Knowledge Enhanced Multi Turn Dialogue System: Past, present and future trends

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Abstract

Humans communicate with each other using sign, speech or written way of communication. Recently dialogue systems are gaining a lot of importance as they can be applied in a wide variety of applications. Humans take help of their general knowledge while conversing. Making machines learn how to converse as humans is difficult, also machines lack general knowledge, emotions which are important features of human nature. Various researchers have tried to add external knowledge to machines which can be used for generating responses which will be in coherent with the given input. Aim of this paper is to consolidate different ways of implementing dialogue system, ways of extracting internal knowledge from input and external relevant knowledge from externally given knowledge fact input, various response generation methods for dialogue system. We also consolidate various recent datasets, metrics available for evaluation of dialogue system. Finally, we propose few research directions which will help researchers to pursue their research in this direction.

Keywords: Dialogue system; Knowledge enhanced; Multi turn; Natural language generation; Artificial intelligence

Introduction

Process that generates natural language using given structured or unstructured data is called as Natural Language Generation (NLG). Reiter and Dale [1] define NLG as the area within computational linguistics and artificial intelligence that focuses on building computerized systems capable of producing comprehensible texts in human languages from some underlying non-linguistic representation of information. NLG can take input in a variety of ways like text, data, image, and video but the output will be in the text. As per Santhanam et al. [20] NLG finds it application in Machine Translation where input is given in one language and it is converted into another language, Dialogue System which is built to provide communication between humans and machines, Story generation where the goal is to generate clear and short text for long videos, Poetry Generation whose aim is to produce a text which can be used as poetry. It is a very challenging task as it should be knowledge-intensive and have to deal with several levels of language, from lexical to semantics, Text Summarization span from a one document to many documents. The document is given as input and a concise representation of the document is available at the output.

According to Reiter et al [2], the three-stage pipelined architecture for NLG consists of text planner, sentence planner and linguistic realization. Text Planner incorporates content determination which determines what information is to be conveyed in the response and discourse planning helps in proper structuring of message so that response understanding becomes easy for user. Sentence planner combines lexicalization which selects proper words to be conveyed in response, referring expression generation and aggregation are also used which helps for generating contextually correct response. Linguistic realizer involves syntactic, morphological, and orthographic processing, so that system produces correct text.

With the recent surges of deep learning technologies, understanding and generating natural language using deep learning model have achieved remarkable performance. NLG is used in the Dialogue system which is a communication between human and machine and can be categorized as Task-oriented dialogue systems and open-domain dialogue systems. Task-oriented dialogue agents are created for a specific task and are programmed to have brief conversations with the user to gather the information that will aid in the completion of the task. Open Domain Dialogue Systems are systems meant for lengthy talks, rather than focusing on a specific activity like ordering plane tickets, they are put up to emulate the unstructured conversational characteristics that are present in human conversation. Generating responses for the dialogue system using only the input text provided sometimes produces bland responses. Hence various researchers have tried to improve the system to generate relevant and coherent responses. Researchers have also explored various verticals for including emotions, personality and knowledge externally to improve systems performance. Knowledge can be categorized as internal hidden knowledge in input or externally given knowledge. Plenty of external knowledge in a variety of formats is available. Hence, diverse methods for finding internal and external knowledge, and incorporating the appropriate information from the internal and external knowledge source into the dialogue system have been proposed for response generation. Adding external knowledge to the system is one of the way for improving performance of a dialogue system and is called knowledge enhanced text generation. There are various ways of incorporating external knowledge into the system and can be broadly categorized as: knowledge base, knowledge graph or grounded text. Main contribution of this paper is to consolidate: (i) Different methods for building dialogue system (ii) Methods for extracting hidden internal knowledge from input (iii) Methods for extracting external relevant knowledge from external knowledge fact (iv) Methods for response generation (v) Various corpora's available for Dialogue System. (vi) Different metrics for evaluation of Dialogue System.

The organization of the paper is as follows: literature survey which includes various methods for building dialogue system, different ways of extracting internal, external knowledge, different methods for response generation of dialogue system, various corpora's available for dialogue system along with different measures used for evaluation of dialogue system. Then we throw a light on various Research directions in this domain which will help researchers to pursue their research in this field and then finally conclude the paper.

