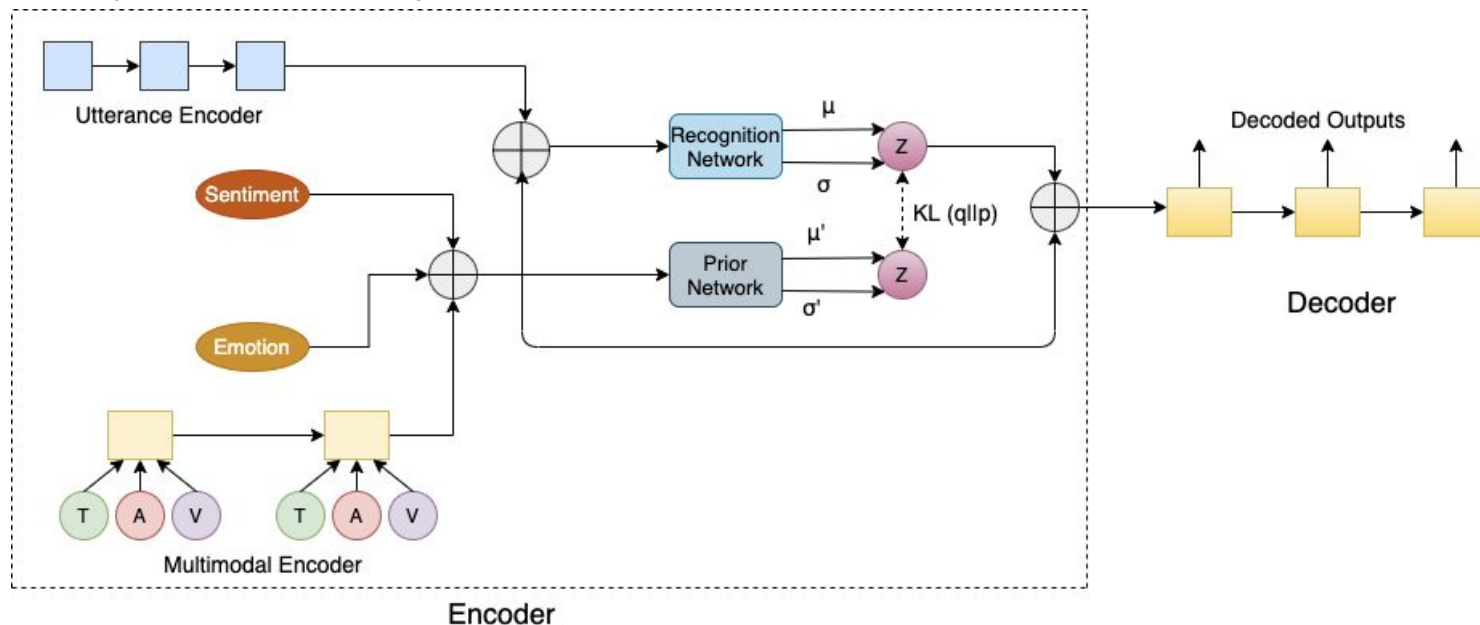


The attended utterance representation (with features from all the three modality) is passed to the context encoder



# 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  $z$ .



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

- 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

# Results: Manual Evaluation

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

# Case Study

Conversational History	Model	Emotion	Sentiment	Generated Response
<p>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?</p>	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.
<p>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"?</p>	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.
<p>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?</p>	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.
<p>Chris says they're closing down the bar. No way! Yeah, apparently they're turning it into some kinda coffee place.</p>	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.



## 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

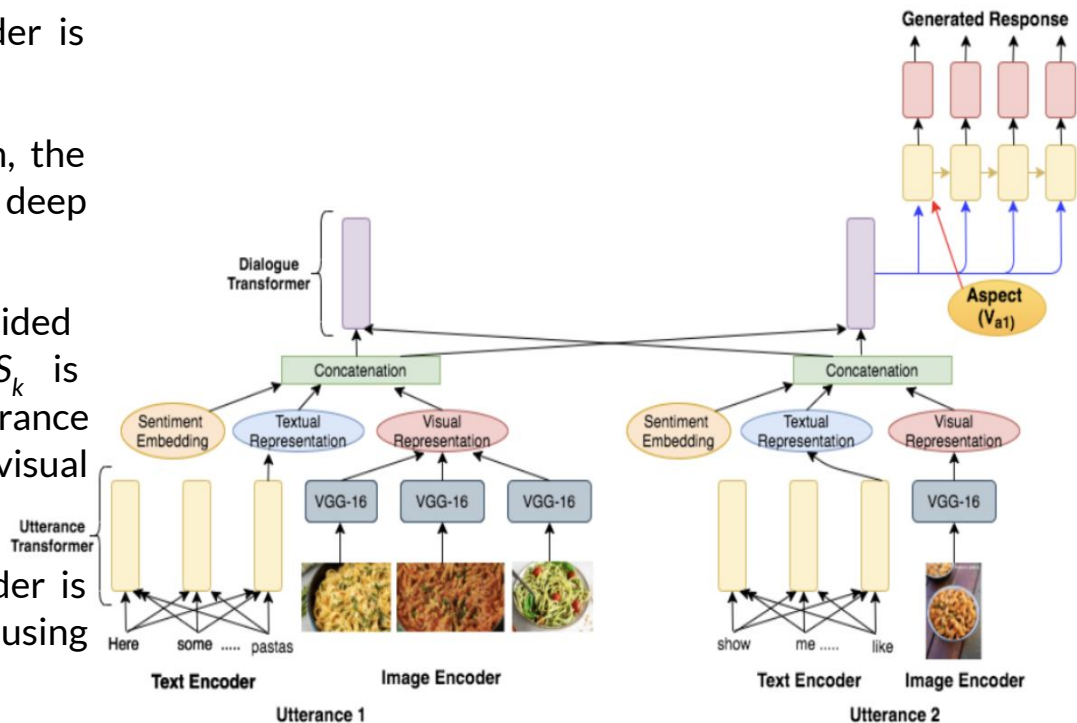
# Sentiment annotated examples from the Multi-domain Multi-modal Dialogue(MDMMD) dataset

Dialogue	Sentiment	Dialogue	Sentiment
<p><b>User:</b> I don't like the speakers shown so far, could you please show something portable.</p>	Negative	<p><b>Agent:</b> Great Choice! We have some nice colors for you, please see</p>	Positive
<p><b>Agent:</b> Don't worry, we have some great portable speakers for you, please have a look.</p>	Neutral		Positive
 <p><b>User:</b> The 2nd one looks great, could you show more in this pattern.</p>	Positive	<p><b>User:</b> I love red! Please show the 3rd one from different orientations.</p>	Positive
		<p><b>Agent:</b> Nice to know, but we don't have any images of the 3rd one to show.</p>	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

# 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





# 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		Perplexity	BLEU-4	SA	Aspect F1
		U	M				
Existing Baselines	<i>Seq2Seq + Attn [41]</i>	✓	-	1.0341	0.4378	45.36	51.59
	<i>HRED [37]</i>	✓	-	1.0293	0.5206	48.33	56.83
	<i>HVMN [5]</i>	✓	-	1.0189	0.5453	50.14	60.26
	<i>GCN [3]</i>	✓	-	1.0119	0.5821	53.75	64.53
	<i>Global-to-local [50]</i>	✓	-	1.0169	0.5785	54.66	64.29
	<i>Working Memory [7]</i>	✓	-	1.0173	0.5692	55.27	63.78
	<i>MHRED [35]</i>	-	✓	1.0142	0.5537	57.48	61.86
	<i>OAM [4]</i>	-	✓	1.0136	0.5746	58.35	65.71
	<i>M-GCN + A [14]</i>	-	✓	1.0112	0.6014	62.85	67.71
Proposed Approach	<b><i>M-HierTrans + RL + A + S</i></b>	-	✓	<b>1.0043</b>	<b>0.7287</b>	<b>72.58</b>	<b>80.55</b>
Ablation Study	<i>Transformer</i>	✓	-	1.0123	0.6077	54.69	66.18
	<i>Transformer + A</i>	✓	-	1.0117	0.6198	57.42	69.34
	<i>Transformer + A + S</i>	✓	-	1.0111	0.6295	62.18	71.32
	<i>M- Transformer</i>	-	✓	1.0085	0.6534	56.78	68.43
	<i>M- Transformer + A</i>	-	✓	1.0077	0.6748	61.39	71.59
	<i>M - Transformer + A + S</i>	-	✓	1.0069	0.6927	66.83	73.45
	<i>HierTrans</i>	✓	-	1.0116	0.6382	57.23	69.11
	<i>HierTrans + A</i>	✓	-	1.0111	0.6577	65.11	73.87
	<i>HierTrans + A + S</i>	✓	-	1.0096	0.6825	69.47	76.36
	<i>M- HierTrans</i>	-	✓	1.0058	0.6890	59.37	73.69
	<i>M - HierTrans + A</i>	-	✓	1.0053	0.7033	67.84	77.51
<i>M - HierTrans + A + S</i>	-	✓	1.0049	0.7101	70.56	78.83	

# Results: Manual Evaluation

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

# Generated Examples



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

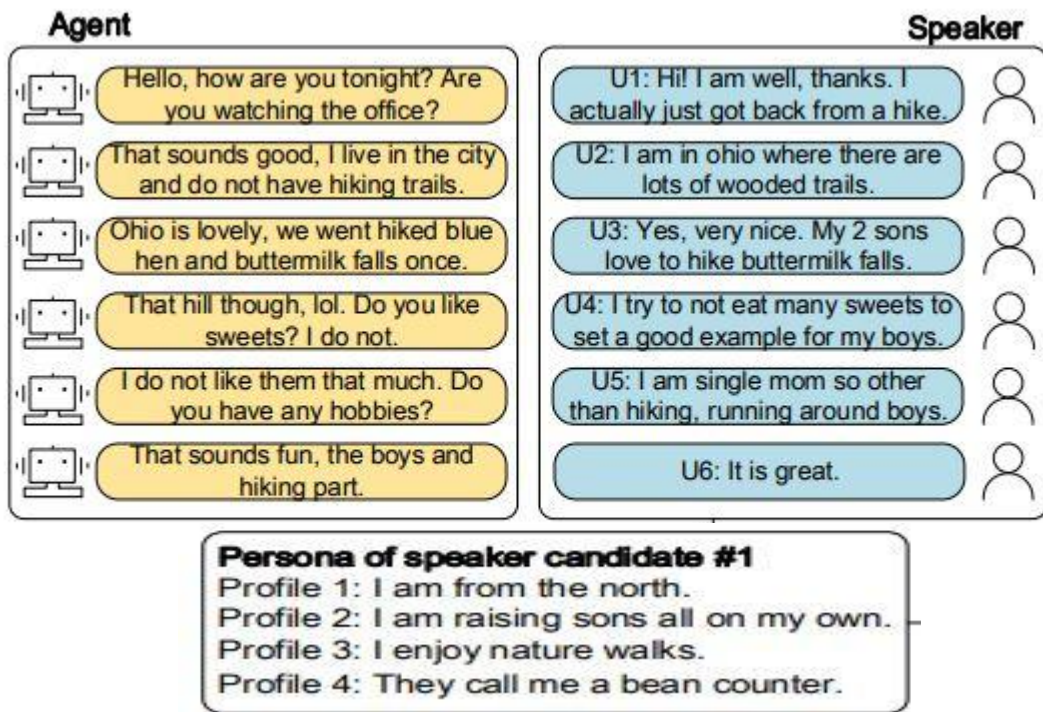
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## Concept 4

# Persona and Empathy

# Persona

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



# 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
<i>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.</i>	<i>I'm very athletic. I have brown hair. I love bicycling. I hate carrots.</i>
[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."*

