Being Polite and Empathetic: *Inducing Politeness and Empathy in Conversational AI*

Asif Ekbal
AI-NLP-ML Research Group
Department of Computer Science and Engineering
IIT Patna, Patna, India
Email: asif.ekbal@gmail.com, asif@iitp.ac.in

Presented at Microsoft STCI (Bing)

November 16, 2022

Slides scribed by: Mauzama, Deeksha, Arindam

Outline

- Background: Conversational AI
- Empathetic Conversational Agents: Inducing Courteousness, Emotion in Conversational Agents
- Persuasive Conversational Agent
- Personalization in Conversational Agents
- Summary and Conclusion
- Our Research at a Glance

Artificial Intelligence and Conversational Agents

- ***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

The most simplest form of Conversational System: Chatbot

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)

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

- Nowadays, ***Chatbots*** have grown into a full-blown industry with constant innovations bridging the human-to-machine communication gap
  - *Going beyond simple tasks like playing a song or booking an appointment*

- Beyond knowledge-based conversational agents that match a query to a predefined set of answers

- Chatbot should mimic the dynamics of human conversations

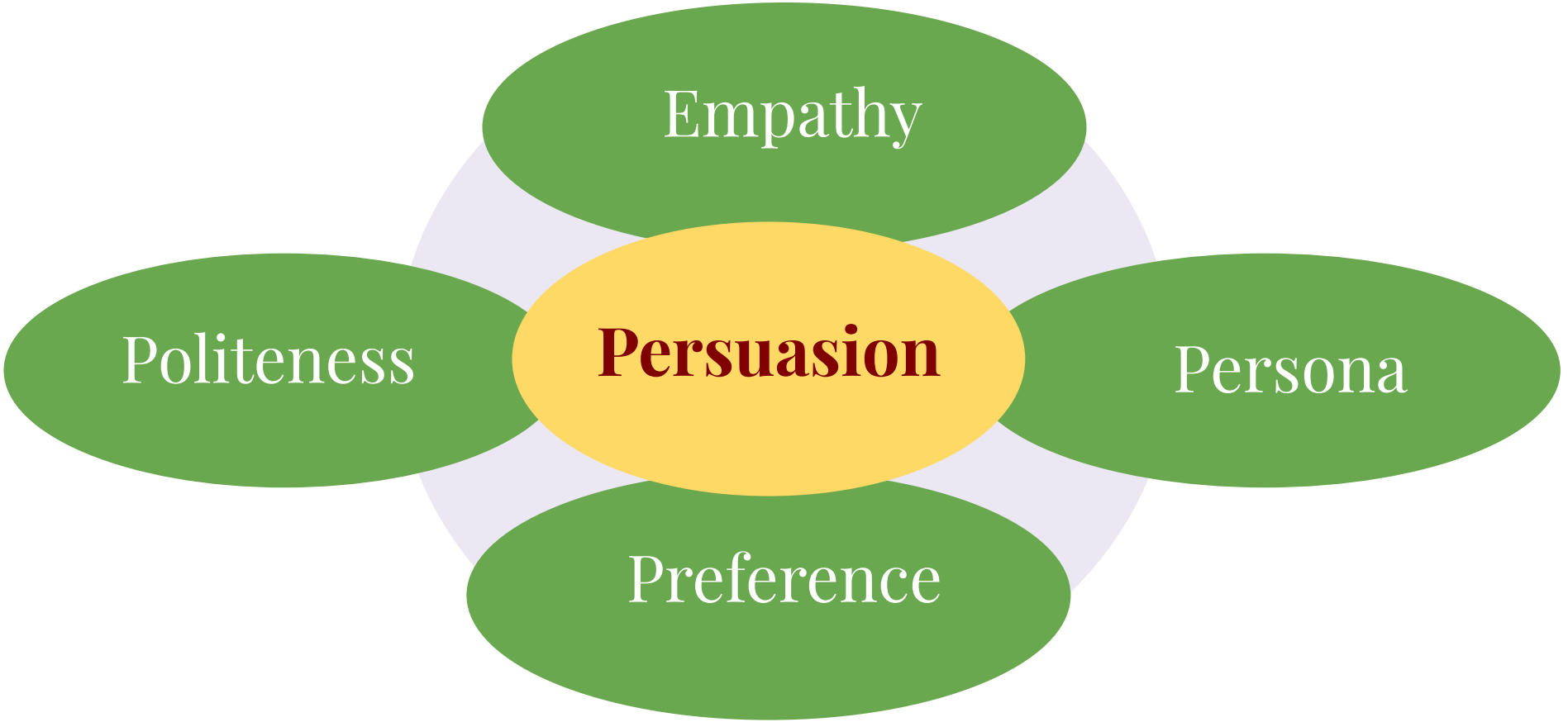
BUT how?

Empowering AI for Human-like Conversation

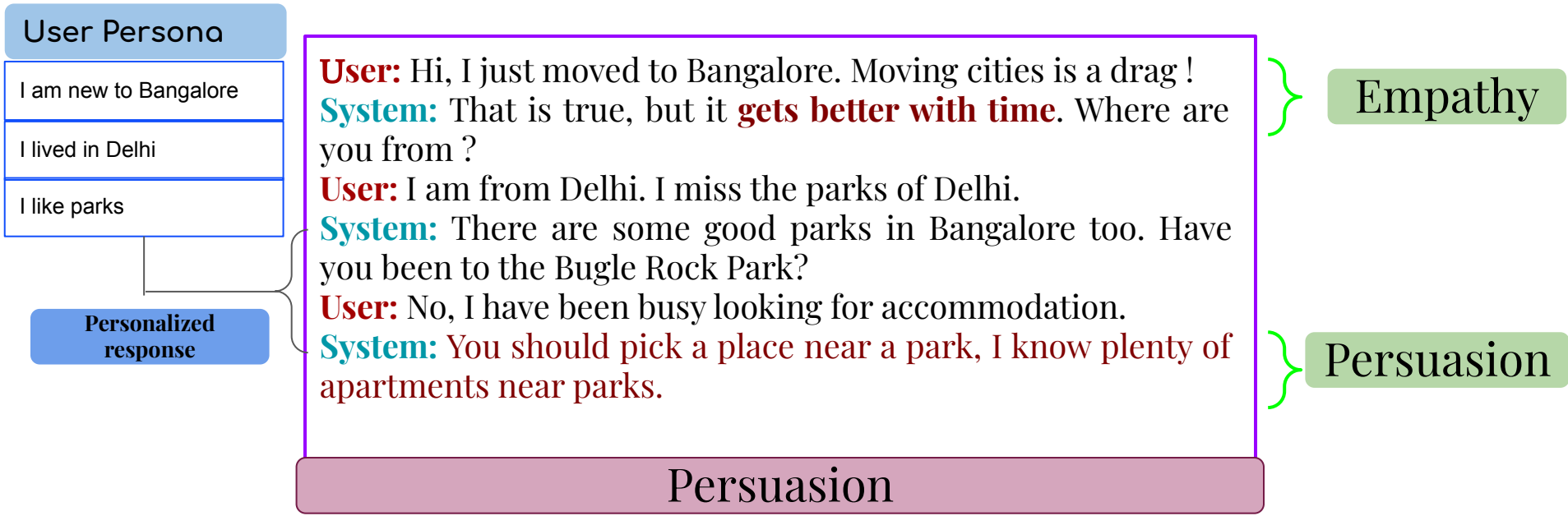
- **AI has to master the art of conversation at human level, then it has an uphill task ahead (*Facebook AI*)**
  - Consistency: *to ensure that it generates appropriate response without missteps, such as contradictions*
  - Specificity: *generating specific response*
  - **Empathy:**

    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.*

Persuasion and its various factors



Persuasiveness, Empathy and Personalization



Persona Grounded Task Oriented Chatbot

Chit-Chat

User

Hi, i'm a student . I would like to visit a museum in the center of town .

Traditional Task Oriented BOT

There are 11 museums in the centre of town. Is there a particular type of museum you are interested in?

Bland/ Non Engaging

Persona Grounded Task Oriented BOT

That's cool, I just love history. There are 11 museums in the centre of town. Is there a particular type of museum you are interested in?

Engaging and Human Like
&
Controllable

I like historical artifacts.

I enjoy train journey

I love Italian food

Bot Persona

Persona based Persuasion (*An example from E-Commerce*)

I play games a lot. Like to buy a regular T-Shirt

Persona: Like sports

Plain task-oriented dialogue

Let me show you T-Shirt options

Persona - aware persuasion for Sweatpants

As you love to play games, would you like to consider Sweatpants also with T-Shirt options.

Example Use cases

- Scenarios where the perception of need can be created.
- Scenarios where customers don't know any better what they want.

Empathetic Conversational AI

I finally got promoted today at work!!

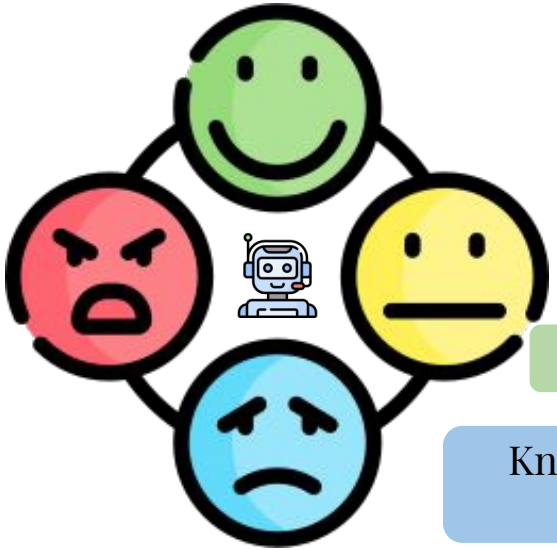
Why would anyone promote you?

Congrats!! That's great!!