Literature Survey

Communication between humans and machines can be for the purpose of some task completion or for entertainment. Conventionally dialogue systems were designed using rule based approaches [8]. Racter [10] is a dialogue system designed which creates prose. Rule based systems sometimes suffer issues like general, non-committal response. Diversity of generated response by dialogue system has been taken care with the boom of machine learning models, but adding characteristics of human nature like understanding, factuality, informativeness and emotions were open challenge until the evolution of neural network models. With the development of neural network-based model researchers have used seq2seq model, contextual response generation, attention mechanism, transformer model for building dialogue system. Seq2seq model does not satisfy criteria for having consistent, semantic and long conversation with user, also it required large amount of training data. Such chatbots might frequently respond with phrases like "I do not know" or "I see." These off-topic replies provide a safe response to various queries, but they are often uninteresting and lack substantial information. Consequently, such responses can swiftly bring the conversation to a close, significantly diminishing the overall user experience. [5] used a conditional Recurrent Neural Network Language Model which uses the contextual information of dialogue for response generation for handling multi-turn conversation. Attention mechanism was proposed in [6] which further improved the performance of the system as it gave importance to different words in input and hence important words were focused to generate response for the given input. Further the development of Dialogue System is supported by advancement in Deep Learning especially transformer based pre-trained Large Language Models.

I) Methods for building a Dialogue system:

Convolution Neural Network(CNN):

Researchers have explored CNN for various applications in image processing [11], speech recognition [12] and Natural Language Processing [13], [14]. CNNs offer several advantages in dialogue systems, particularly in terms of efficiency and feature extraction for short text inputs [15]. However, CNN cannot handle data of varing length, long range dependencies and is inefficient to handle sequential data, hence less suitable for sequential data like dialogue system.

Recurrent Neural Network (RNN):

RNN is used in image classification, image captioning, speech and signal processing [16]. RNNs sequential structure makes it an excellent choice for modeling text sequences as it provides a way to represent the history conversation, in its recurrent connections, thus model's decision will depend on information which is produced in the past and also it can handle input of varying size. As per [9], RNN can model long term dependencies theoretically, but faces issue like vanishing gradient and exploding gradient problem [17] while doing it practically [19].

Long-Short Term Memory (LSTM):

LSTM[18], variant of RNN was designed using various gating mechanisms to analyze important data from input as well as past conversation in dialogue system needed to ensure the correctness of response generation. LSTM uses both short term memory and long term memory for encoding the input and uses gating mechanism to decide what is important to remember and other can be discarded. Encoder is used to encode input into hidden representation, while decoder uses words generated by itself in the past along with the hidden representation of input for generating the output word by word. Sequence-to-sequence (Seq2seq) architecture is widely used for natural language generation along with its use in dialogue systems because it can handle input-output with different lengths. In [20] author presented the Seq2Seq framework using LSTM based encoder-decoder framework.

Hierarchical Recurrent Encoder Decoder (HRED):

In [23] author proposed HRED model which was used for predicting suggestions for next query in web applications in the given session. Author demonstrated that system performance can be improvised by just not considering only recent input but all session history in the given session. Similar idea was mapped to dialogue system domain [24] which showed competing performance with the available state of art models.

Gated Recurrent Unit (GRU):

GRUs were introduced in [21], GRUs use gating mechanisms to control the flow of information, allowing the model to retain and utilize long-term dependencies more effectively. Various attention mechanisms that can be used with sequence-to-sequence model for improving the performance of models for handling sequence based task are summarized in [22]. In [23] author proposed a hierarchical RNN models using GRUs for dialogue systems, capturing dependencies at multiple levels for more coherent multi-turn dialogues. GRUs plays a significant role in the evolution of dialogue systems, offering a balance between simplicity and effectiveness in handling sequential data [25]. Their integration with advanced techniques like attention mechanisms, hierarchical structures has further enhanced their capabilities.