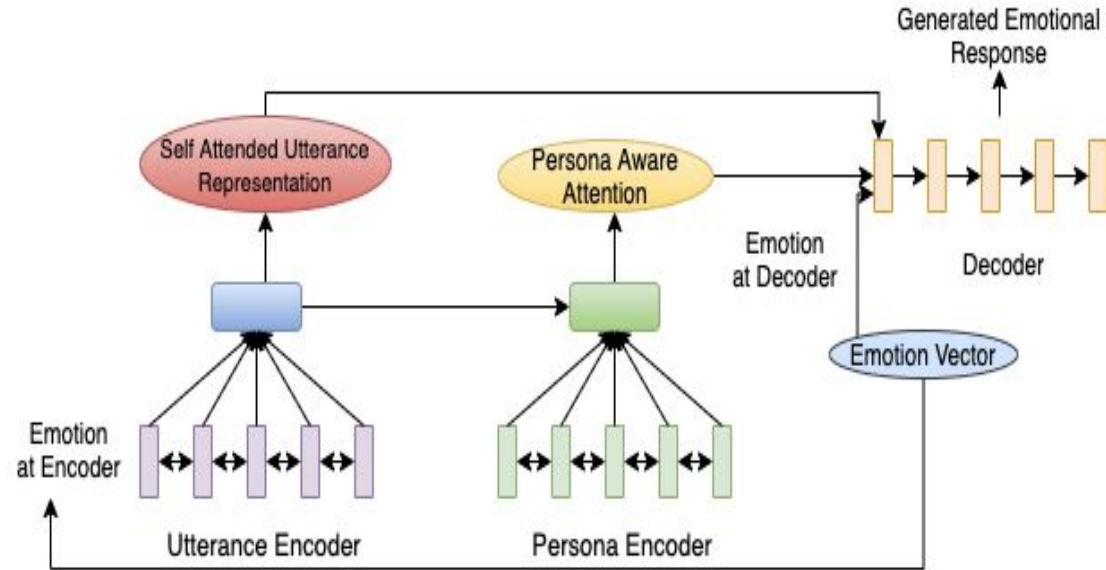
# Dataset



- 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



# 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	<b>Seq2Seq + Attn + PAA + EE</b>	<b>55.59</b>	<b>0.099</b>	<b>0.162</b>	<b>0.65</b>	<b>0.0189</b>	<b>0.0844</b>
	<b>Seq2Seq + Attn + PAA + ED</b>	<b>52.68</b>	<b>0.108</b>	<b>0.169</b>	<b>0.67</b>	<b>0.0210</b>	<b>0.0923</b>

# Results: Manual Evaluation

Model Description		Fluency			Emotion		Persona Consistency	
		0	1	2	0	1	0	1
<b>Baseline Approaches</b>	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
<b>Proposed Approaches</b>	<b>Seq2Seq + Attn + PAA + EE</b>	<b>19.64</b>	<b>38.65</b>	<b>41.71</b>	<b>55.72</b>	<b>44.28</b>	<b>49.85</b>	<b>50.15</b>
	<b>Seq2Seq + Attn + PAA + ED</b>	<b>18.15</b>	<b>37.32</b>	<b>44.53</b>	<b>53.91</b>	<b>46.09</b>	<b>48.11</b>	<b>51.89</b>

# Generated Examples

Dialog Input	Persona Information		Ground-Truth	Generated Response
<p>[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 .</p>	<p>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.</p>	<p>Persona 2            I'm very athletic.            I have brown hair.            I love bicycling.            I hate carrots.</p>	<p>I also cook, and I ride my bike to work.</p>	<p><b>Seq2Seq:</b> I also cook.   <b>Seq2Seq+PAA+EE:</b> Really! I like to cook and ride a bike to work. (surprise)   <b>Seq2Seq+PAA+ED:</b> Wow that's nice, but I like to cook and ride bike to work. (surprise)</p>
<p>[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.</p>	<p>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.</p>	<p>Persona 2            I m from Texas.            I like basketball.            I work many hours.            My favorite band is imagine dragons.</p>	<p>I work a lot.</p>	<p><b>Seq2Seq:</b> I work alot.   <b>Seq2Seq+PAA+EE:</b> That's nice to hear but I have a busy schedule. (disappointed)   <b>Seq2Seq+PAA+ED:</b> Ohh good for you but I work alot for my basketball. (disappointed)</p>




## Highlight 2

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



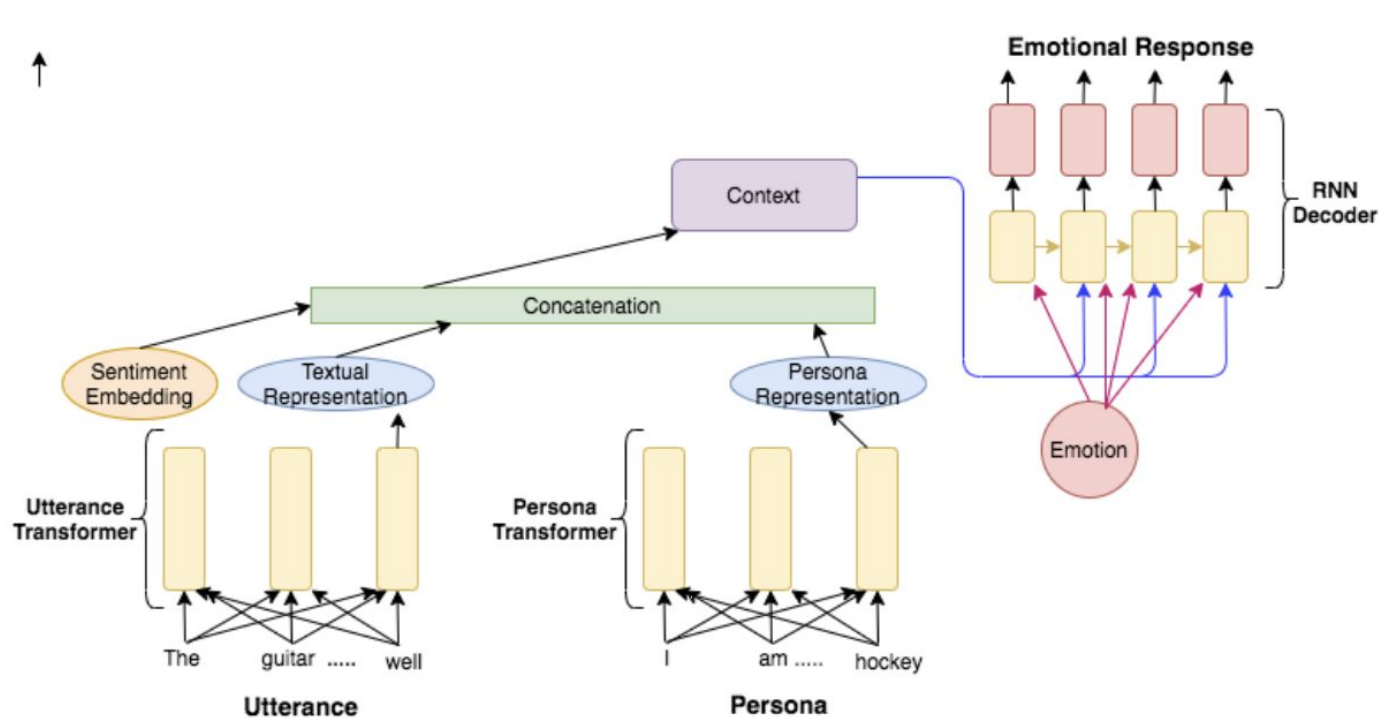
# What has been done in this work?

- 
- 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>I am primarily a meat eater.</i> <i>I am a guitar player.</i> <i>Welding is my career field.</i> <i>My parents don't know I am gay.</i>	<i>I've a sweet tooth.</i> <i>I'm a babysitter and drive a mercedes.</i> <i>I'm the middle child of 3 siblings.</i> <i>I'm getting married in six months.</i>
[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)	

# Sentiment and Persona guided Emotional Dialogue Generation Framework



# Dataset

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

# Results: Automatic Evaluation

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

# Results: Manual Evaluation

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

# Generated Examples

Dialog Input	Persona Information		Ground-Truth	Generated Response
<p>[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.</p>	<p>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.</p>	<p>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.</p>	<p>What do you weld?            houses?  <b>Neutral</b></p>	<p><b>Seq2Seq:</b> What is weld? ;UNK; ;UNK;  <b>HRED:</b> What you weld?  <b>Seq2Seq+E+P:</b> Wow! What you weld mostly? (surprise)  <b>HRED+E+P:</b> Really! Do you weld houses? (surprise)  <b>Proposed:</b> Wow that's great, what do you weld mostly, is it houses? (surprise)</p>
<p>[Person 1] Hi! do you like turtles?            [Person 2] I have two cats actually.            [Person 1] I have a turtle his name is Speedy.</p>	<p>Persona 1            I don't pick up my toys.            I have a pet turtle.            I like to play with my dolls.            I'm fourteen.</p>	<p>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.</p>	<p>I am a cat person.  <b>Positive</b></p>	<p><b>Seq2Seq:</b> I have cats.  <b>HRED:</b> I like cats mostly.  <b>Seq2Seq+E+P:</b> Turtles are nice but I like cats. (joy)  <b>HRED+E+P:</b> Nice name for a pet, but I love cats. (joy)  <b>Proposed:</b> That is an adorable name for a turtle! but I am a cat person. (joy)</p>

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## Concept 5

# Politeness and Empathy



# 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)



## 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

# Example I (Expressing Apology / Empathy )

somebody from @VerizonSupport please help meeeee 🙄🙄🙄🙄 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 meeeee 🙄🙄🙄🙄 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.**

# 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)

# 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.

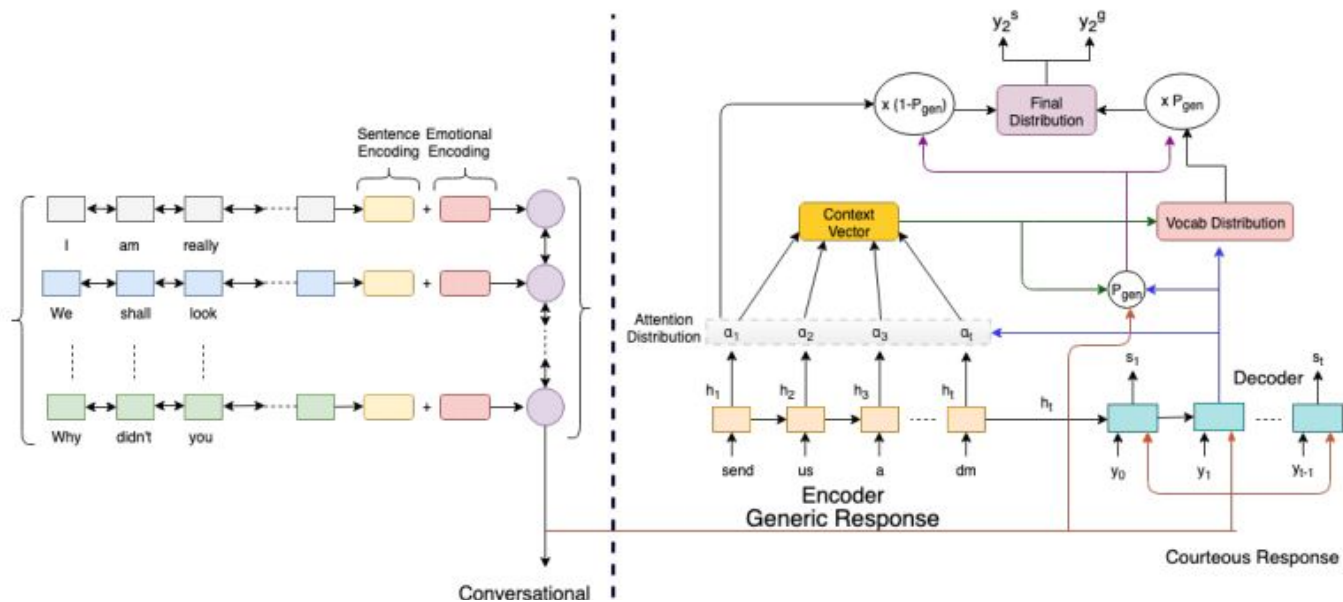
- **Annotations**

- 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

# Proposed Methodology





# Results: Automatic Evaluation

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

P: Pointer Generator Model; EE: Emotional embedding

# Results: Human Evaluation

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

All values are in percentages.