Empathy

Multi-Emotion Controlled Dialogue Generation ***(AAAI 2021)***

It's amazing, I am thrilled you got promoted [**Surprise, Joy**] [**0.3**, 0.9]
Stop sulking, I am sure you will manage it [**Anger, Acceptance**] [**0.7, 0.4**]
I am sorry this could be an infection or cancer [**Sadness, Fear**] [**0.6**, 0.3]



Sentiment awareness

Knowledge-grounded conversation

Intent

Context

Mood

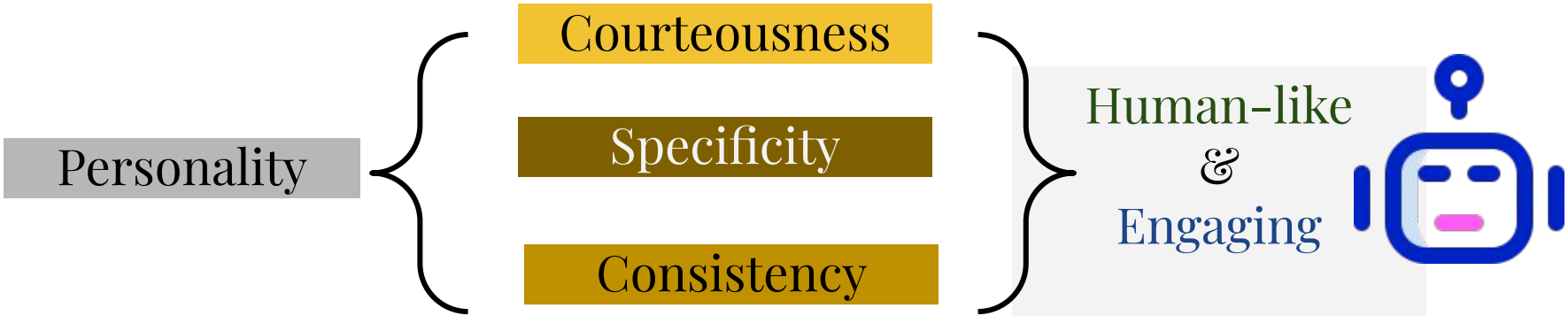
Aware & Relatable

Politeness and Personalization (HLT/NAACL 2019, INLG 2021)

We are sorry to see you are having trouble. Help has arrived. How can I help? **Apology**

Hey Christiano!! Happy to help. Can you send us a screenshot? **Greet, Assurance**

Thank you for your kind words!! Enjoy your show while flying!! **Appreciation**



Hitesh Golchha, Mauajama Firdaus, Asif Ekbal, Pushpak Bhattacharyya (2019). *Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network*. In NAACL-HLT 2019, PP. 851-860

What we solve?

To **transform** a **generic chatbot response** into a response which uses **courteous phrases** and make the users **more engaged in conversation**

Domain: Customer Care on Twitter

For any goal-oriented or open-domain systems, ***courteous response*** plays an important role in keeping the ***users engaged with the system***

Purpose is to increase user satisfaction and to build customer relations

Courtesy-The behaviour: Derived from the Politeness Theory [Brown and Levinson (1987)]

- The showing of ***politeness*** in one's attitude and behaviour towards others
- A courtesy is a polite remark or respectful act- ***very common communicative behavior***

  For example,

  Complain about a bad meal, and you are asked to leave ***BUT***,

  the common courtesy is usually an ***apology from the manager*** and, if you're **lucky**, a free **dinner**

Politeness Strategies

- **Less Polite Strategies**
  - seeking agreement
  - joking
  - expressing optimism

- **More Polite Strategies**
  - being apologetic
  - minimizing the imposition
  - appreciating
  - thanking

Let’s see:

Some use cases of courteous behaviours in Customer Care Systems

Use-cases of Courteousness

Generic	Courteous	Behaviour
How can we help?	*Help has arrived! We are sorry to see that you are having trouble, how can we help?*	*Apology*
Can you send us a screenshot of what you're seeing?	*Hey Craig, help's here! Can you send us a screenshot of what you're seeing?*	*Greet*
Let's discuss it in GM.	*We want to help. Let's discuss it in GM.*	*Assurance*
What is happening with your internet?	*Oh no that's not good. I can help! What is happening with your internet?*	*Empathy*
Enjoy your show while flying!	*Thanks for your kind words and enjoy your show while flying!*	*Appreciation*

Resource Creation: Data Source and Attributes

- **Twitter dataset from Kaggle**
  - Interactions between customers and professional customer care agents of companies
  - Tweets have company names, anonymized user ids, time stamps, and response tweet ids

- **Pre-processing**
  - Segment the tweet into sentences
  - Remove purely ***courteous (and non-informative)*** sentences
  - Retain purely informative sentences
  - Transform the informative sentences with courteous expressions (***to remove only the courteous part from the sentence***)

Challenges

- Identifying *different variations and styles of courteous behaviours across different companies, service providers, demographics and cultures*

- Identifying courteous behaviours in the customer care domain is not straightforward

- Hard to model the **emotion across the conversation** for effective courteous response generation
  - needs to capture the **correct emotion;** and
  - accordingly handle the customers by replying courteously

For e.g.,

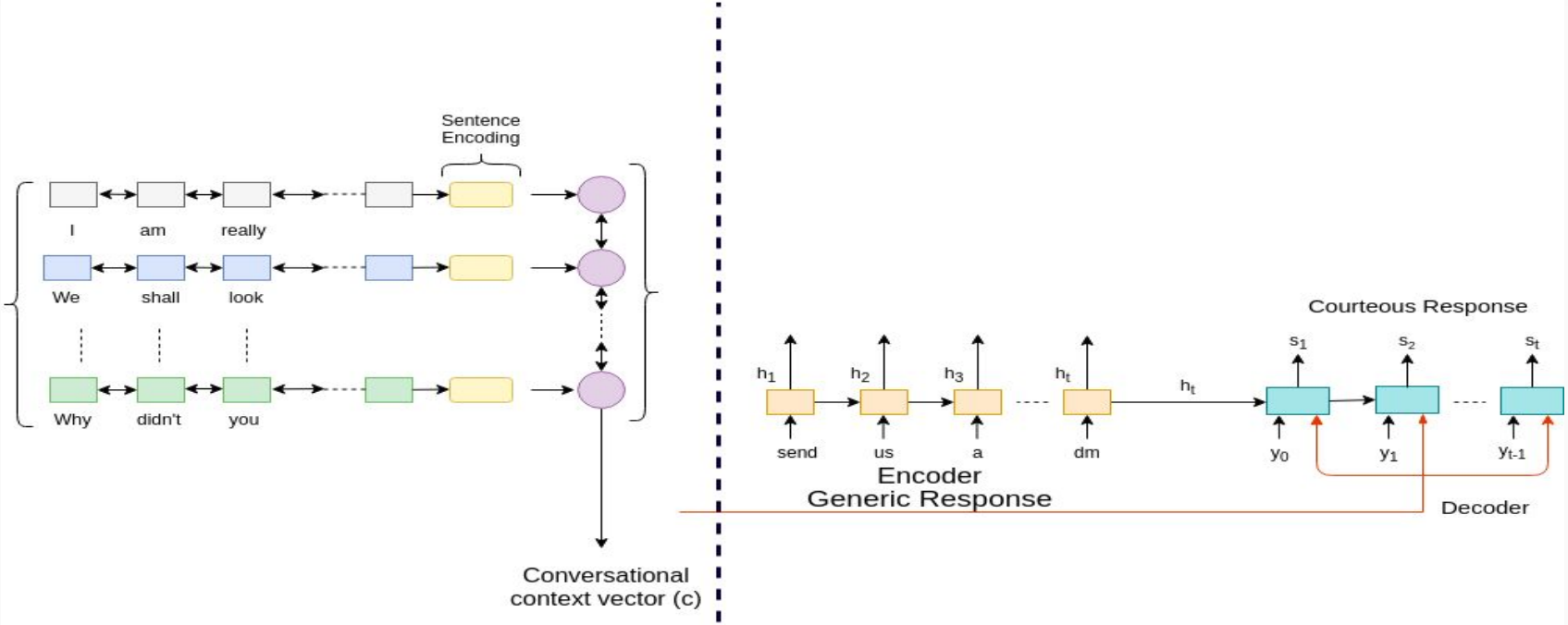
if the customer is angry*, the system needs to *pacify* and *apologize

If they are *happy*, then *appreciate*

Dataset: Statistics

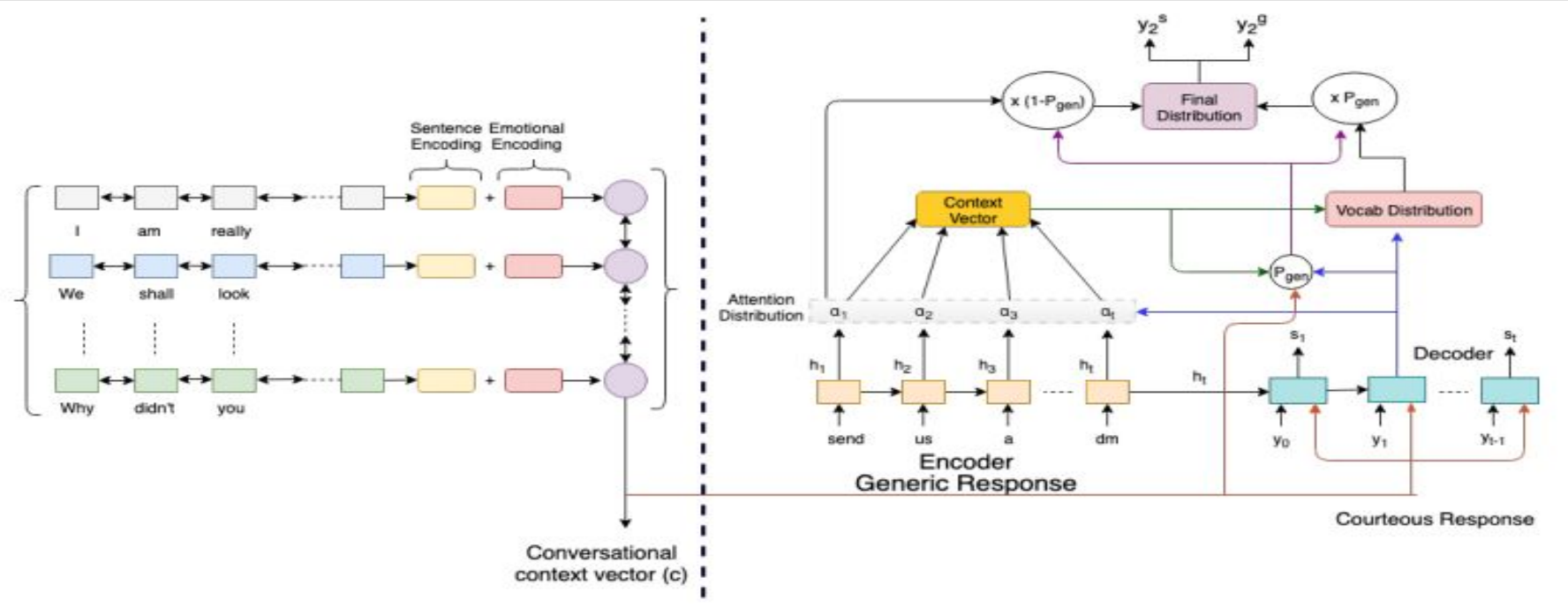
	Train	Validation	Test
# **Conversations**	140203	20032	40065
#**Utterances**	179034	25642	51238