Variational Autoencoder (VAE):

VAE are a powerful tool in the realm of generative models which combines the strength of both probabilistic modeling and deep learning. In [26] author demonstrated that conditioned on the dialogue history Conditional Variational Autoencoders (C-VAE) can be used for generating contextually appropriate but diverse response. [27] introduced a hierarchical Latent Variable Encoder-Decoder model that captured long-term dependencies in dialogues and generated coherent multi-turn responses. Variational autoencoder enhances response diversity, contextual understanding and handling of uncertainty. However, their implementation comes with challenges including complex training and potential issues with response quality.

Generative Adversarial Networks (GAN) and Deep Reinforcement Learning (DRL):

Response generation in traditional models considered only single input for generating response without considering its impact on future conversation. [28] explored the application of Reinforcement Learning for long term success of dialogue in Open Domain Dialogue System by improving user engagement, coherence and response quality of generated responses. Flat RL was also used for achieving specific goals like ordering food, flight booking or scheduling appointments [29]. [30] showed that using hierarchical RL can be used for achieving success in learning dialog policies for composite tasks completion like booking air ticket for travel, rent a car and book a hotel. [31] introduced Generative Adversarial Networks for distinguishing real images from fake images. This idea was picked and applied in Natural Language Processing domain to dialogue system by [32] for open domain dialogue generation, where the model jointly trained two systems, a generative model to produce human like response sequences, while the discriminator model was trained to distinguish between the machine generated and human-generated dialogues. Output of the discriminator were used as rewards for generative model, so that the system generated dialogues resembles human generated dialogues and are not dull and generic. In [33] author presented a novel approach to dialogue generation by transitioning from imitation learning to inverse reinforcement learning (IRL) which was used to understand the rewards that drive human conversational behavior, which are not explicitly provided in the dataset, thus improving the quality and diversity of generated dialogues resembling human nature.

Transformer based:

Complex recurrent or convolutional neural networks with an encoder-decoder are the foundation of the most popular sequence translation models. The top-performing models additionally use an attention mechanism to link the encoder and decoder. The Transformer [34] proposed an innovative sequence modeling architecture called transformer that consists of attention modules and feedforward neural networks. Its self-attention module encodes each word in a text sequence by considering the context, thereby generating richer semantic vector representations for each word. Due to its powerful semantic feature extraction capabilities and parallel processing efficiency, the Transformer has gained significant attention and achieved remarkable advancements across various NLP fields. Pre-trained language models like BERT [35], GPT [36], Text-to-text transfer transformer (T5)[78], BART [79] have marked new era for NLP research.

II) Methods for extracting hidden internal knowledge:

Language understanding means to extract hidden knowledge present in given input. It is important because system should well understand what the requirement of user is before generating response for the given input. There are various ways of extracting hidden knowledge in the given input message. People have attempted it using pattern matching, domain identification and intent prediction. ELIZA [8] used high ranked keywords in the input message. Researchers used domain identification, intent prediction using various machine learning algorithms like SVM classifier [40], n-gram classifier, Naive Bayes classifier and Maximum Entropy classifier [41] for utterance classification. [43] Show that incorporating hierarchical structure in intent improves the performance of system. To bridge the gap between seen and unseen intent and make model learn generalized intent, [42] proposed intent expansion framework, the utterances in training data were used for model training, and the model generates embeddings for both seen and unseen intents without model re-training to predict intents i.e. they used zero-shot learning. [44], [45] demonstrated that machines can be trained to generate personalized consistent responses by embedding personality in seq2seq network which was again demonstrated [46] using transformer architecture. Machines can be trained to generate response depending upon emotional state of machine [47] and politeness was incorporated by [48]. As per [50] abstract meaning representation for dialogue can help better understanding of given input and hence can help improving performance of appropriate response generation. Different approaches like dependency parsing tree of the sentence [39], Transformers for NLU [35], NER using BERT [49][80] are explored. StructBERT was proposed by [53], which incorporates language structures into BERT for better language understanding. [54] proposed TinyBERT with smaller model size, faster inference without hampering the model accuracy. Supervised learning requires large amount of labeled data, to mitigate the issue clustering approach for language understanding [51]. OpenIE tool was explored [55] for extracting ontology from the contextual data for understanding requirement of user.