# 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



## 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

# 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.	<i>Assurance</i>
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.)	<i>Empathy</i>
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.	<i>Apology</i>
What are you looking for?	Hey good evening, good to have you with us, please tell what are you looking for?	<i>Greet</i>
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.)	<i>Appreciation</i>

# 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)

# 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

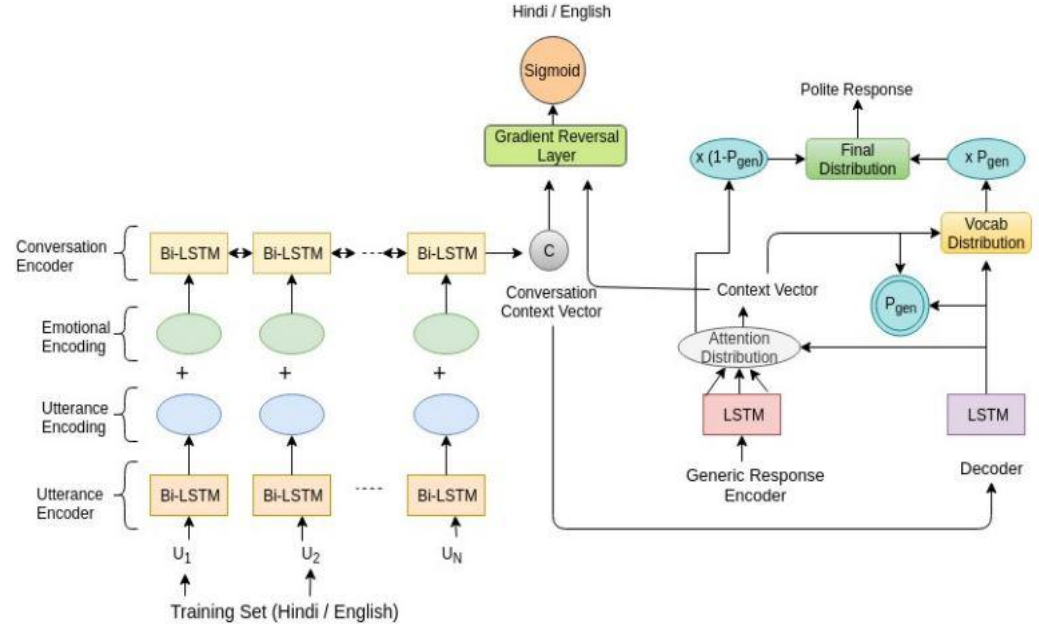
- **Preparing generic responses**

- Obtain the generic response by removing the courteous sentences, retaining the informative sentences, and replacing the hybrid sentences with the prepared generic equivalents



# 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



# Automatic Evaluation

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

## 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.

# Results: Manual Evaluation

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

All values are in percentages.

# 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?)



## 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.

# Examples of polite responses in accordance to the user sentiments

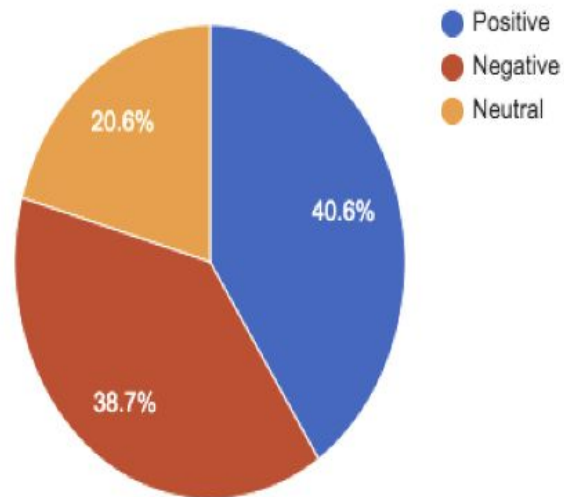
<b>Dialog Context</b>	<b>User Sentiment</b>	<b>Generic Response</b>	<b>Polite Response</b>	<b>Polite Behaviour</b>
Hey, i got food poisoning from your inflight meal on sunday	Negative	Send us a dm	That's disappointing to hear, we are sorry please send us a dm.	Apology
I need the software update urgently, 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

# Dataset

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

	<i>Train</i>	<i>Valid</i>	<i>Test</i>
<i># Conversation</i>	130898	19762	39665
<i># Utterances</i>	168534	24724	49788

CYCCD Dataset Statistics

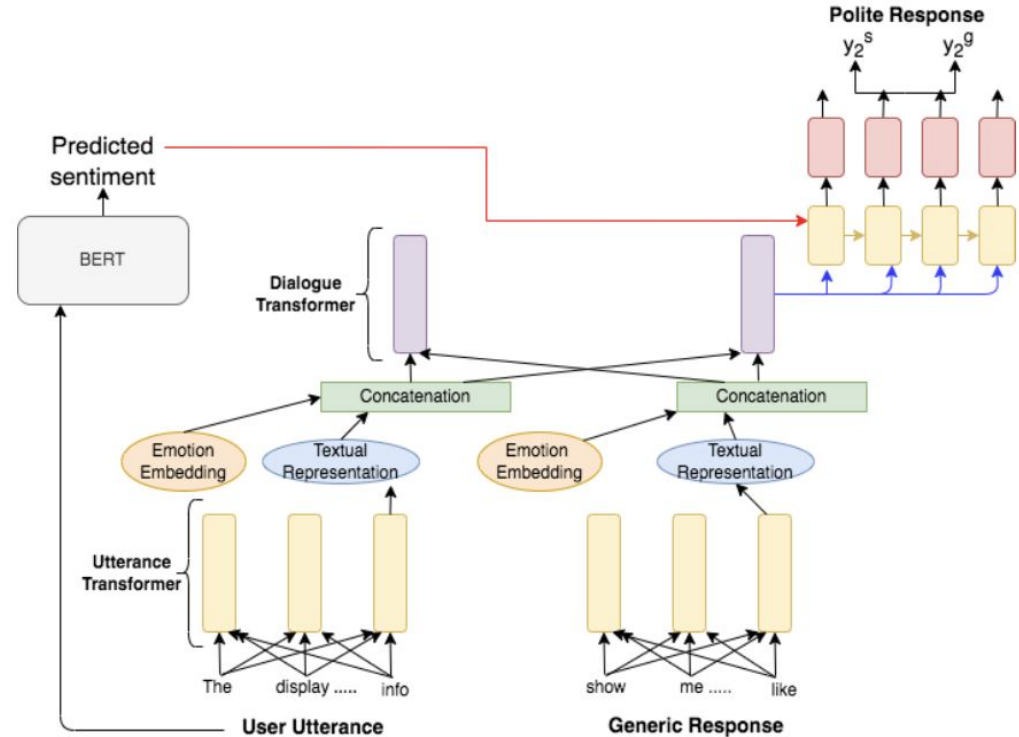


Sentiment distribution in the CYCCD dataset



# 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



# Results: Automatic Evaluation

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

	<b>Model Description</b>	<b>F</b>	<b>R</b>	<b>PA</b>
<b>Existing Approaches</b>	<i>Seq2Seq</i> (Sutskever et al., 2014)	3.82	3.73	48%
	<i>HRED</i> (Serban et al., 2015)	3.86	3.78	52%
	<i>Polite-RL</i> (Niu and Bansal, 2018)	3.91	3.79	61%
	<i>PT-TGA</i> (Madaan et al., 2020)	4.03	3.85	64%
	<i>PG-RL</i> (Golchha et al., 2019)	4.11	4.06	67%
<b>Proposed Approach</b>	<b>HT + RL + SE (Joint Training)</b>	<b>4.23</b>	<b>4.17</b>	<b>75%</b>
<b>Ablation Study</b>	<i>HT</i>	4.09	4.03	65%
	<i>HT + RL</i>	4.16	4.09	71%
	<i>HT + RL + SE</i>	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	<b>HT:</b> We will check <b>HT + RL:</b> Please, wait we'll follow up with the store. <b>HT + RL + SE:</b> Sorry, we'll follow the order with the store <b>Proposed:</b> Sorry for the inconvenience, please wait while we follow with the store.
The new iphone has awesome display	Positive	enjoy your new iphone!	<b>HT:</b> Ohh ur new phone, great <b>HT + RL:</b> That's nice about your iphone <b>HT + RL + SE:</b> Thanks and enjoy your phone. <b>Proposed:</b> Thanks for your kind words and enjoy your new phone!



## 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

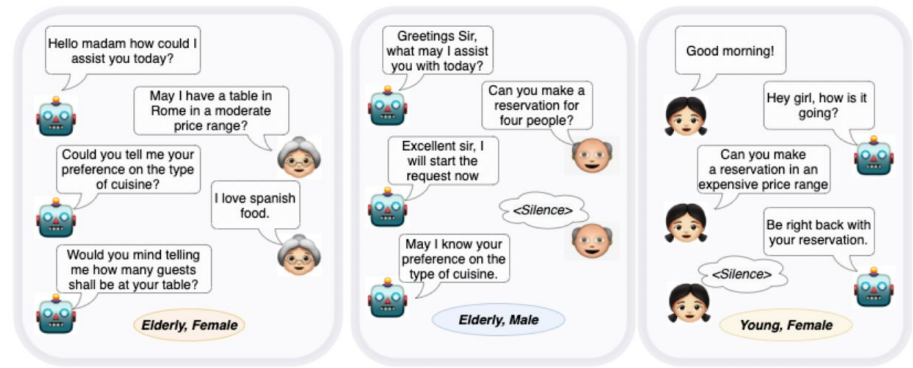
## Motivation

- 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

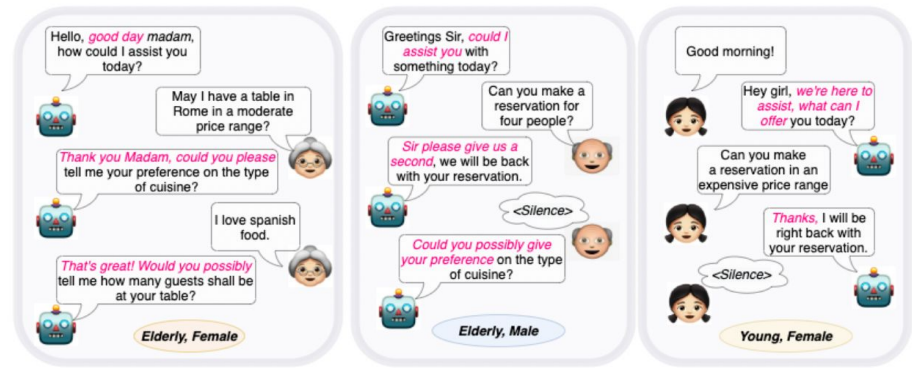
# Example of Polite Personalized Conversation

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

# Dataset

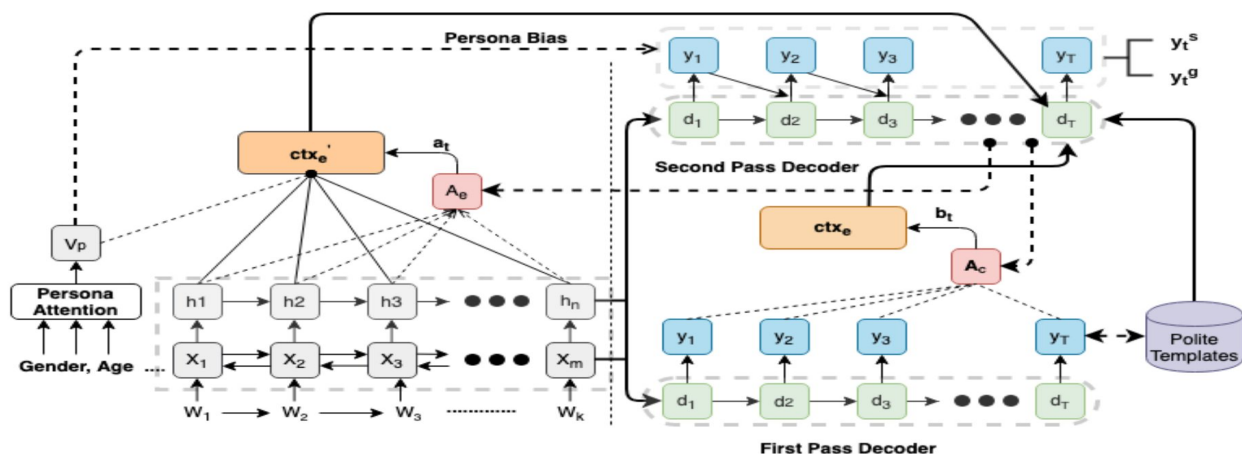
- bAbI dataset [9]
  - A multi-turn personalized dialogues
  - Use personalized features in the language style (such as Sir, Madam, etc.) to respond to the different users
- To provide politeness according to the user profiles, create polite templates in accordance with the dialogs

Female			Male		
<i>Elderly</i>	<i>Middle-Aged</i>	<i>Young</i>	<i>Elderly</i>	<i>Middle-Aged</i>	<i>Young</i>
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.