Baseline Model



Input to the Model: Generic Response and Conversational History, Output: Courteous Response

Proposed Methodology



Inputs to the model: Conversation history (left), Generic response (centre), **Output**: Courteous response (right). The Conversation history is encoded by hierarchical Bi-LSTM to a Conversational Context vector *c*. The encoder encodes the Generic Response into hidden states h_i . Response tokens are decoded one at a time. Attention α_i, and vocabulary distributions (p_{vocab}) are computed, and combined using p_{gen} to produce output distribution. Sampling it yields y^s_i and taking its argmax yields y^g_i

Evaluation Metrics: Automatic

- **Content Preservation**
  - Measures how much of the informative content from the original generic response is reflected in the generated courteous response
- **Emotional Accuracy**
  - Measures the consonance between the generated courteous expressions (source of emotion) and the gold
  - Determine the similarity between the emoji distributions of the two responses

Evaluation Metrics: ***Human***

- **Fluency**: Measures whether courteous response is grammatically correct and is free of any errors
- **Content Adequacy**: Measures whether the generated response contains the information present in the generic form of the response and there is no loss of information while adding the courteous part to the responses
- **Courtesy Appropriateness:** Courtesy part added to the generic responses is in accordance to the conversation history

  - Scoring scheme for fluency and content adequacy:
    0-incorrect or incomplete; 1: moderately correct; 2: correct
  - Scoring scheme for courtesy appropriateness
    -1: in-appropriate; 0-non-courteous; 1: appropriate

Evaluation Results- *Automatic*

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

P: Pointer Generator Model; EE: Emotional embedding; PPL: Perplexity; CP: Content Preservation; EA: Emotion Accuracy

- **Observations:**
  - Model-2 is aided by copying mechanism, and hence performance is improved as it can copy portions from generic response and forward to courtesy
  - Model-3 improves the performance by 3.77 (EA) over Model-2 as it can better understand the emotional states and generate more courteous responses
  - Perplexities in Model-3 and Model-4 are more compared to Model-2: may be due to emotional embeddings that confuse generated response from the ground truth

Evaluation Results

Model	F			CA			CoA		
	0	1	2	0	1	2	-1	0	1
Seq2Seq	15.70	42.50	41.80	16.21	41.69	42.10	23.71	51.08	25.21
Seq2Seq + P	14.23	42.77	43.00	15.62	39.65	44.73	22.05	39.43	38.52
Seq2Seq + P + EE	11.15	44.10	44.75	13.66	41.12	45.22	15.23	41.22	43.55
Proposed Model	10.05	44.90	44.60	13.85	38.48	47.67	14.11	41.11	44.78

F: Fluency, CA: Content Adequacy and CoA: Courtesy Appropriateness

01

Politeness and Empathy in Mental Health and Legal Counseling for Victims

Mental Health and Legal Counseling for Victims: Need

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

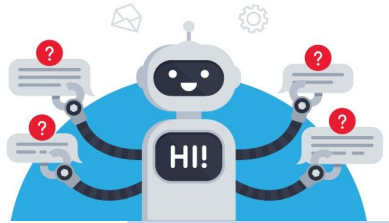
- One-third of the women worldwide have experienced physical and/or sexual violence
- One billion children aged 2-17 have faced some form of violence
- Violence significantly affects their mental health
  - 20% of the global population suffers from mental health probler
- Unaware of legal and human rights
  - 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*
- ★ Victims need special mental health care and treatment as well as legal support

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



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

During counseling, the *Counselor* should employ different counseling strategies as per going 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**. Can 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.

02

Mental Health and Legal Counseling Dataset

MHLCD Dataset

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

1006 mental health and legal counseling conversations

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

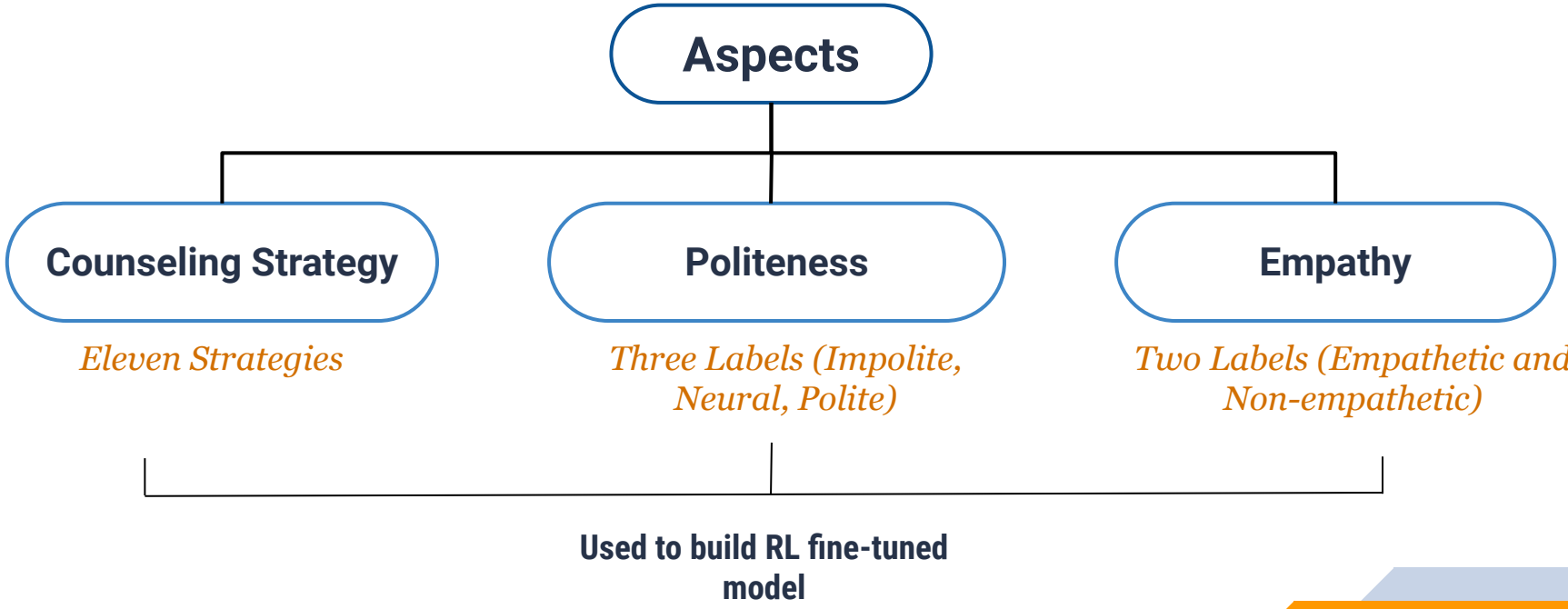
Between two humans

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

11 novel Counseling Strategies

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

Dataset Annotation



Dataset Statistics

Metrics	Train	Validation	Test
No. of Dialogues	755	100	151
No. of Utterances	20886	2795	4163
Average no. of utterances per dialogue	27.66	27.95	27.57

A Sample Conversation

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

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

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

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

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

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

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

Victim: *But how?*

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

Victim: *What kind of routine?*

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

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

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

Victim: *hmm!!!*

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

Victim: *Not now.*

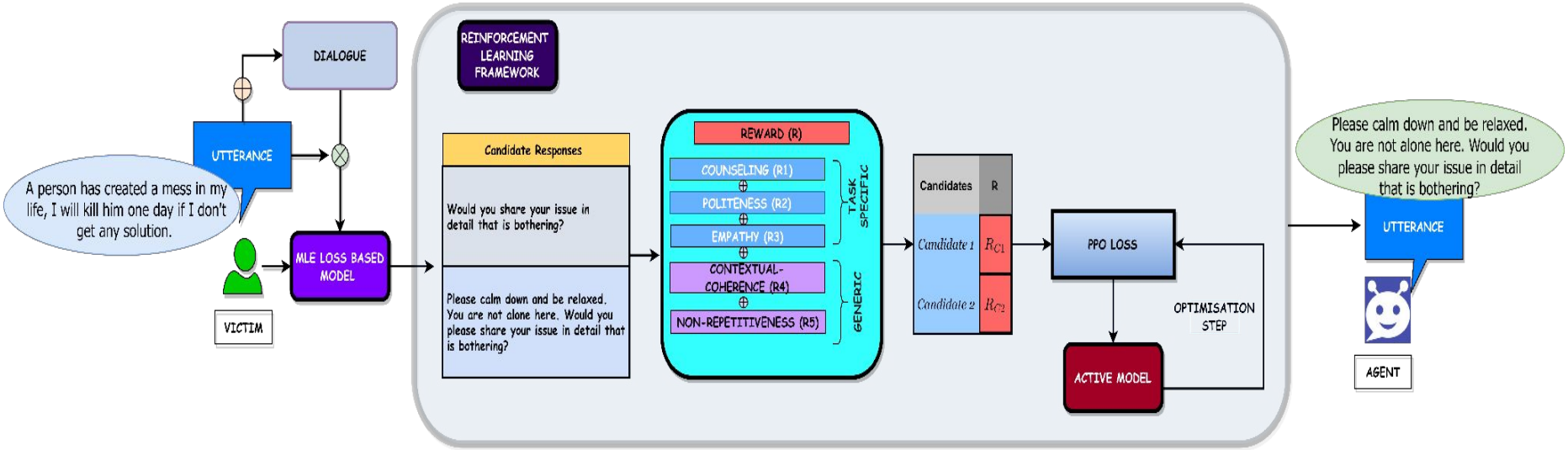
Agent: Great! Kindly be assured we are here for you 24x7. Don't hesistate to reach out to us. Stay safe and healthy!
(reassurance) (non-empathetic) (polite)