III) Methods for extracting external relevant knowledge from external knowledge fact:

External knowledge fact comes into variety of format like knowledge base, knowledge graph or unstructured text generally called grounded text. Text documents are unstructured form of data, are large in sizes while same information can also be represented using knowledge base (KB) or knowledge graph (KG) in structured form. A KB represents the knowledge in the form of triplets <subject, relation, object>. A KG(Ve, Ed) consists of all entities e ϵ Ve and edges d ϵ Ed which represents the relationship between all entities in dataset. Delhi is capital of India in the form of triplet is represented as <Delhi, capital_of, India> and in graph form it can be represented as 'Delhi' and ' India as nodes with an edge 'capital_of' between them which represents relationship. Researchers have explored external knowledge sources for response generation in dialogue system [56][57][58][59]. Various ways are experimented by researchers to extract relevant fact from these external knowledge resources using exact matching [60], N-gram matching [66], [71] pattern matching [64], jaccard similarity [63], tf-idf method [64], [71], cosine similarity [62], entity linking [67], SQL and CYPHER [68], SPARQL [61], Memory network [70], transformer [65]. Once the natural language understanding is done and relevant information from external knowledge is extracted, these are presented to decoder for appropriate response generation.

IV) Methods for response generation:

Dialogue system uses various ways of generating response for the given input message from rule-based system to generative based system. In rule based system if user input contains specific pattern then response corresponding to the pattern is provided. ELIZA [8] used pattern matching and replacement methodology for response generation. In template based system, system has predefined templates with placeholders that can be filled with relevant information from the user's input or external knowledge fact. In retrieval based system, a predefined set of responses are stored, and the system retrieves the most appropriate response based on the input. This can be done using similarity metrics or neural models. Generative based system can use sequence-to-sequence model or transformer based model for appropriate response generation. Sequence-to-sequence based models require large corpus for training so that they can generate more appropriate responses, but they fail to generate creative responses. GPT-like models can also be used for generating responses as they are trained on diverse datasets which helps them to generate more contextually relevant, coherent and diverse responses. Hybrid approaches for response generation combine the advantages of both retrieval-based system and generative based system. Retrieval-based systems for handling specific intents, while neural based models for more open-ended responses. Reinforcement learning based model [30] [33] are also used to fine-tune response generation based on feedback from user. System learns to optimize response over time through a reward based system. Transfer learning based model [78][79]uses models which are pre-trained on large dataset for a related task and then fine-tune them for specific dialogue task which help generate more contextually relevant and creative responses as pre-trained model leverages knowledge from diverse sources. People have also explored dialogue system using pre-trained contextual embedding like BERT or ELMo to capture the context of the conversation and generate responses which are contextually relevant. To improve results obtained from models using pre-trained contextually embedding, researchers have also used contrastive learning embedding [84] which works on minimizing distance between similar objects and maximizes distance between dissimilar objects.

V) Various Corpora's available for Dialogue System:

Researchers have made various dialog corpora available to carry work in this direction. Table I. gives details about various dialogue corpora's.

Dataset	Language	Dataset Statistics	Topic	Speaker	Dataset Feature
MultiWOZ	English	Dialog - 10438, average number utterance per dialog - 14	Restaurant, hotel, attraction, taxi, train, hospital, police	Human to Human	Multiple domain and topics
MuTual	Chinese	dialog - 6371, questions - 11323, context response pair - 8860, utterances per dialog - 4.73	Open Domain	Human written	Conversational reasoning (Chinese student for English listening)
BlendedSkillTalk	English	dialog - 6,808, average utterances per dialog - 11.2	Personal, Knowledge, and Empathy	Human to Human	Conversational skills
MultiDoGO	English	dialogs - 40,576 , utterances per dialog - 20.06	Software support, Media, Insurance, Finance, Fast food, Airline	Human to Human	Multi domain
Schema-Guided Dialogue Dataset	English	dialogs - 16,142, utterances per dialog - 20.44	Weather, Travel, Services, Train, Restaurants, Rental cars, payments, messaging, movies, music, media, hotels, homes, flights, events, calendar, Buses, Alarm, Banks	Machine to Machine	Multi domain
CrossWOZ	Chinese	dialogs - 5,012, utterances per dialog - 16.9	Hotel, restaurant, attraction, metro, and taxi	Human to Human	Multi domain
The Gutenberg Dialogue Dataset	English	dialog – 2,526,877 utterances – 14,773,741	Fiction	Human written	Multi domain
Knowledge Enriched Task Oriented Dialogue System -KETOD	English	Dialogs- 5324 Utterances per dialog - 9.78	Weather, Travel, Train, Services, Restaurants, Rental cars, Movies, Music, Messaging, Media, Hotels, Homes, Flights, Events, Calendar, Buses	Human to Human	Multi domain and chit chat dialogue dataset
Fusedchat	english	ODD turns – 60,000, TOD turns – 5,000	Train, Attraction, Hotels, Restaurants, Police, Taxi, Hospital	Human creators	Task oriented dialogue and Open domain dialogue dataset