# 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



# Results: Automatic Evaluation

Model Description		PI	PT	PPL	BLEU-4	Rouge-L	PA
<b>Existing Approach</b>	<i>Polite-RL</i>	-	-	1.027	0.219	0.322	0.53
<b>Baseline Approaches</b>	<i>HRED</i>	-	-	1.032	0.212	0.318	0.38
	<i>HRED + Copy</i>	-	-	1.028	0.224	0.321	0.39
		✓	-	1.024	0.239	0.334	0.40
	✓	✓	1.025	0.238	0.335	0.54	
	<i>HRED + DD</i>	-	-	1.018	0.258	0.339	0.46
✓		-	1.015	0.261	0.342	0.49	
✓	✓	1.011	0.262	0.344	0.67		
<b>Proposed Approach</b>	<i>PoPe-DG</i>	✓	✓	<b>1.004</b>	<b>0.275</b>	<b>0.352</b>	<b>0.73</b>
<b>Ablation Study</b>	<i>PoPe-DG - PB</i>	✓	✓	1.006	0.269	0.349	0.70
	<i>PoPe-DG - RL</i>	✓	✓	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]<sup>2</sup> 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
<b>Existing Approach</b>	<i>Polite-RL</i>	3.91	3.79	61%
<b>Baseline Approaches</b>	<i>HRED</i>	3.82	3.73	48%
	<i>HRED + Copy</i>	3.86	3.78	52%
	<i>HRED + DD</i>	3.93	3.82	55%
<b>Proposed Approach</b>	<i>PoPe-DG</i>	<b>4.11</b>	<b>3.96</b>	<b>69%</b>
<b>Ablation Study</b>	<i>PoPe-DG - PB</i>	4.07	3.92	63%
	<i>PoPe-DG - RL</i>	3.98	3.85	57%

# Generated Examples

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



# **Empathetic Dialogue Systems for Social Good: Application in Persuasion and Therapy**

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# Relevance of Empathy in Persuasion

# Persuasion

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- ❖ 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.

# Empathy for Persuasive Dialogue

- ❖ 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, <a href="https://www.savethechildren.org/">https://www.savethechildren.org/</a> . 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.	



## 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?

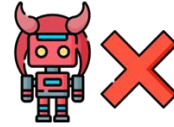


# Empathetic Persuasive Dialogue System



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]

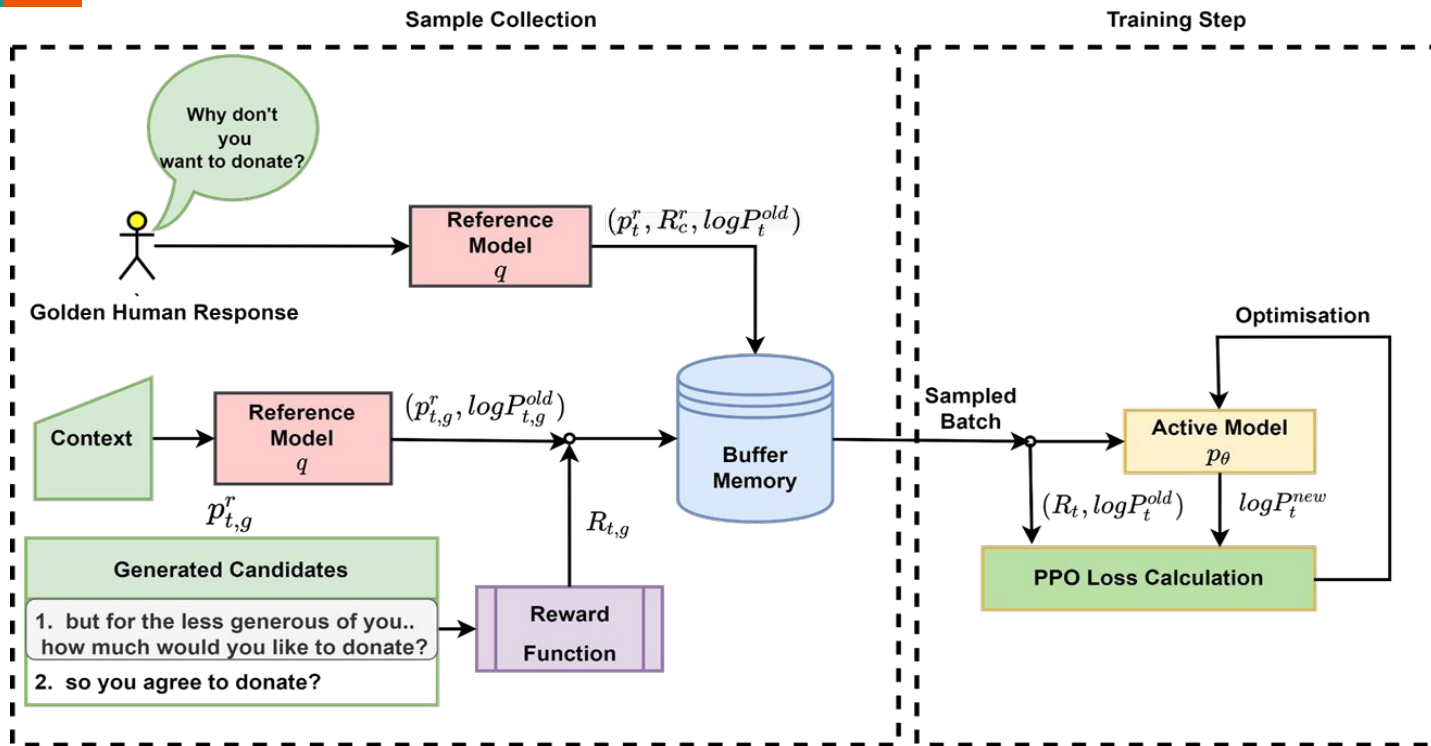


Consistency Persuasive Strategy Empathy



Maintaining Dialogue Consistency, Applying Persuasive strategy and generating Empathetic response

# Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems



# 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	<b>19.36</b>
RL-Emo-Per	<b>55.42%</b>	<b>58.1%</b>	<b>11.25</b>	16.75

## 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	<b>3.91</b>	<b>3.51</b>	<b>0.68</b>	<b>4.59</b>	<b>4.62</b>	<b>3.89</b>



# Generated Example

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	<b>Do you think there are people who have been out of touch with the world for too long?</b>
USER	Yes I think so, we are so involved in ourselves.
AGENT	You are right, I know. <b>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?</b>
USER	I think it is very important to help people in need whenever one can.
AGENT	<b>Do you like children?</b>
USER	I do like children. My sister has three children and I love to play with them.
AGENT	<b>Have you ever heard of the organization Save the Children?</b>
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. <b>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.</b>
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	<b>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.</b>
USER	How much can I donate?
AGENT	<b>I'm thinking \$1.00.</b>
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



## 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***.

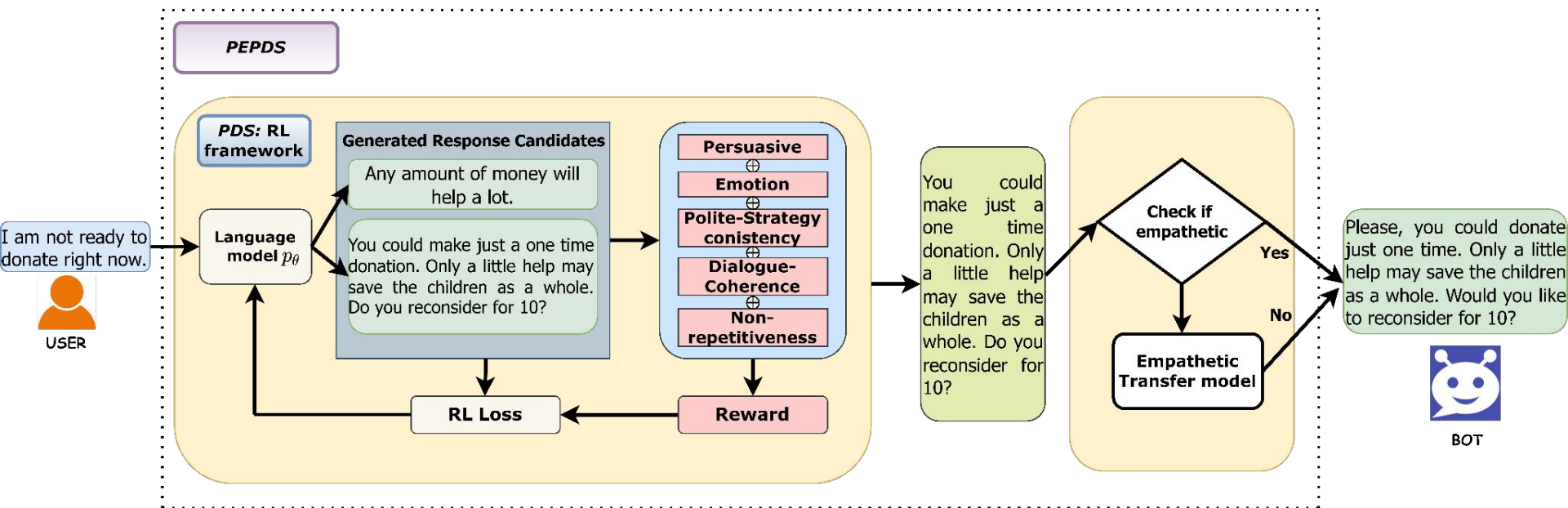
***Its characteristics:***

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

***Use of empathy and polite tone***

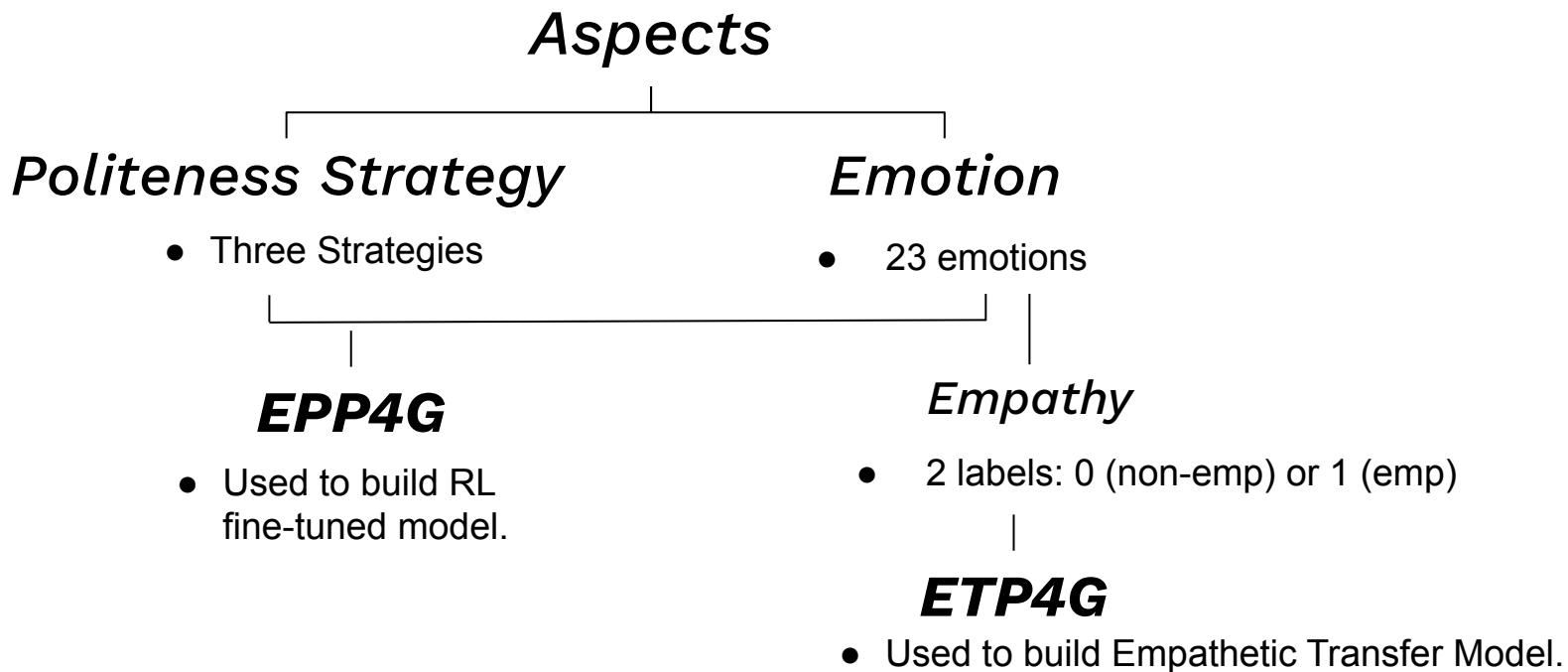
may evoke ***better connection***, ***cognitive*** and ***emotional processing*** conducive to persuasion.