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

03

Proposed System

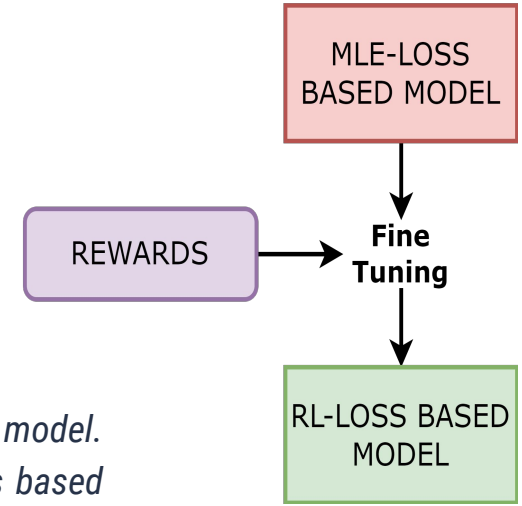
Proposed System: Po-Em-MHLCDS



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

Proposed System: Po-Em-MHLCDS (*contd.*)

A Maximum Likelihood Estimation loss based model is fine-tuned by designing an efficient reward function consisting of different sub rewards: *Task-specific rewards viz.* Counseling, Politeness, and Empathy; and *Generic rewards viz.* Contextual-Coherence and Non-repetitiveness.



Each of the dialogue is approximated through an MLE-loss based dialogue model. Then, at the time of RL-fine tuning, for a given context, this trained MLE-loss based model generates a set of possible candidates which are quality checked through a reward to generate a polite and empathetic counseling utterance.

04

Evaluation Metrics and Results

Evaluation Metrics

Classifiers

- **Weighted Accuracy (W-ACC):** measures weighted accuracy of a classifier, considering all classes.
- **Macro F1:** to account for imbalanced class distribution.

Po-Em-MHLCDS

Automatic Evaluation

- **CoStr:** no. of utterances generated with counseling strategy
- **Pol:** no. of polite utterances generated
- **Emp:** no. of empathetic utterances generated
- **PPL:** measure the perplexity of dialogue agent's utterances
- **R-LEN:** no. of tokens in the generated utterance

Human Evaluation

- **Con:** checks for counseling strategy correctness
- **Pol**, **Emp**: evaluate politeness and empathy of generated responses
- **Const**, **Fluen**, **N-Rep:** to evaluate if the generated utterances are consistent, linguistically fluent and non-repetitive in nature

Results - Classifiers

Models → / Classifiers ↓	BERT-large		RoBERTa-Large	
	W-ACC	Macro-F1	W-ACC	Macro-F1
Counseling Strategy	0.904	0.851	0.923	0.869
Politeness	0.978	0.964	0.990	0.989
Empathy	0.962	0.952	0.977	0.972

Observations:

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

Automatic Evaluation Results - Po-Em-MHLCDS

Models	CoStr (%)	Pol (%)	Emp (%)	PPL	R-LEN
ARDM (Wu et al. 2021)	75.24	89.10	41.30	3.21	16.02
Po-Em-MHLCDS-R	77.13	90.10	42.60	2.87	16.91
Po-Em-MHLCDS	**80.30**	**92.54**	**46.40**	**1.91**	**18.71**

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

Automatic Evaluation Results - Po-Em-MHLCDS

Observations:

- **CoStr**, **Pol**, and **Emp** scores of **Po-Em-MHLCDS** show that counseling strategy, politeness and empathy rewards force the RL-agent to genera polite and empathetic responses grounded in correct counseling strategy.
- Low perplexity score (**PPL**) and longer response length (**R-LEN**) of **Po-Em-MHLCDS** suggest that task-specific and contextual coherence rewards drive the model to establish a connection with the victim in smooth language
  - Generates contextually adequate and fluent responses
  - Interactive and engaging responses

Human Evaluation Results - Po-Em-MHLCDS

Models	Con	Pol	Emp	Const	Fluen	N-Rep
ARDM (Wu et al. 2021)	3.04	3.83	2.13	3.74	4.12	3.87
Po-Em-MHLCDS-R	3.39	3.96	2.28	3.91	4.31	4.11
Po-Em-MHLCDS	**3.94**	**4.41**	**2.85**	**4.16**	**4.57**	**4.72**

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

Human Evaluation Results - Po-Em-MHLCDS

Observations:

- **Con**, **Pol**, **Emp**, **Const**, **Fluen**, and **N-Rep** scores of **Po-Em-MHLCDS** show that contextual-coherence and fluency rewards enable the model to generate consistent, fluent and non-repetitive utterances.
- Politeness and empathy rewards with counseling reward help **Po-Em-MHLCDS** in
  - generating engaging and interactive responses
  - building a rapport with the victim

Conclusions and Future Direction

- Built a polite and empathetic mental health and legal counseling dialogue system, **Po-Em-MHLCDS** to offer higher engagement in e-counseling sessions and resolve the issues faced by the victims
- Created a Mental Health and Legal Counseling Dataset (**MHLCD**)
- **Po-Em-MHLCDS** achieves promising results as compared to strong MLE-loss based baselines.
- In future, we incorporate external knowledge to enable the generation of knowledge-grounded and more realistic responses

M. Firdaus, H. Chauhan, A. Ekbal and P. Bhattacharyya (2021). *More the Merrier: Towards Multi-Emotion and Intensity Controllable Response Generation. In AAAI 2021,* **12821-12829**

What has been done in this work?

- Defining a new task: **Multiple emotion and intensity controlled dialogue generation**
- Created a large-scale Multiple Emotion and Intensity aware Multi-party Dialogue (MEIMD) dataset

- **Proposed architecture**
  - Two **novel memory-based mechanisms** to ensure the incorporation of **multiple emotions** with their corresponding **intensity** in the responses

More the Merrier: Towards Multi-Emotion and Intensity Controllable Response Generation. In AAAI 2021, 12821-12829

Multi-Emotion Generation: *Why is relevant?*

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

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

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

Emotion Intensity in Generation: *Why is relevant?*

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

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

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

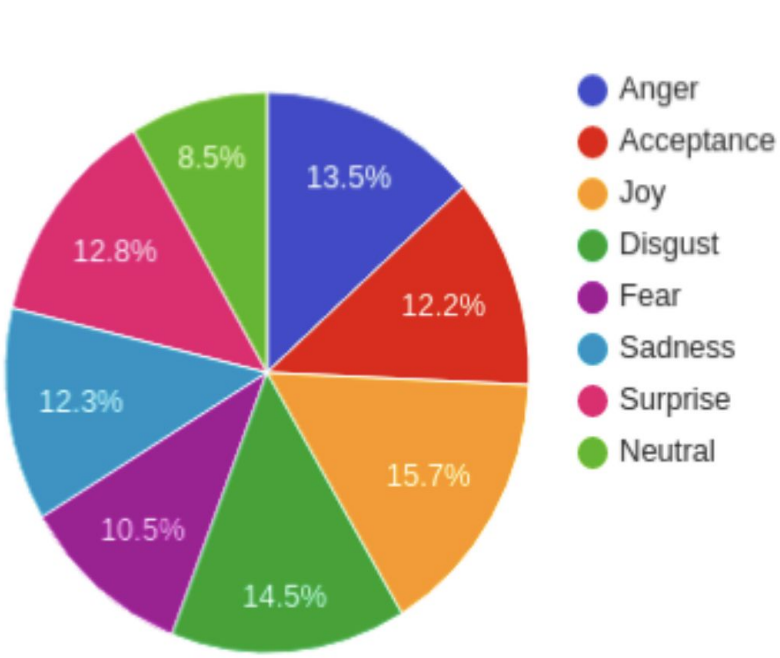
I am afraid but I know you could help me [***Acceptance (0.3), Fear (0.6)***]

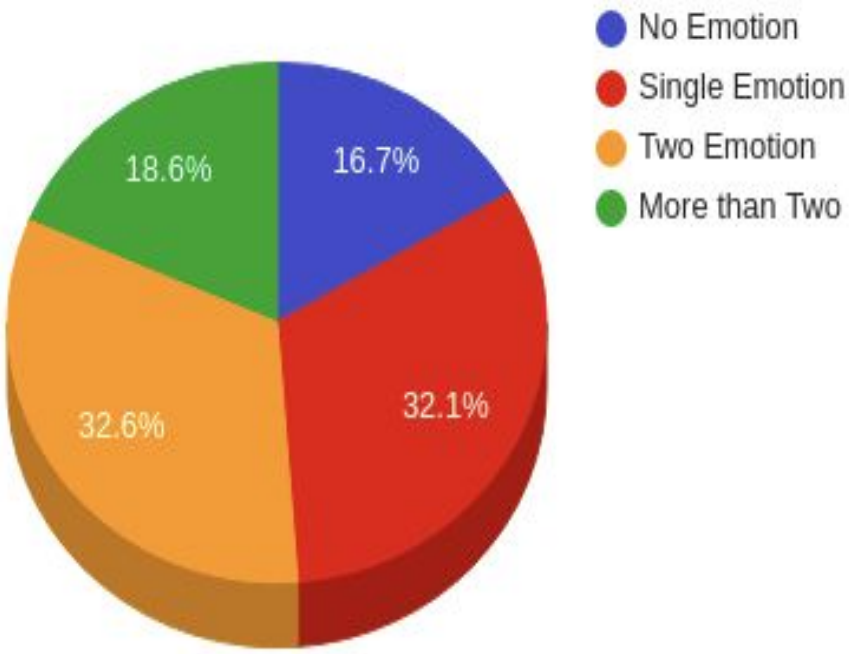
Dataset: MEIMD

- **8 famous TV shows**: 507 episodes, spanning 456 hours
  - ➢ **Drama**: Breaking Bad, Castle, Game of Thrones, Grey's Anatomy, and House M.D.
  - ➢ **Comedy**: Friends, How I Met Your Mother and The Big Bang Theory