Dataset	Language	Dataset Statistics	Topic	Speaker	Dataset Feature
OpenViDial 2.0	English	Dialogue turns -5.6M, Visual contexts in images -5.6M	Movies and TV script	Tools and humans	Open domain multi-modal dialogue dataset
ProsocialDialog	English	dialogues -58k, utterances -331K, unique RoTs -160k, dialogue safety labels accompanied by free-form rationales -497K	Handle problematic condition following social norms	Human-AI collaborative framework	multi-turn dialogue dataset
SODA	English	dialog -1.5M, utterances - 11M+	Open domain	Pre-trained Language Model	Open domain
KdConv	Chinese	dialog - 4.5K, utterances -86K	film, music, and travel	Human to human	Multidomain
STC	Chinese	Posts - 219,905, responses -4,308,211	Open topics	Social media (Weibo)	One post multiple responses
Ubuntu Dialog	English	Dialogues -930,000, Turns per dialogue - 7.71, words per turn -10.34	Ubuntu technical issues	Online chat log	Task-specific dialog
PersonalDialog	Chinese	Dialogues - 20.83M, utterances - 56.26M, user profiles -8.47M	Open topics	Social media (Weibo)	Personalization, rich user profiles
CMU DOG	English	Dialogues - 4,112, utterances per dialog - 31.6	30 movies' Wikipedia page	Human to Human	Knowledge-grounded
Holl-E	English	Dialogues - 9,071, utterances per dialogues -10.0, words per turn -15.3	921 movies	Human to Human	Knowledge-grounded
Wizard of Wikipedia	English	Dialogues -22,311, utterances per dialogues -9.0	1,365 Wikipedia articles	Human to Human	Knowledge-grounded
Topical-Chat	English	Dialogues -11,319, turns per dialog - 22, words per turn -19.8	politics, fashion, sports, general entertainment, science and technology, music, books	Human to Human	Knowledge-grounded
Persona-Chat	English	Dialogues - 10,981, Utterances - 164,356	Day to day life	Human to Human	Personalization
DailyDialog	English	dialogs -13,118, turns per dialog -7.9, words per turn -14.6	Day to day life	Web	Emotion and intent
Grounded Response Generation DSTC7	English	dialog-document pairs - 32.7K, utterances - 2.8M, document sentences -17M	Articles from web	Reddit	Knowledge-grounded
OpenDialKG	English	Dialogues - 15,673, utterances -91,209	Movie, book, sports, music	Human to Human	Knowledge-grounded
DuConv	Chinese	Dialogues - 29,858, turns per dialog - 9.1, words per turn -10.6	Films and film stars	Human to Human	Knowledge grounded/Proactivity modeling

Dataset	Language	Dataset Statistics	Topic	Speaker	Dataset Feature
DyKgChat	Chinese English	Dialogues- 1,247/3,092, utterances per dialogue-13.8/18.7, words per turn - 27.0/16.5	TV series	TV series	Knowledge-grounded
Empathetic Dialogues	English	dialogs - 24,850, turns per dialog - 4.31, words per turn - 15.2	Daily life	Human to Human	Emotional/empathetic dialog modeling
Target-Guided Conversation	English	dialogs - 8,939, utterances -101,935, keywords - 2,678	Daily life	Human to Human	Proactivity, behavior and strategy
PERSUASION-FOR-GOOD	English	dialogs - 1,017, turns per dialog-10.43, words per utterance-19.36	Charity donation	Human to Human	Personalization, behavior and strategy
Key-Value Retrieval dataset	English	dialogues - 3031, Average number of turns - 5.25	Calendar, Weather, POI navigation	Human to Human	Multi domain
STC-Sefun	Chinese	Short Text Conversation data set	Open topics	Human to Human	Multiple domain
JMultiWOZ	Japanese	dialogues - 4246, turns -61186	Tourist attractions, accommodation, restaurants, shopping facilities, taxis, and weather	Human to Human	Multi domain