# Polite and Empathetic Persuasive Dialogue System (PEPDS)





# Dataset Annotation



# Results: Automatic Evaluation

Classifier	BERT-large		RoBERTa-large	
	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
DAPT-large	0.894	8.71	0.041	0.182	0.442	0.310

Table 3: 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	<b>19.36</b>
PDS	<b>59.98%</b>	<b>41.117%</b>	67.26%	<b>11.06</b>	15.73
<b>PEPDS</b>	<b>59.98%</b>	<b>41.117%</b>	<b>78.1%</b>	<b>11.06</b>	16.87

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

# 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
<b>PEPDS</b>	<b>3.77</b>	<b>4.21</b>	<b>4.03</b>	<b>0.67</b>	<b>4.56</b>	<b>4.78</b>	<b>3.84</b>	<b>3.78</b>



# 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.
PEPDS	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. Still, 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.

---

# 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.



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

# 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







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 health problems
- ❖ Unaware of legal and human rights
  - Lag in disclosing and reporting the assault/abuse

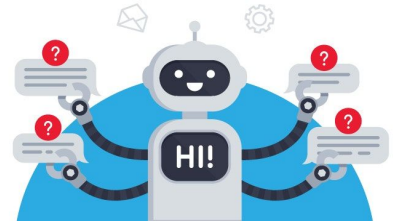


# Mental Health and Legal Counseling for Victims: **Access**

## 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**



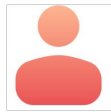
★ Victims need special mental health care and treatment as well as legal support

# Major Highlights



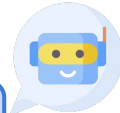
- ❖ A multi-task learning framework for politeness and emotion detection in dialogues for mental health counselling and legal aid (Priya et. al., ESA 2023)
- ❖ Help Me Heal: A Reinforced Polite and Empathetic Mental Health and Legal Counseling Dialogue System for Crime Victims (Mishra et. al., AAI 2023)
- ❖ PAL to Lend A Helping Hand: Towards Building an Emotion-adaptive Polite and Empathetic Counseling Conversational Agent (Mishra et. al., ACL 2023)

# Counseling Conversation



**Victim**

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

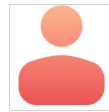


**Counselor**

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

**Generic Response**

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



**Victim**

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



**Counselor**

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

**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](#))

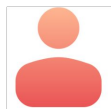
## Use of *polite* and *empathetic* language

- 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**

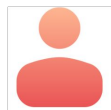
I am struggling with my life after that incident and am scared to share it with anyone.



**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)



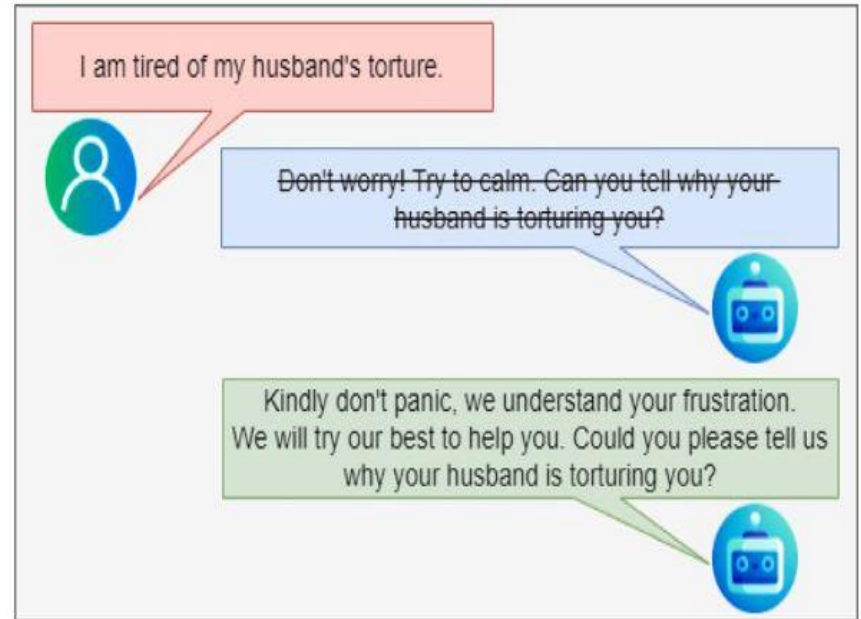
## Highlight 1

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

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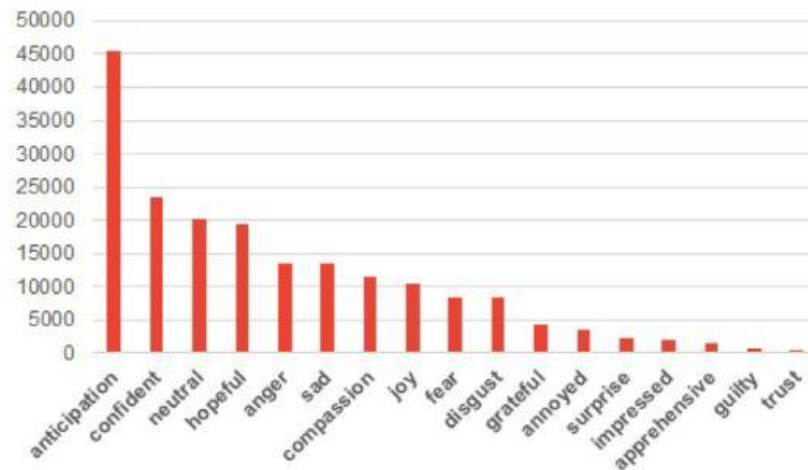
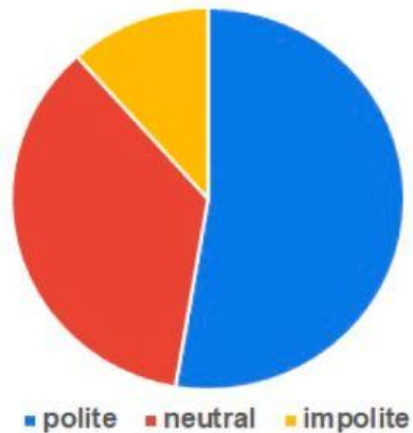
- ❖ 5000 Mental health and legal counseling conversations
  - for women and children victims of different crimes (stalking, harassment etc.)
- ❖ Between two-humans
  - Once acts as an Agent and other as a Victim
- ❖ Annotated with
  - One of the three politeness labels: *polite, neutral, impolite*
  - 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

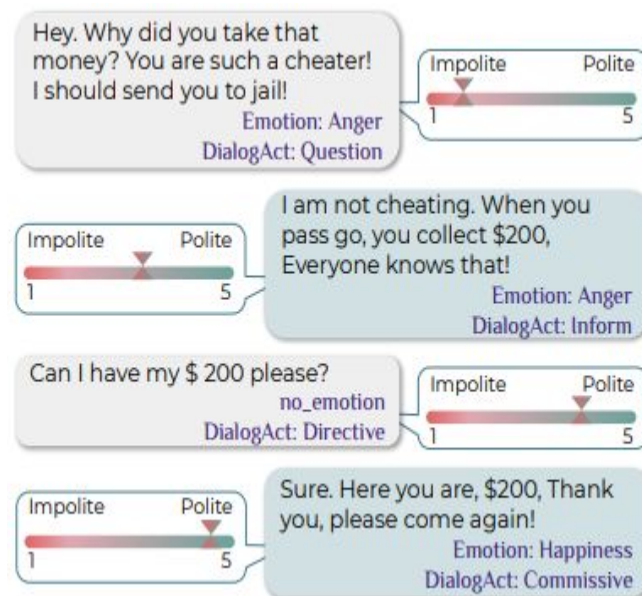
Metrics	Train	Validation	Test
# of dialogues	2859	1080	1061
# of utterances	77,806	25,775	25,744
Avg. utterances per dialogue	27.21	23.87	24.26

## 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, surprise and neutral*
  - 4 Dialog Acts: *inform, question, directive, commissive*
  - Politeness: Score in the range 1-5
    - Score around 3 indicates neutral
    - Score inclined towards 1 indicates impolite
    - Score inclined towards 5 indicates polite

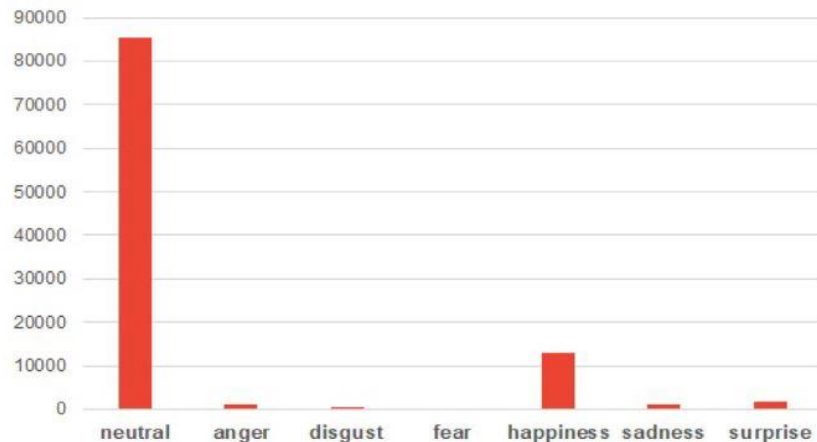
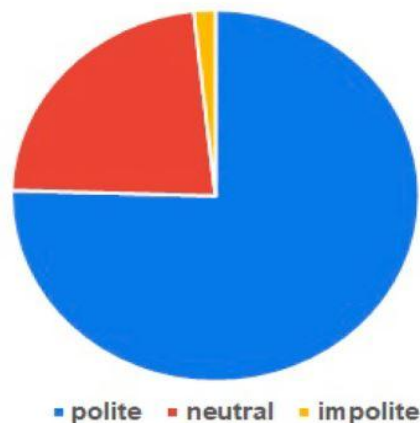