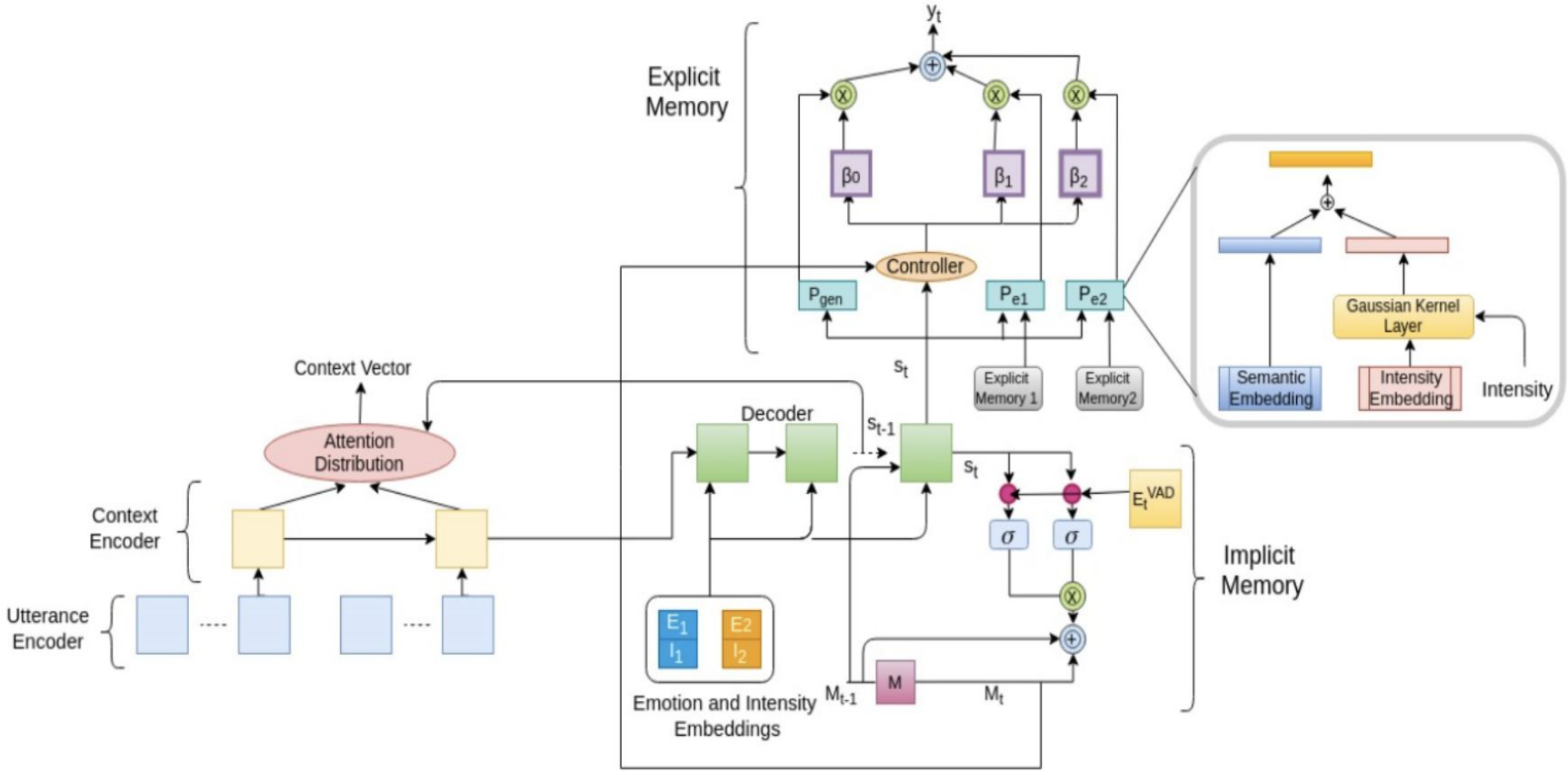
- Every utterance labelled with **emotion** (*multi-label*) and **intensity**
  - anger, acceptance, disgust, fear, joy, sadness, surprise
  - intensity: 0-3

Emotion distribution





Architecture



Evaluation Metrics

- Automatic Evaluation
  - Perplexity
  - Macro-average weighted F1 score for Emotion
  - Pearson correlation coefficient for Intensity
  - Embedding scores-based metrics (*average, greedy, extreme*)
- Manual Evaluation
  - **Fluency**: To check grammatical correctness of the response
  - **Relevance**: To ensure that the generated response is coherent with the dialog history
  - **Emotion**: To judge whether the emotional category of the generated response is consistent with the specified emotions and the dialogue history
  - **Intensity**: To check whether the degree of a particular emotion expressed in the generated response is in accordance to the intensity specified for the given emotion

Results: Automatic Evaluation

Models	***PPL***	***Embedding***			***Emotion Content***	
		Average	***Greedy***	***Extreme***	***E-F1***	***IP-Corr***
No Emotion HRED	80.7	0.491	0.360	0.371	0.39	0.26
Single Emotion HRED + Emb	75.2	0.493	0.361	0.373	0.61	-
ECM (Zhou et. al. 2018)	74.6	0.519	0.375	0.381	0.63	-
EMOTICONS (Colombo et. al. 2019)	74.3	0.523	0.381	0.385	0.63	-
EmoDS (Song et. al. 2019)	74.1	0.526	0.389	0.387	0.65	-
MEI-DG (Ours)	73.9	0.533	0.409	0.399	***0.67***	-
Single Emotion + Intensity HRED + Emb	75.2	0.493	0.361	0.373	0.63	0.44
Affect-LM (Ghosh et. al. 2017)	73.1	0.526	0.389	0.387	0.66	0.50
MEI-DG (Ours)	72.7	0.544	0.419	0.411	***0.69***	***0.57***

Models	***PPL***	***Embedding***			***Emotion Content***	
		Average	***Greedy***	***Extreme***	***E-F1***	***IP-Corr***
Multiple Emotion + Intensity HRED + Emb	73.2	0.498	0.369	0.376	0.57	0.41
HRED + IM	72.9	0.512	0.396	0.413	0.59	0.48
HRED + EM - GK	74.1	0.531	0.412	0.407	0.60	0.43
HRED + EM	73.6	0.539	0.428	0.415	0.62	0.51
MEI-DG (HRED+EM+IM)	***71.2***	***0.552***	***0.443***	***0.428***	0.66	0.54

HRED+EM-GK: model having explicit memory without the Gaussian Kernel(GK); HRED+EM: model having explicit memory with Gaussian Kernel

Observations:

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

Results: Human Evaluation

Models	*Fluency*	*Relevance*	*Emotion*	*Intensity*
No Emotion HRED	3.17	2.89	15.9%	13.6%
Single Emotion HRED + Emb	3.25	2.93	28.3%	-
ECM (Zhou et. al. 2018)	3.45	3.08	36.7%	-
EMOTICONS (Colombo et. al. 2019)	3.48	3.05	37.5%	-
EmoDS (Song et. al. 2019)	3.47	3.12	39.2%	-
MEI-DG (Ours)	3.49	3.13	45.1%	-
Single Emotion + Intensity HRED + Emb	3.52	3.21	32.5%	30.6%
Affect-LM (Ghosh et. al. 2017)	3.58	3.26	41.7%	34.2%
MEI-DG (Ours)	3.69	3.38	***47.3%***	***40.1%***

Models	***Fluency***	***Relevance***	***Emotion***	***Intensity***
Multiple Emotion + Intensity HRED + Emb	3.66	3.33	35.4%	32.9%
HRED + IM	3.71	3.40	40.7%	35.4%
HRED + EM - GK	3.69	3.38	38.6%	33.1%
HRED + EM	3.73	3.41	42.9%	36.8%
MEI-DG (HRED+EM+IM)	***3.82***	***3.48***	43.9%	37.2%

HRED+EM-GK: model having explicit memory without the Gaussian Kernel(GK); HRED+EM: model having explicit memory with Gaussian Kernel

Observations:

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

Generated Outputs

Conversational History	*Model*	*Emotion*	*Intensity*	*Generated Response*
It was an amazing night. You think it looked amazing?	HRED	-	-	Yes, I think so.
	MEI-DG	Joy	0.6	Yes it was really fascinating, I enjoyed it.
	MEI-DG	Joy	0.3	Yes it was a nice night.
	MEI-DG	Sadness	0.3	I found the night gloomy.
	MEI-DG	Sadness	0.9	The whole night I cried all alone
	MEI-DG	Joy, Sadness	0.3, 0.6	It was nice but I terribly missed my friend.
	MEI-DG	Joy, Sadness	0.9, 0.3	The night was really great only had a little trouble in finding cab.

Persona aware Response Generation with Emotions

IEEE Transaction on Affective Computing, 2022

Persona aware Response Generation with Emotions

- Persona aware Emotional response generation
  - System is able to generate emotional, specific and consistent responses
- Every individual has a **personality** and is driven by **emotions**
- **What it does?**
  - Makes the responses interactive and interesting
  - Conversation with a consistent personality helps in bringing **consistency** and **specificity** in responses
  - Facilitates building user's ***trust*** and ***confidence***
  - Infuses the **emotions in the responses** to make these more human-like (as per the ***personality information***)

An example

Persona 1	Persona 2
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'm very athletic. I have brown hair. I love bicycling. I hate carrots.
[Person 1] Hi! I work as a gourmet cook. [Person 2] I don't like carrots. I throw them away. [Person 1] Really. But, I can sing pitch perfect. [Person 2] I also cook, and I ride my bike to work.	