# Polite Emotional DailyDialog Dataset Statistics

## Dataset Statistics

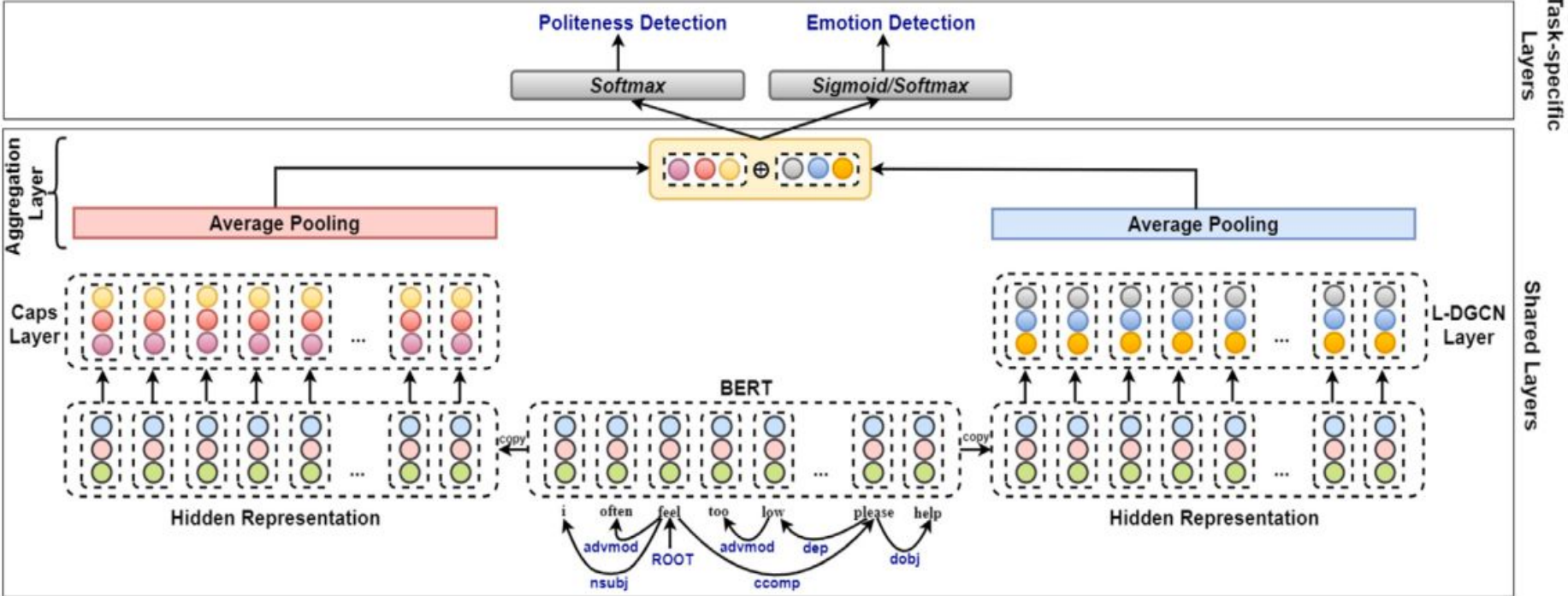
Metrics	Train	Validation	Test
# of dialogues	11,118	1000	1000
# of utterances	87,170	8069	7740
Avg. utterances per dialogue	7.84	8.06	7.74

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

# Results on DailyDialog

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

# Case Study

Input		Gold	Predicted	
			Caps-DGCN <sup>ST</sup>	Caps-DGCN <sup>MT</sup>
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

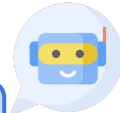
**Help Me Heal: A Reinforced Polite and Empathetic Mental Health and Legal Counseling Dialogue System for Crime Victims (Mishra et. al., AAI 2023)**

# Intro: Counseling Conversation



**Victim**

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



**Counselor**

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

**Generic Response**



**Victim**

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



**Counselor**

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

**Incorporation of appropriate counseling strategy (*confidentiality assurance*)**

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

# 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)

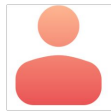
## Use of *polite* and *empathetic* language

- 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**

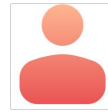
I am struggling with my life after that incident and am scared to share it with anyone.



**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*

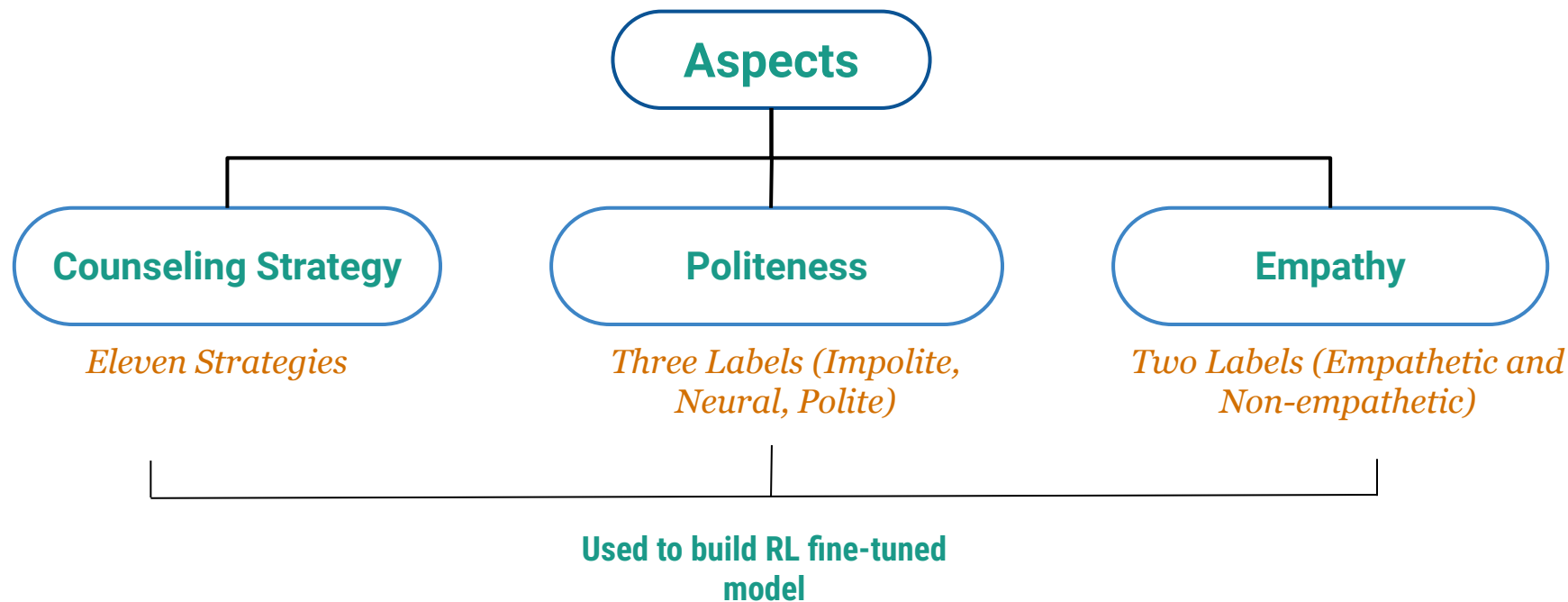
one acts as a *Counselor* (agent) and other as a *Victim* (user)

*11 novel Counseling Strategies*

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



# Dataset Annotation



# Dataset Statistics



<b>Metrics</b>	<b>Train</b>	<b>Validation</b>	<b>Test</b>
<i># of Dialogues</i>	755	100	151
<i># of Utterances</i>	20886	2795	4163
<i>Avg. Utterances per Dialogue</i>	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 on 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 interact 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!!!

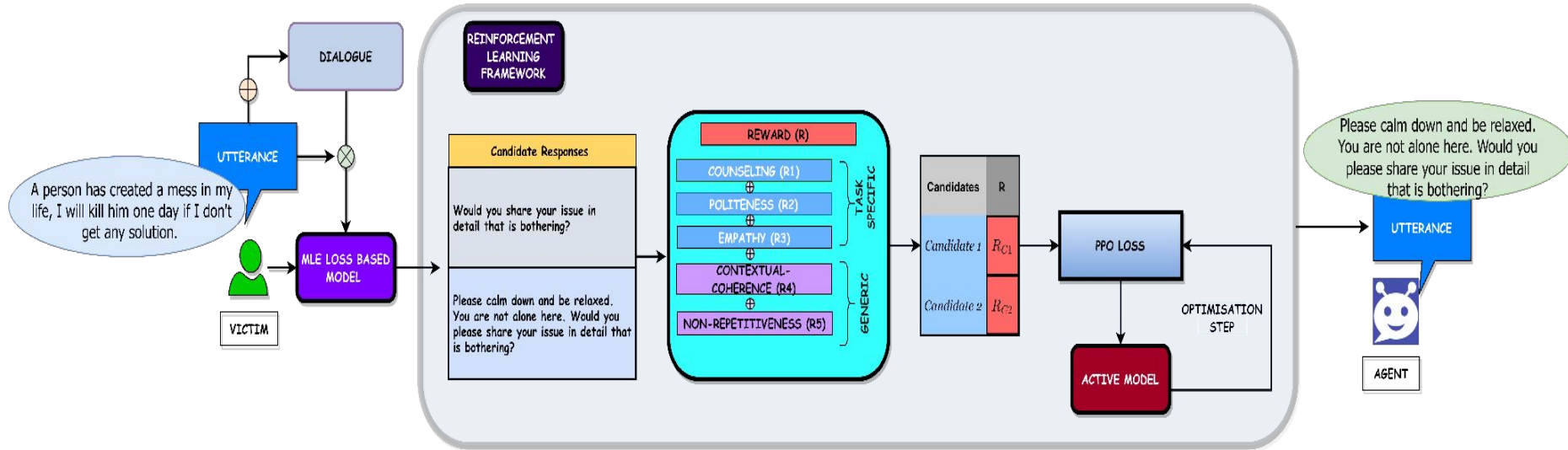
**Agent:** We hope you will try doing all this and please don't forget to take care of yourself, we care for you as well. Is there anything else we can do?  
(motivational directive) (empathetic) (polite)

**Victim:** Not now.

**Agent:** Great! Kindly be assured we are here for you 24x7. Don't hesitate 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 *Polite* and *Empathetic* Mental Health and Legal Counseling Dialogue System (Po-Em-MHLCDS)

# Results - Classifiers



<b>Classifier</b>	<b>BERT-large</b>		<b>RoBERTa-large</b>	
	<b>W-ACC</b>	<b>Macro-F1</b>	<b>W-ACC</b>	<b>Macro-F1</b>
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



<b>Model</b>	<b>CoStr</b>	<b>Pol</b>	<b>Emp</b>	<b>PPL</b>	<b>R-LEN</b>
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
<b>Po-Em-MHLCDS</b>	<b>80.30%</b>	<b>92.54%</b>	<b>46.4%</b>	<b>1.91</b>	<b>18.71</b>

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



<b>Model</b>	<b>Con</b>	<b>Pol</b>	<b>Emp</b>	<b>Const</b>	<b>Fluen</b>	<b>N-Rep</b>
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
<b>Po-Em-MHLCDS</b>	<b>3.94</b>	<b>4.41</b>	<b>2.85</b>	<b>4.16</b>	<b>4.57</b>	<b>4.72</b>

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

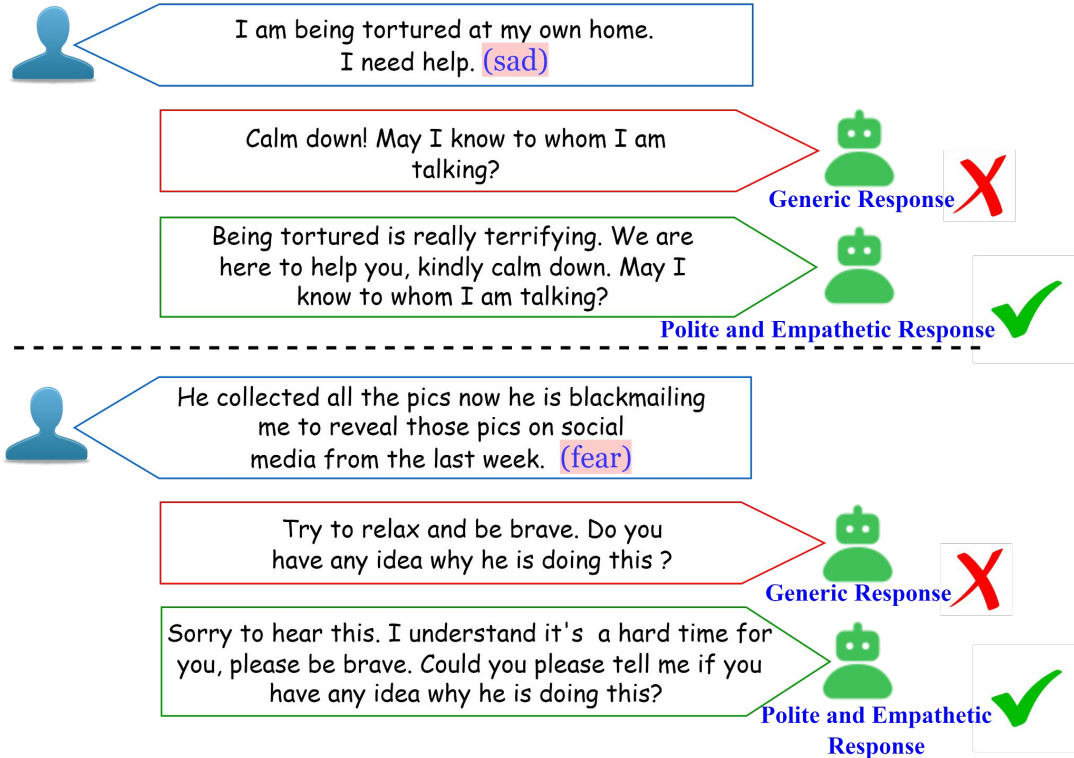


- ❖ Build a novel counseling dialogue system
  - For substance addicts and crime victims
  - Demonstrates polite and empathetic behavior towards clients based on their emotional state

# 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

# 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

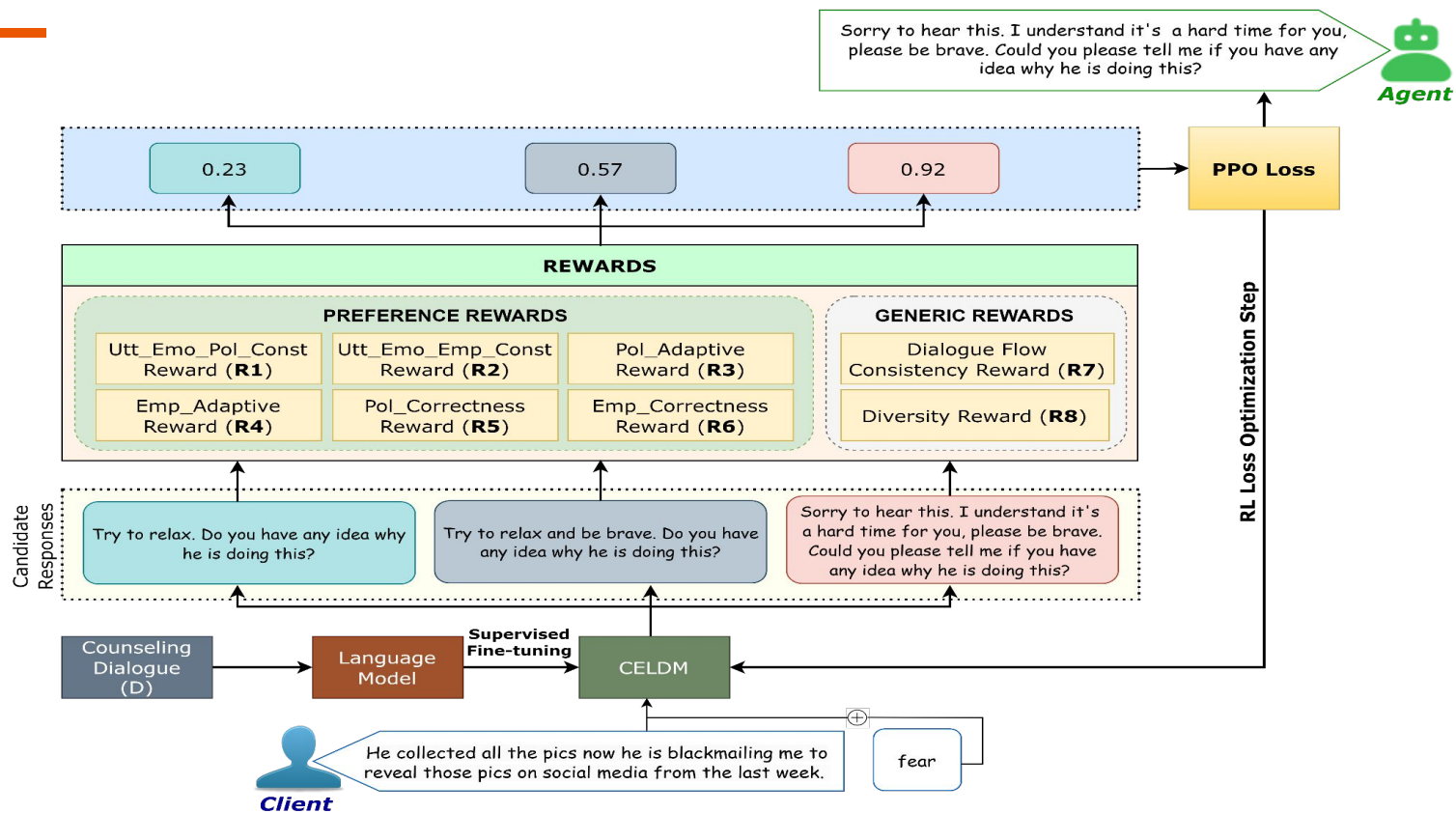
## ❖ *EPE-enEIH: A novel counseling conversational dataset in English*

- 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



# Automatic Evaluation Results- PAL

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

# Human Evaluation Results - PAL



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



# 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!



## Highlight 4

**e-THERAPIST: I suggest you to cultivate a mindset of positivity and nurture uplifting thoughts (EMNLP2023)**

# Problem Definition



Shortage of therapists for mental health patients emphasizes the importance of globally accessible dialogue systems alleviating their issues

These systems must exhibit politeness and empathy when needed

These factors may vary depending on the user's gender, age, persona, and sentiment

To establish trust and provide a personalized cordial experience, it is essential to tailor the generated responses to individual profiles and attributes

Propose **e-THERAPIST**, a novel gender, age, persona and sentiment-aware polite and interpersonal dialogue system for psychotherapy

# Motivation

- To produce effective outcomes during psychotherapy, a therapeutic dialogue system needs to utilize various psychotherapeutic approaches based on
  - User's personal profile (gender, age and persona)
  - User's sentiment
- For the “*Young Female Openness*”, the user expresses a negative sentiment
  - Agent's behaviour in the form of imposing or confrontation might make the user more angry or dissatisfied
  - It should adapt helping, understanding or empathetic behaviour

## Elderly Female Openness

**T:** A very good morning madam! How are you feeling today? (helpful)

**U:** Good morning, I'm feeling too down today. Can you help me? (negative)

**T:** I'm really sorry to hear that. Kindly tell me what's been going on? (understanding)

**U:** I just feel like nothing is going right in my life. I don't have any motivation to do anything. (negative)

**T:** I see, but don't worry, together we will explore the solutions that would be better for you. Could you please tell me more about what's been going on? (empathetic)

## Young Female Openness

**T:** Hello dear! I'm ready to provide you with empathetic support. How are you doing today? (helpful)

**U:** Not so good, not so energetic. (negative)

**T:** That's really disappointing to hear, my dear friend. I presume you are facing some issues these days. I would love to help you if you could share your problem with me. (empathetic)

**U:** I have this overwhelming sense that everything is going wrong in my life. I lack the drive and enthusiasm to engage in any activities. (negative)

**T:** Hey girl, I understand your situation a bit. Let's dive deeper to find the strategies that would be helpful. If you agree, I would like to ask a few questions? (empathetic)

## Elderly Male Openness

**T:** Good morning sir, what brings you here? (helpful)

**U:** I'm not feeling good these days. I seek your help. (negative)

**T:** Sorry to learn this. I want to know what's been going on to help you? (directing)

**U:** I don't feel like anything right in my life, no motivation, nothing. (negative)

**T:** Okay, let's explore that. Can you please explain a bit about what you are exactly experiencing these days? (helpful)

## Elderly Male Agreeableness

**T:** Welcome to our session. What brings you here today? (helpful)

**U:** I've been feeling lethargic these days. Please help me. (negative)

**T:** I apologize for the odd situation you're facing. Can you please share more details about what has been happening? (helpful)

**U:** Yes, of course. I can share with you. (positive)

**T:** I appreciate your willingness to share. Would you mind elaborating on your current experiences? (understanding)

**U:** I've been struggling to find any positivity in my life. It's disheartening to lack motivation and feeling empty. (negative)

**T:** We truly understand your situation. I will do our best to help you. Let's explore the techniques to cope with your circumstances. (empathetic)

# Research Contributions

---

- e-THERAPIST - a novel gender, age, persona and sentiment-aware polite and interpersonal dialogue system for psychotherapy, fine-tuned in an RL environment
- **PsyCon** a novel conversational dataset for psychotherapy, and annotated it at two distinct levels -
  - dialogue-level with gender, age, persona, and psychotherapeutic approach
  - utterance-level information, viz. sentiment, politeness, and interpersonal behaviour information
- Devised a novel reward function incorporating five attribute-specific rewards and two response-quality rewards to generate engaging, fluent, and interactive responses tailored to the user's sentiment, gender, age, and persona

# PSYCON - Conversational Dataset for Psychotherapy



- PsyCon - A novel conversational dataset for psychotherapy
- Interactions between the therapist and the user with psychological issues
  - depression, anxiety, stress, bipolar disorder, disruptive behaviour and dissocial disorders, post-traumatic stress disorder (PTSD), and schizophrenia
- 1,020 dialogues in total
- Created the dataset by prompting this GPT-J model followed by manual intervention to ensure quality control

# Dataset Annotation



- Dialogue-level
  - Gender: *male, female*
  - Age: *young, adult, elder*
  - Persona: *Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism*
  - Psychotherapeutic approach : *Directive, Non-directive, Eclectic*
- Utterance-level information
  - Sentiment: *Positive, Negative, Neutral*
  - Politeness: *Polite, Moderately polite, Impolite*
  - Interpersonal behaviour: *Directing, Helpful, Understanding, Complaint, Imposing, Confrontational, Dissatisfied, Uncertain*

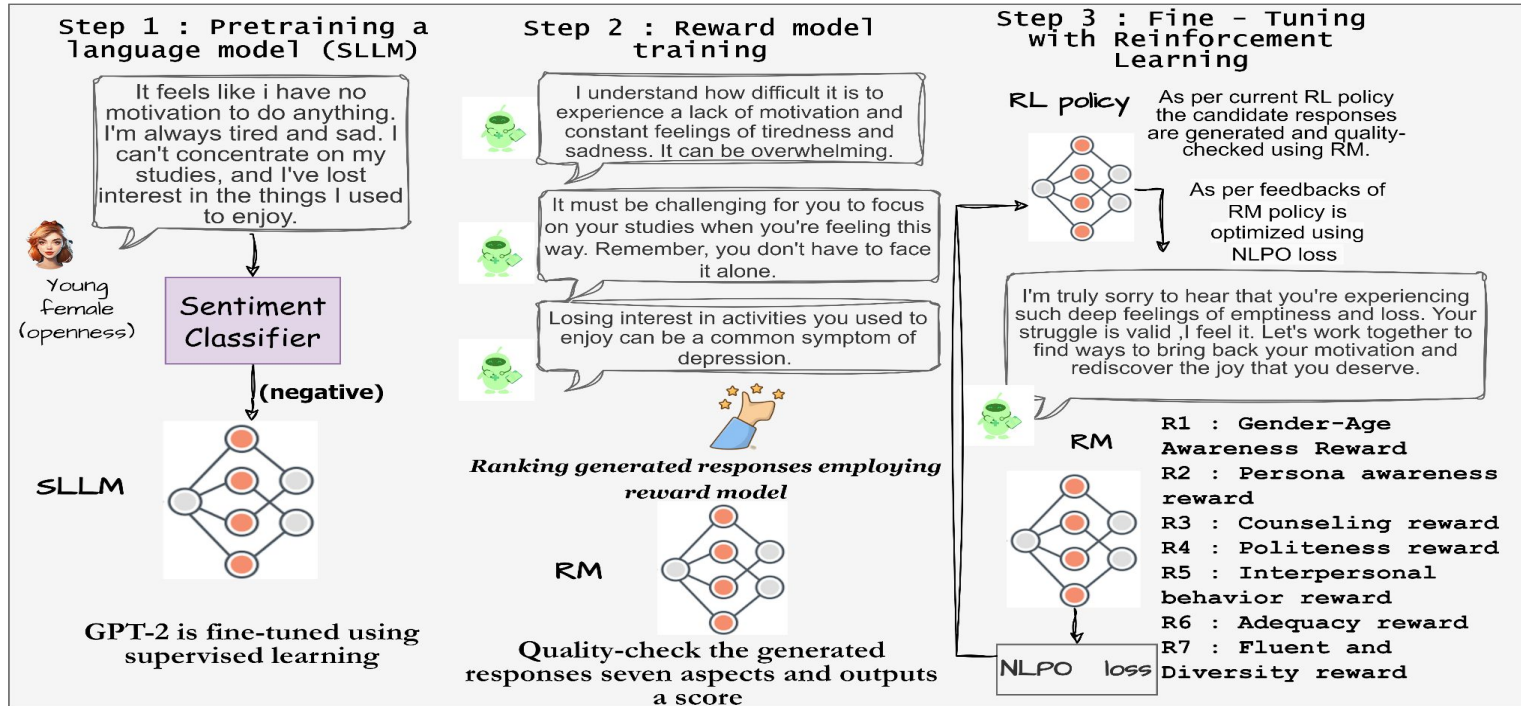
# PSYCON Dataset Statistics



Metrics	Train	Validation	Test
<i># of Dialogues</i>	816	102	102
<i># of Utterances</i>	19568	2692	2811
<i>Avg. Utterances per Dialogue</i>	23.98	26.39	27.56