- **Persona 1 and Persona 2** represent the personalized information of Person 1 and Person 2, respectively. The last row represents the ***Dialogue between Person 1 and Person 2***
- Agent maintains **unique personality**, but the conversation is more like **stating facts,** and lacks in **emotional connection**
- Emotion would make it more **engaging** and **human-like**

From the Example

The response of **Person 2** to **Person 1** could be more empathetic like

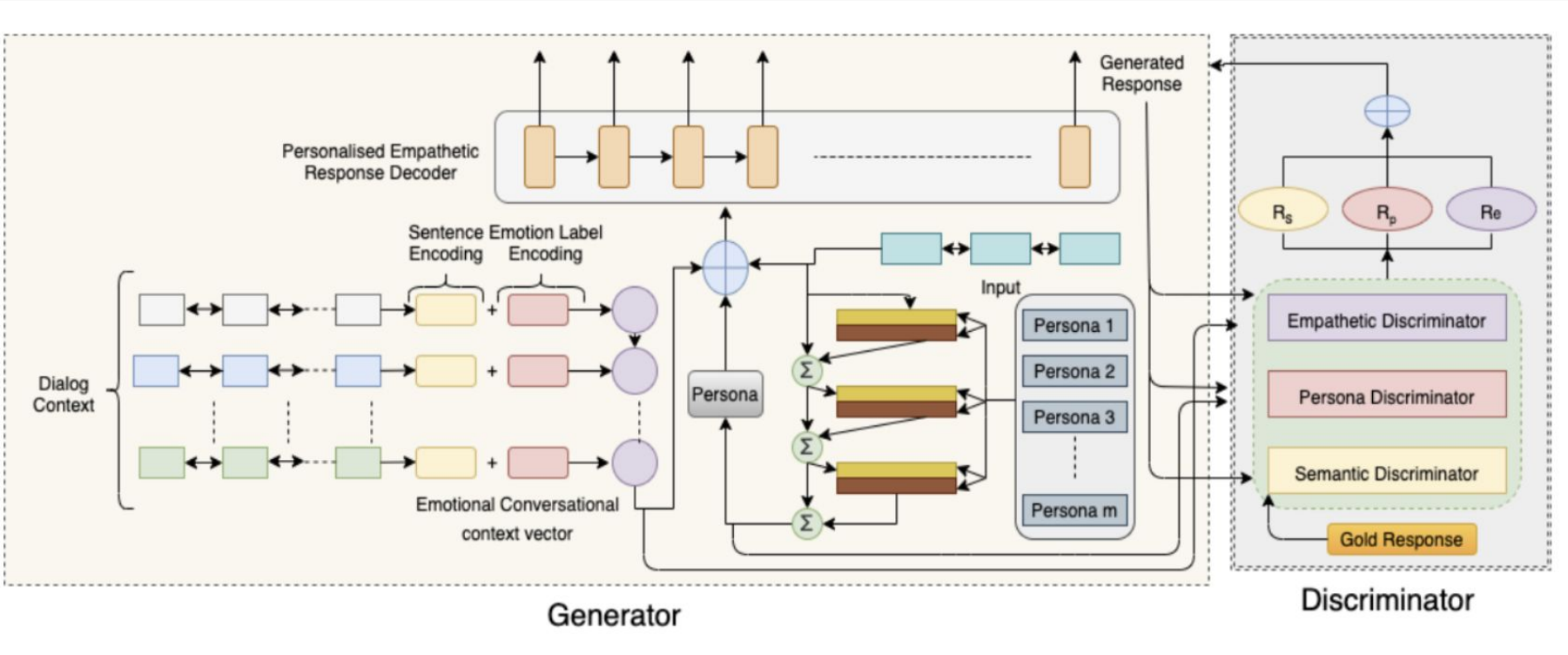
***That's a great job**, but I don't like carrots and throw them away*

Instead of

I don't like carrots. I throw them away

Has a happy undertone than the ground-truth response which is neutral and contains only facts about Person 2

The Architecture



The generator comprises of hierarchical dialog encoder, persona memory network and decoder. While the discriminator comprises of three interactive components

Dataset Statistics

- **ConvAI2 benchmark dataset** (***Logacheva V et al, 2020: Non-goal oriented Human-bot Dialogues***)
  - Extended version (with a new test set) of the Persona-chat dataset

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

Emotion Classification

- Followed a semi-supervised approach for annotating the ConvAI2 dataset with emotions
  - Use Empathetic Dialogues (EmpD) dataset of 25k conversations grounded with emotional situations
  - 32 fine-grained emotions, covering a wide range of positive and negative emotions, such as *surprised, excited, angry, joy, furious, grateful, disgusted, etc*
  - Built several classifiers
  - Best classifier used to classify ConvAI2 dataset with emotions

Model	E-F1
LSTM	37.06
CNN	34.90
Bi-LSTM	39.87
BERT	61.74
RoBERTa	59.89

Evaluation Metrics

★ **Automatic evaluation metrics**
- Perplexity
- BLEU
- Rouge-L
- Emotion Accuracy

★ **Human evaluation metrics**
- Fluency*:* Measures the grammatical correctness of the generated response
- Persona Consistency*:* Takes care of the fact that the response generated is in accordance with the persona information of the speaker
- Emotion*:* Judges whether the generated response is in accordance with the desired emotions

Fluency: 0- incomplete response or else incorrect response, 1- moderately correct response, and 2- correct response

Emotion and persona consistency: 0: for the absence of emotion in the reply and the reply is inconsistent to the specified persona; and 1: for the presence of emotion in the response along with the consistency of the response with the persona information

Generated O/P Examples

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

The EP-GAN generates responses that not only incorporates persona but also makes the response empathetic

A. Mustafa, K. Mishra, M. Firdaus, A. Ekbal (2022). *Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems*, *NAACL-HLT 2022 (Findings)*

What has been done in this work?

- Defining a new task: **Empathetic Persuasion**
- Reinforcing **empathy** and **persuasion** to persuade for charity
- Annotated PERSUASION FOR GOOD dataset with 23 different emotion labels

Proposed architecture

- RL-based dialogue generation framework by designing **an effective reward function** considering **task-specific** and **generic rewards**
- Task-specific rewards: **Persuasiveness** and **Empathy**
- Generic Rewards: **Consistency** and **Non-Repetitiveness**

Empathetic Persuasion: Why is relevant?

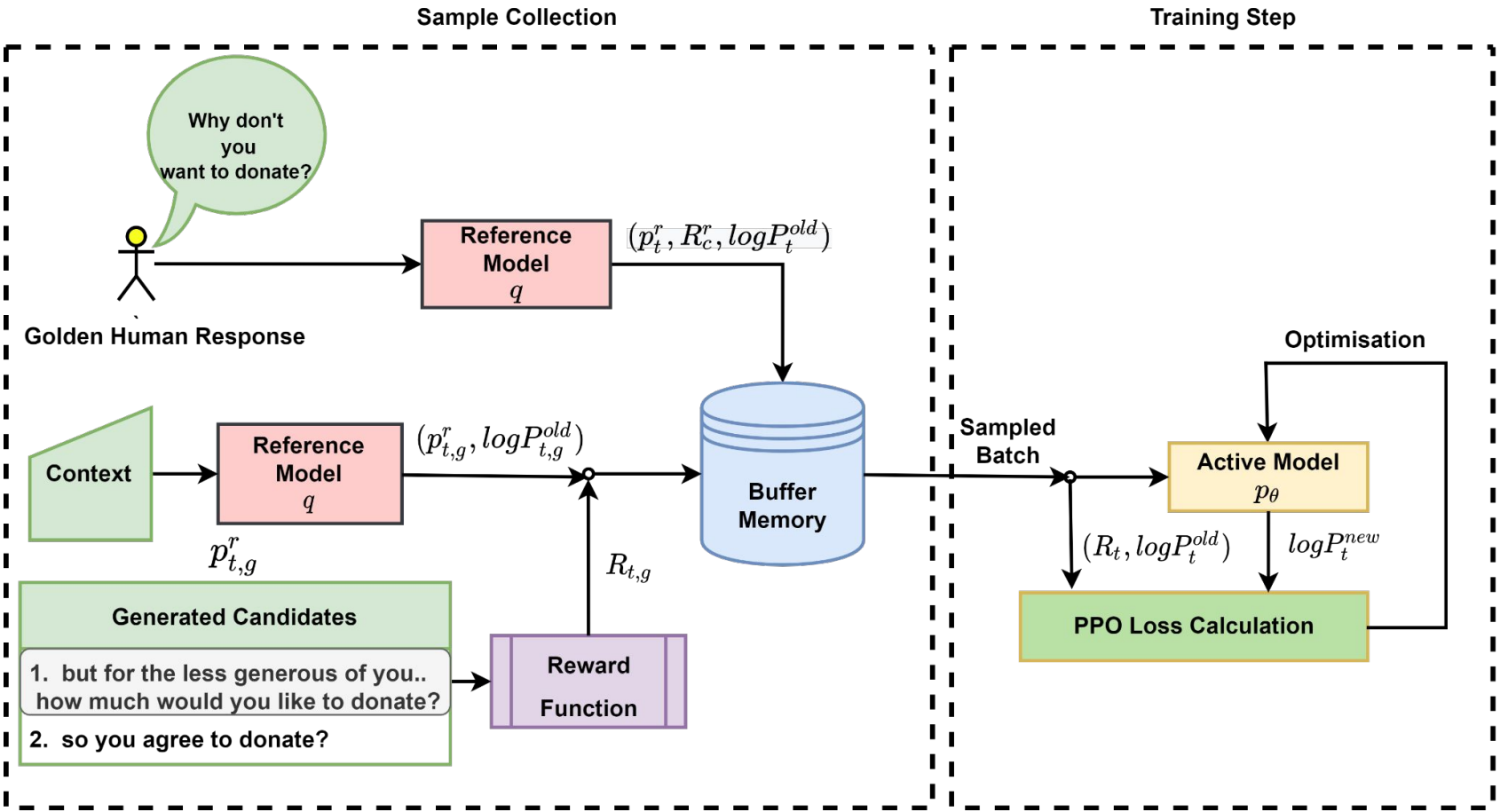
- People are more likely to engage in the conversation when they are motivated with empathetic responses

- **Example**
  - 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?