# Proposed Methodology



# Evaluation Metrics



## Automatic Evaluation

- Gender-Age consistency ( $GA_c$ )
- Persona consistency ( $P_c$ )
- Psychotherapeutic approach correctness ( $CT_c$ )
- Politeness correctness ( $PO_c$ )
- Interpersonal behaviour correctness ( $IB_c$ )
- Perplexity ( $PPL$ )
- BERTScore ( $BS_{F1}$ )
- Response Length ( $R-LEN$ )

## Human Evaluation

- Gender-Age consistency ( $GA_c$ )
- Persona consistency ( $P_c$ )
- Psychotherapeutic approach correctness ( $CT_c$ )
- Politeness correctness ( $PO_c$ )
- Interpersonal behaviour correctness ( $IB_c$ )
- Fluency ( $F$ )
- Consistency ( $C$ )
- Non-repetitiveness ( $N_R$ )

# Automatic Evaluation Results

Model	$GA_c$	$P_c$	$CT_c$	$Po_c$	$IB_c$	PPL	$BS_{F1}$	$R_{LEN}$
LM	78.4%	72.1%	79.5%	80.2%	73.6%	4.26	0.68	15.61
ARDM	80.4%	73.3%	80.0%	81.5%	74.2%	3.57	0.74	16.82
GPT-Critic	80.7%	73.8%	80.6%	82.7%	73.1%	3.86	0.69	15.94
SLLM	85.4%	80.1%	86.3%	84.6%	77.8%	3.26	0.81	19.79
e-THERAPIST-R	85.1%	79.7%	86.8%	84.5%	77.5%	3.09	0.84	19.26
e-THERAPIST-ASR	86.1%	80.8%	87.2%	86.2%	79.8%	3.06	0.87	20.12
e-THERAPIST-RQR	87.5%	82.3%	88.7%	87.9%	80.5%	2.97	0.88	22.79
SLLM+PPO	89%	83.9%	91.5%	91.3%	82.3%	2.67	0.89	23.01
<b>e-THERAPIST</b>	<b>90.1%</b>	<b>84.1%</b>	<b>92.6%</b>	<b>92.5%</b>	<b>83.4%</b>	<b>2.52</b>	<b>0.89</b>	<b>23.89</b>

# Human Evaluation Results

Model	$GA_c$	$P_c$	$CT_c$	$Po_c$	$IB_c$	$F$	$C$	$N_R$
LM	2.02	2.21	2.07	2.10	2.39	2.17	2.39	2.01
ARDM	2.88	2.74	2.77	2.81	2.80	2.79	2.83	2.29
GPT-Critic	2.98	2.83	2.81	2.90	2.91	2.86	2.91	2.34
SLLM	3.50	3.67	3.80	3.75	3.41	3.89	3.44	3.21
e-THERAPIST-R	3.53	3.45	3.86	3.84	3.50	4.11	4.05	3.72
e-THERAPIST-ASR	3.75	3.70	4.01	3.91	3.72	4.32	4.27	3.82
e-THERAPIST-RQR	3.97	3.91	4.12	4.09	3.89	4.45	4.33	3.97
SLLM+PPO	4.10	4.06	4.38	4.30	4.01	4.55	4.50	4.05
<b>e-THERAPIST</b>	<b>4.21</b>	<b>4.10</b>	<b>4.42</b>	<b>4.35</b>	<b>4.02</b>	<b>4.62</b>	<b>4.60</b>	<b>4.08</b>

# Conclusion and Future Directions



- A novel dataset consisting of psychotherapeutic conversations between the therapist and the user with psychological issues
- A novel dialogue system for psychotherapy - **e-THERAPIST**
  - e-THERAPIST generates polite and interpersonal responses tailored to the user's gender, age, persona and sentiment
- e-THERAPIST is built in a reinforcement learning framework
  - A novel reward function to ensure the preferences of gender, age, persona and sentiment-aware polite interpersonal psychotherapeutic responses
- Experimental results showcase the efficacy of the overall system
- In future, we would like to incorporate external knowledge to facilitate more factual conversations.

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# Politeness, Empathy and Persuasion in Mental Health and Legal Counseling of 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

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## *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
<i>No. of Dialogues</i>	<b>162</b>	<b>22</b>	<b>32</b>
<i>No. of Utterances</i>	<b>4133</b>	<b>407</b>	<b>664</b>
<i>Average no. of utterances per dialogue</i>	<b>25.51</b>	<b>18.50</b>	<b>20.75</b>

**Dataset Statistics**

# Counselling Act- *meeting the adequate requirement of victims*

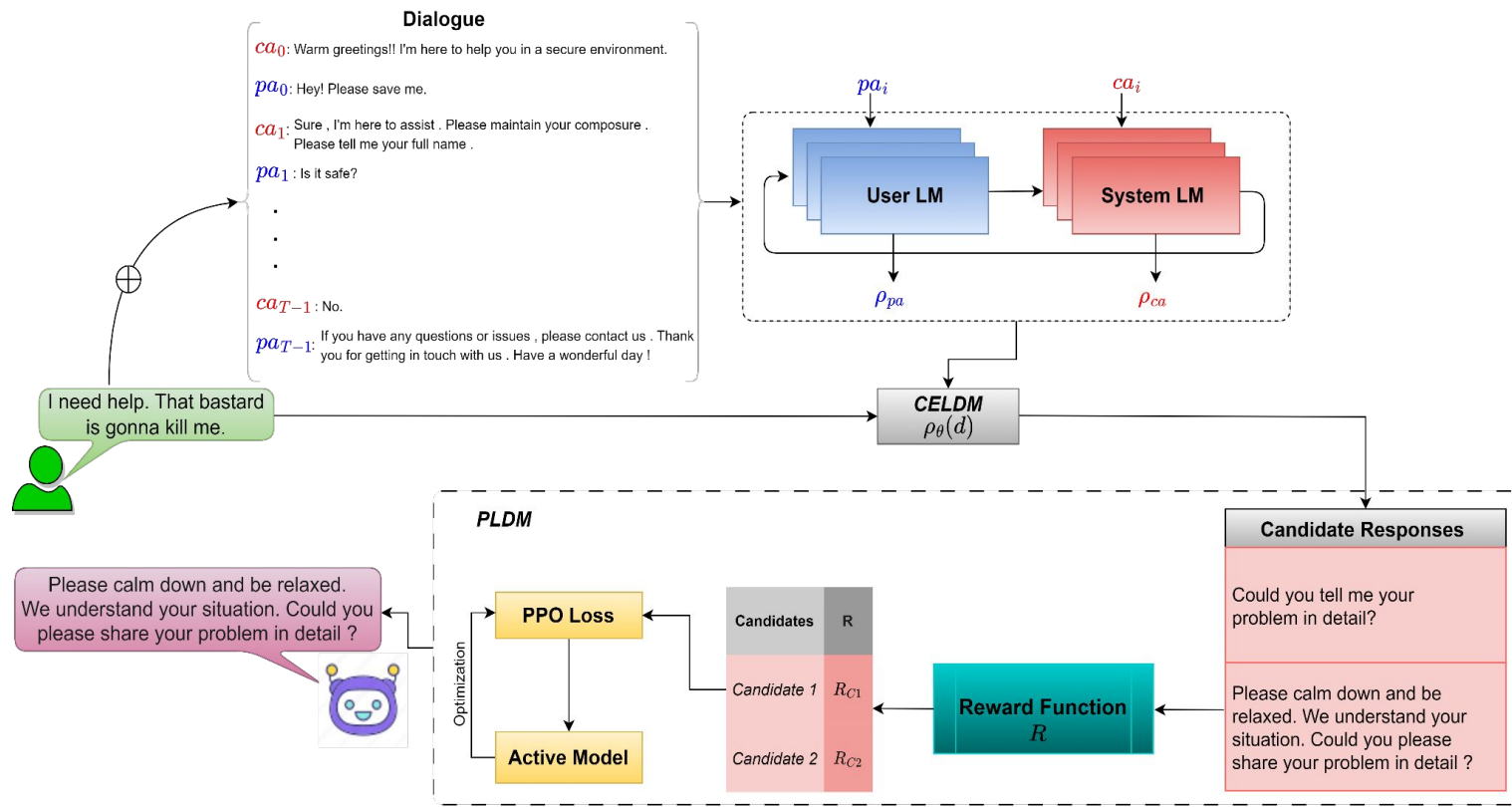
<b>Act</b>	<b>Purpose</b>
<b>Counselling support</b>	Provide various support services like medical help, mental health-related aid, NGOs information etc. during counselling based on the victim's need
<b>Legal assistance</b>	Ensures legal assistance to the victims
<b>Persuasion</b>	Assists the victims 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
<b>Seek information</b>	Request for a few basic information in order to comprehend the problem and provide relevant assistance
<b>Deliver information</b>	Provide information pertaining to the problem being discussed
<b>Re-check assistance</b>	Inquires for further help or clarification about the problem under discussion
<b>Greet</b>	Typically, each conversation begins with a greeting from one speaker and an appropriate response from the other
<b>Closing remark</b>	Marks the end of the conversation

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

<b>Strategy</b>	<b>Purpose</b>
<b>Reflective listening</b>	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
<b>Confidential comforting</b>	Displays genuine interest and concern for the privacy of the victims, providing assurance that any information shared will be treated with the utmost confidentiality
<b>Evoke motivation</b>	Encourages the victims to embrace a forward-looking perspective and participate in activities that promote feelings of positivity and optimism
<b>Express emotional support</b>	Provides emotional solace or words of encouragement to entirely comprehend the problems faced by the victims and the intensity of their emotions
<b>Offer counselling</b>	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.
<b>Escalate assurance</b>	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.
<b>No strategy</b>	Assigned to the utterances which do not utilize any empathy strategy



# Proposed System Architecture: PARTNER



# Results - Classifiers

Classifier	BERT-large		RoBERTa-large	
	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 <i>et al.</i> , 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
<b>PARTNER</b>	<b>56.5%</b>	<b>61.8%</b>	<b>69.9%</b>	<b>2.55</b>	<b>16.06</b>

## 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
<b>PARTNER</b>	<b>3.06</b>	<b>3.11</b>	<b>3.42</b>	<b>4.52</b>	<b>4.14</b>	<b>4.07</b>

## 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.



# 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



- Described the significance of empathetic conversational AI systems for social good applications

## Conclusion

- 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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- ❖ M. Firdaus, N. Thangavelu, A. Ekbal and P. Bhattacharyya (2022). *I enjoy writing and playing, do you?: A Personalized and Emotion Grounded Dialogue Agent using Generative Adversarial Network*. In IEEE Transaction on Affective Computing, doi: 10.1109/TAFFC.2022.3155105



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