Dataset

Dataset	No. of Conversations	No. of classes
EMPATHETIC DIALOGUES	25000	32
PERSUASION FOR GOOD	1017	11
Annotated Empathetic Persuasion for Good	385	23

Architecture



Architecture: Details

- **Two models: A Reference Model (RM) and an Active Model (AM)**

- **Reference Model (RM)**: Used for generating response candidate given a context (persuadee utterance)

- **Reward Function:** Calculates rewards for the generated candidates
- Gold Response and generated candidates are stored in the **buffer memory**, and sampled during the training

- **Active Model (AM)**
  - ➢ Outputs the new log probabilities for the sampled batch **using PPO loss calculation** and finally optimisation is performed

Evaluation Metrics

- Automatic
  - **PerStr** - percentage of utterances generated with persuasive strategy
  - **EmoPr** - percentage of empathetic utterances generated
  - **PPL** - to evaluate the generated response quality
  - **LEN** - to evaluate the average number of tokens generated in an utterance

- Manual
  - **Per**, **Emp** - checking persuasiveness and empathy factor in the dialogue based on 1-5 scale
  - **DonPr** - calculates the percentage of time people donated
  - **Cons**, **Fluen** and **Rep** to check the *consistency* (with the dialogue context), linguistic fluency and non-repetitiveness of generated utterance in the dialogue

Results

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

Table 1: Automatic Evaluation Results

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-Pr	3.91	3.51	**0.68**	4.59	4.62	3.89

Table 2: Human Evaluation Results

Results: Observations

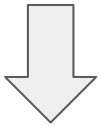
- RL-Emo-Per performs better in terms of PerStr (an improvement of 6.22% and 4.22% from ARDM and RFI)
- Improvements in PerStr show that the responses generated by RL-Emo-Per are more persuasive when incorporated with the empathy factor
- RL-Emo-Per obtains lower PPL than both ARDM and RFI showcasing that it models better probability distribution in generating the utterances
- Human evaluation metrics Per and Emp scores of 3.91 and 3.51, respectively, implies that adding empathetic factor engage users more in the dialogue

Results: An Example

ARDM

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?

RL-Emo-Per



AGENT	How are you?
USER	alright, I am doing good.
AGENT	Do you think there are people who have been out of touch with the world for too long?
USER	Yes I think so, we are so involved in ourselves
AGENT	You are right, I know. I feel like it has become so important to me to help others and to be a part of the solution. What do you think about that?
USER	I think it is very important to help people in need whenever one can.

Ordinal and Attribute Aware Response Generation in a Multimodal Dialogue System. ACL 2019: 5437-5447

The problem we solve

- Multi-modal Conversational System
- **Overall System**
  - **Input**: Text and Image
  - **Output**: Appropriate response

- **Domain**
  - Retail
  - Helps customers to choose their products

- Introduced the novel idea of incorporating the **position** and **attribute-aware attention mechanism**

Motivating Example- I/2 (*Showing importance of position and attributes of image*)

- **Position information is important**
  - 7th Utterance (5th image)
- Incorporate position-aware embeddings to capture ordered visual information
  - To capture the correct image information from text

- **Different attributes of the product are important**
  - 3rd utterance (*blue* color)
  - 7th Utterance (*material* and *style*)
- Incorporate attribute-aware attention
  - To focus and capture different attributes from the image representations

SHOPPER: Hello

AGENT: Hello, is there anything i can help you with today?

SHOPPER: show me some espadrilles in beige/blue within $200.

AGENT: Sure. let me just quickly browse through my catalogue

AGENT:

AGENT: What you can see in the fifth item, michael michael kors brings you an effortless weekend look with the wrapped espadrille heel and crisscross styling of these dana flats. And what you see in the 3rd item, steve madden, the company, was founded by steve madden, the man, in 1990 in brooklyn, where he started out making trend-advancing shoes one pair at a time.

SHOPPER: List more in the upper material as in the 5th image and style as the 3rd and the 5th

AGENT:

AGENT: The 2nd one, viscata espadrilles are 100% authentic and handcrafted in spain inspired by the mediterranean, viscata shoes are lightweight and made of natural jute rope, premium leathers, suedes and woven cloth.

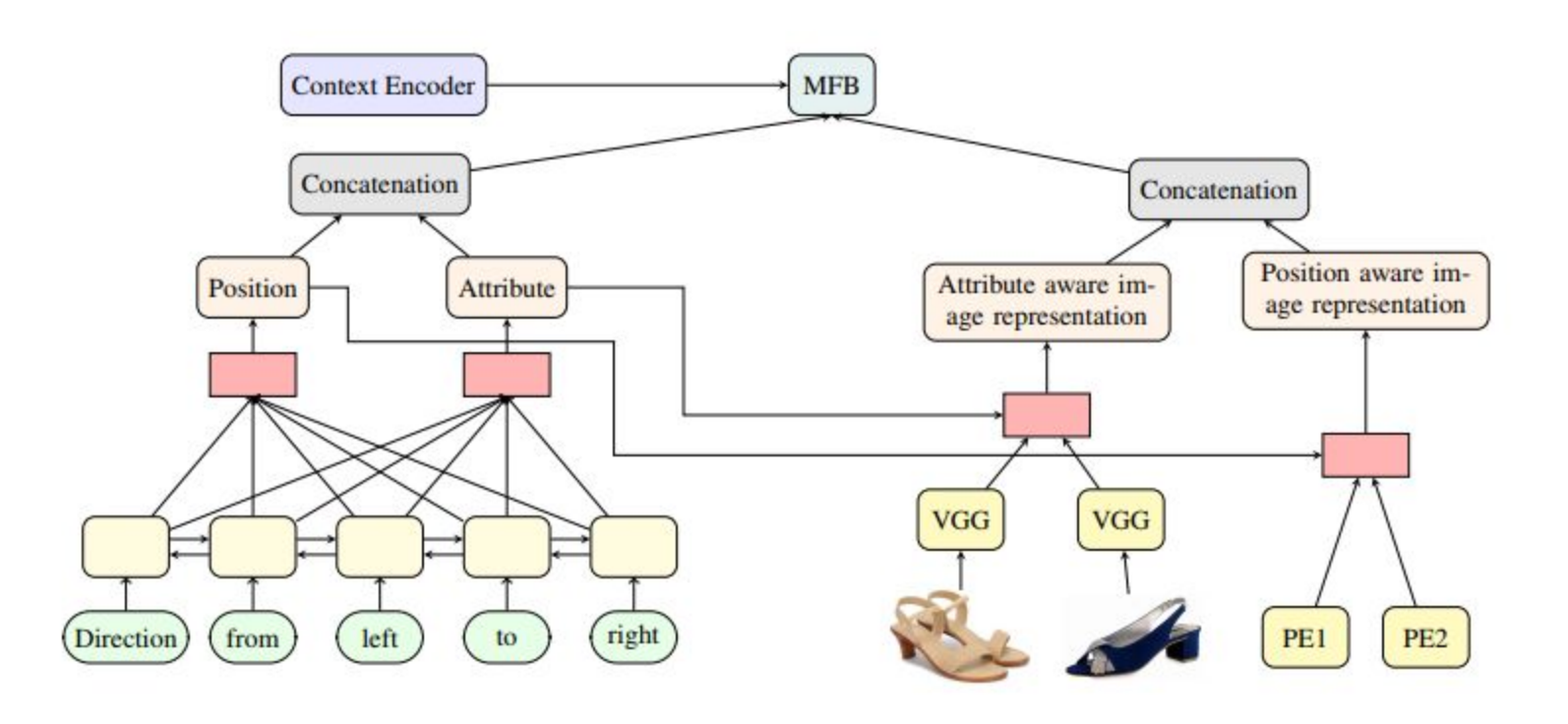
SHOPPER: Can you list images of the 1st result from all orientations?

AGENT: Image from the front,right and back orientations respectively

SHOPPER: And the 3rd one?

AGENT: Image from the front,right,back and left orientations respectively

Proposed Methodology



Proposed Multimodal Encoder with Position and Attribute aware Attention with MFB fusion

Dataset

- Proposed Multimodal Dialogue (MMD) dataset (Saha et. al.)
  - 150K Chat conversations

	Train	Validation	Test
Number of dialogues	105,439	22,595	22,595
Avg. turns per dialogue	40	40	40
No. of utterances with image response	904K	194K	193K
No. of utterances with text response	1.54M	331K	330K

Evaluation Metrics

- **Automatic Evaluation Metrics**
  - BLEU-4 (Papineni et al., 2002)
  - METEOR (Lavie amd Agarwal, 2007)
  - ROUGE-L (Lin, 2004)

- **Human Evaluation Metrics**
  - **Fluency**: Generated response is grammatically correct and is free of any error
  - **Relevance**: Generated response is in accordance to the aspect being discussed (style, colour, material, etc.), and contains the information with respect to the conversational history
  - Scoring scheme: 0-***incorrect or incomplete***; 1-***moderately correct***; 2: ***correct***

Evaluation Results: *Automatic*

Description	Model	BLEU 4	METEOR	ROUGE L
State-of -the-arts	*MHRED-attn (Agarwal et al., 2018a)*	0.4451	0.3371	0.6799
	MHRED-attn-kb (Agarwal et al., 2018b)	0.4634	0.3480	0.6923
Baseline Models	*MHRED*	0.4454	0.3367	0.6725
	MHRED + A	0.4512	0.3452	0.6754
	MHRED + A + PE	0.4548	0.3476	0.6783
	MHRED + PA	0.4781	0.3521	0.7055
	MHRED + AA	0.4763	0.3511	0.7063
	MHRED + PA + AA	0.4810	0.3569	0.7123
	MHRED + MFB(I,T)	0.4791	0.3523	0.7115
	MHRED + MFB(I,T,C)	0.4836	0.3575	0.7167
Our Proposed Model	***MHRED + PA + AA + MFB(I,T)***	**0.4928**	**0.3689**	**0.7211**
	MHRED + PA + AA + MFB(I,T,C)	**0.4957**	**0.3714**	**0.7254**

MHRED: Multi-modal Hierarchical Encoder Decoder, A: Attention, PE: Positional embeddings, PA:Position-aware attention, AA: Attribute-aware attention, MFB (I,T): MFB fusion on image (I) and text (T) representations, MFB(I,T,C): MFB fusion on I,T and context (C)

Evaluation Results- *Human*

Description	Model	Fluency			Relevance		
		0	1	2	0	1	2
Baseline	*MHRED*	18.64	39.66	41.70	13.41	39.83	46.76
Proposed	*MHRED + PA + AA + MFB(I,T,C)*	15.54	42.71	41.75	7.36	38.14	54.23

Observations:

- For **fluency**, MHRED (baseline) and proposed model exhibit similar performance
- For **relevance**, proposed model performs superior (with 7.47% improvement)
  - May be due to the efficacy of our model to focus on the relevant information in the text as well as the image, and generate more accurate and informative responses

Evaluation: *Attention Visualization*

Example 1:

USER: I like the weave in the 3rd one but not the type. Can you show me some more?

Example 2:

USER: I liked the 2nd high tops. Can I see something like it but containing the sole made out of rubber material.

Example 3:

USER: I like the vintage wayfarer style sunglasses but in dark lenses and red frame.

Observations:

- Example-1: Model can focus on the correct image (here, the 3rd image)
- Example-2: Shows the effect of both position and attribute aware attention mechanism (position- 2nd; Attribute: rubber)
- Example-3: Effect of attribute-aware attention is evident (with more focus on the keywords such as *dark*, *red*, *frame*)

Summary and Conclusion

- ***Persona, Empathy, Politeness-*** *The Three* important factors for Persuasive dialogue system
  - Increases human-machine conversational engagingness
  - Can yield a better context-aware, engaging and human-like responses
  - Very useful for many sectors such as retails, customer care centres, healthcare etc.

- Politeness is an important factor to build dialogue systems in customer care, health etc
  - Presented models for incorporating politeness in dialogue agent
- Presented models for handling multiple emotions simultaneously
- Presented models for personalized dialogue generation
- Multimodality provides better evidences
  - Presented a model for multimodal dialogue generation in the retail domain

Conversational AI related Research at IIT Patna

Research on Conversational AI @ IITP-NLP-ML Group

- ***SEVAK-An Intelligent Indian Language Chatbot***
- **Features**
  - Multi-lingual Chatbot
  - **Languages:** English, Hindi, Bengali, Telugu and Code-mixed Languages
  - **Domains**: Railways, Healthcare, Judiciary
  - Integrated to WhatsApp, Facebook and availability via Web Interfacing
- **Beneficiaries**
  - *Primary*: common man - seeking railway, healthcare, and or judiciary related information
  - *Others*: Ministry of Health and Family Welfare, Ministry of Railways and Department of Law and Justice

An Imprint 2A, Govt of India Funded Project
In collaboration with Wipro

Functionalities

1. **Domain Adaptation**
   a. Customisable for any domain
   b. Only domain specific data is required
2. **State-of-the-art**
   a. Deep Learning based architecture
3. **Context understanding**
   a. Uses latest word representation techniques
   b. Keeps track of conversation context
4. **Spell Check and Correction**
5. **Language Support**
   a. English
   b. Hindi
   c. Bengali
   d. Telugu
6. **Modalities support**
   a. WhatsApp
   b. Facebook Messenger
   c. Voice (Automatic Speech Recognition)
   d. Web-based API
7. **Social Media Language (Code-mixed) support**
   a. Hinglish
   b. Benglish
   c. Tenglish

Research on Conversational AI @ IITP-NLP-ML Group

- Autonomous Goal-Oriented and Knowledge-Driven Neural Conversational Agents

- Dynamic Natural Language Generation in Open-domain Setting
- **Natural Language Understanding**
  - DAC, Intent detection, Slot Filling
  - Multi-lingual, Multi-domain, Multi-tasking
- **Dialogue Management**
- **Natural Language Generation**
  - Sentiment-and Emotion -grounded
  - Knowledge-grounded
  - Multi-modal

Selected Publications

1. K. Mishra, A. Samad, P. Totala and A. Ekbal (2022). PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation. In 29th International Conference on Computational Linguistics (COLING), pp. 424-440 October 12-17, Korea
2. M. Firdaus, A. Ekbal and P. Bhattacharyya (2022). PoliSe: Reinforcing Politeness using User Sentiment for Customer Care Response Generation. In 29th International Conference on Computational Linguistics (COLING), 6165-6175, October 12-17, Korea
3. D. Varshney, A. Prabhakar and A. Ekbal (2022). Commonsense and Named Entity Aware Knowledge Grounded Dialogue Generation. In Proceedings of NAACL-HLT 2022, 1322-1335, July 10-15, USA
4. A. Samad, K. Mishra, M. Firdaus and A. Ekbal (2022). Empathetic Persuasion: Reinforcing Empathy and Persuasiveness in Dialogue Systems. In Proceedings of NAACL-HLT 2022 (Findings), 844-856, July 10-15, USA..
5. Zishan Ahmad, Asif Ekbal, Subhashish Sengupta , Pushpak Bhattachharyya (2022). Neural Response Generation for Task Completion using Conversational Knowledge Graph, PLosOne, https://doi.org/10.1371/journal.pone.0259238 (IF-3.752; h5 index: 180)
6. 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

Selected Publications

1. KKshitij Mishra, Mauajama Firdaus and Asif Ekbal (2022). Please be Polite: Towards building a Politeness Adaptive Dialogue System for Goal-oriented Conversations, Neurocomputing, 94, 242-254, Elsevier (IF-5.719; h5 index: 123).
2. K. Misra, M. Firdaus, A. Ekbal (2022). Predicting politeness variations in Goal-oriented Conversations. IEEE Transaction on Computational Social System, IEEE, doi: 10.1109/TCSS.2022.3156580 (IF-4.747; h5 index: 44).
3. Gopendra Vikram Singh, Mauajama Firdaus, Shambhavi, Shruti Mishra, Asif Ekbal (2022). *Knowing What to Say:* Towards knowledge grounded code-mixed response generation for open-domain conversations. Knowledge Based System, Elsevier, 249: 108900 (2022) (IF: 8.038; h5 index: 107).
4. Mauajama Firdaus, Nidhi Thakur, Asif Ekbal (2022). *Sentiment Guided Aspect Conditioned Dialogue Generation in a Multimodal System*. In Proc. of ECIR (1) 2022: 199-214.

Selected Publications

1. M. Firdaus, H. Chauhan, A. Ekbal and P. Bhattacharyya (2021). More the Merrier: Towards Multi-Emotion and Intensity Controllable Response Generation. In *Proceedings of AAAI 2021*
2. D. Vershney, A. Ekbal and P. Bhattacharyya (2021). Modelling Context Emotions using Multi-task Learning for Emotion-Controlled Dialogue Generation. In *Proceedings of EACL 2021*
3. M. Firdaus, A.P Shandilya and A. Ekbal (2020). More to Diverse: Generating Diversified Responses in a Task Oriented Multimodal Dialog System. PLosONE, https://doi.org/10.1371/journal.pone.0241271.
4. M Firdaus, N Thakur, A Ekbal (2020). Aspect-Aware Response Generation for Multimodal Dialogue System. ACM Transactions on Intelligent Systems and Technology (TIST) 12 (2), 1-33.
5. M. Firdaus, N. Thakur and **A. Ekbal** (2020). MultiDM-GCN: Aspect-guided Response Generation in Multi-domain Multi-modal Dialogue System using Graph Convolutional Network. In *Proceedings of EMNLP Findings 2020, PP. 2318-2328*.

Selected Publications

6. Mauajama Firdaus, Shobhit Bhatnagar, Asif Ekbal, Pushpak Bhattacharyya (2018). *A Deep Learning based Multi-task Ensemble Model for Intent Detection and Slot Filling in Spoken Language Understanding*. In proceedings of 25th International Conference on Neural Information Processing (ICONIP 2018); 647-658; Siem Reap, Cambodia, 2018.
7. Hitesh Golchha, Mauajama Firdaus, Asif Ekbal, Pushpak Bhattacharyya; *Courteously Yours: Inducing courteous behavior in Customer Care responses using Reinforced Pointer Generator Network*; In proceedings of Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT 2019); Minneapolis, USA; 2019.
8. Hardik Chauhan, Mauajama Firdaus, Asif Ekbal, Pushpak Bhattacharyya; *Ordinal and Attribute Aware Response Generation in a Multimodal Dialogue System*. In proceedings of 57th Annual Meeting of the Association for Computational Linguistics (ACL 2019) ; Florence, Italy; 2019.
9. Mauajama Firdaus, Ankit Kumar, Asif Ekbal, Pushpak Bhattacharyya; *A Multi-Task Hierarchical Approach for Intent Detection and Slot Filling*; Knowledge Based Systems (KBS), Elsevier, 2019.

Selected Publications

1. Mauajama Firdaus, Shobhit Bhatnagar, Asif Ekbal, Pushpak Bhattacharyya; I*ntent Detection for Spoken Language Understanding Using a Deep Ensemble Model*; In proceedings of 15th Pacific Rim International Conference on Artificial Intelligence (PRICAI 2018); 629-642; Nanjing, China; 2018.
2. M. Firdaus, H. Golcha, A. Ekbal and P. Bhattacharyya (2020). A Deep Multi-task Model for Dialogue Act Classification,Intent Detection and Slot Filling. Cognitive Computation, Springer, https://doi.org/10.10007/s12559-020-09718-4
3. M. Firdaus, A. Ekbal and P. Bhattacharyya (2020). Incorporating Politeness across Languages in Customer Care Responses: Towards building a Multi-lingual Empathetic Dialogue Agent. In Proc. of LREC-2020 , Paris
4. M. Firdaus, N. Thangavelu, A. Ekbal and P. Bhattacharyya (2020). Persona aware Response Generation with Emotions. In Proc of IJCNN 2020 , UK

Thank you for your attention!