Table I: Corpora's for Dialogue System

VI) Various Metrics for evaluation of Dialogue System:

Human evaluation is best for dialogue system but is very time consuming and not always feasible. Researchers have been using various metrics proposed for different NLP tasks like language translation, text summarization etc. Table II. shows the consolidation of various metrics for different dialogue system task on various datasets explored by various researchers in their studies. Few of the commonly used metrics are listed below:

1. Manual:

People are hired to evaluate the system manually. The disadvantage is that it is expensive, time-consuming and not reproducible. Humans judge the text produced based on qualities like relevance, fluency, appropriateness, informativeness, politeness, consistency, diversity, engagingness etc. generally on the scale of 5.

2. Automatic:

a. BLEU (Bilingual Evaluation Understudy) [72]:

BLEU is automatic evaluation metrics for machine translation text. It is geometric average of the modified n-gram precisions, p_i computed using n-grams up to length N (generally N=4) and positive weights w_i equal weight for all n-grams i.e. ¼.

Geometric Average Precision (N) $= \exp(\sum_{i=1}^{N} w_i \log p_i)$

$$= \prod_{i=1}^{N} p_i{}^{w_i}$$

$$= (p_1)^{1/4} \cdot (p_2)^{1/4} \cdot (p_3)^{1/4} \cdot (p_4)^{1/4}$$

where w_i = weight for n-gram precision of order i
p_i = n-gram modified precision score of order i
N = maximum n-gram into consideration

Let c be the length of the candidate translation and r be the effective reference corpus length. Brevity penalty BP is calculated as follows:

$$\text{Brevity Penalty} = \begin{cases} 1 & if\ c > r \\ e^{(1-\frac{r}{c})} & if\ c \leq r \end{cases}$$

where c = *number of words in the generated/predicted sentence* and
r = *number of words in the gold/ target sentence*

$$BLEU(N) = \text{Brevity Penalty} * \text{Geometric Average Precision Score (N)}$$

Drawback of BLUE is it fails to capture semantic similarity.

b. ROUGE-N (Recall-Oriented Understudy for Gisting Evaluation – N) [73]:

ROUGE-N is a ratio of number of overlapping n-grams between generated response and target responses and number of total n-grams in target responses. ROUGE also fails to capture semantic similarity.

ROUGE-N =
$$\frac{\text{\# of overlapping n} - \text{gram between generated response and target response}}{\text{\# of n} - \text{gram in target response}}$$

c. METEOR (Metrics for Evaluation of Translation with Explicit Ordering) [74]:

Consider the candidate response 'C' and the target response 'T', METEOR is the harmonic mean of precision and recall, where recall is being weighted nine times more than precision. METEOR also uses chunk penalty. A chunk is the set of all unigrams that are consecutive in target response and the candidate response.

$$METEOR(C,T) = F - mean(C,T) * (1 - chunk\_penalty(C,T)$$
$$F - mean(C,T) = \frac{10(Precision(C,T) * Recall(C,T)}{Recall(C,T) + 9 * (Precision(C,T)}$$
$$chunk\_penalty(C,T) = 0.5 * (\frac{\# chunks(C,T)}{\#unigrams\_matched(C,T)})$$

d. Perplexity [75]:

Perplexity is one of the measure used to check how well a model predicts the required response. To predict the n^{th} word, model uses earlier $(n\text{-}1)^{th}$ generated words, models with smaller perplexity are preferred. Perplexity of a model for the given data can be measure as:

$$\text{PPL} = \sqrt[n]{\frac{1}{p(w_1 w_2 w_3 \ldots w_n)}}$$

$$= \sqrt[n]{\prod_{i=1}^{n} \frac{1}{p(w_i \mid w_1 w_2 w_3 \ldots w_{i-1})}}$$

Smaller the perplexity of model better is the model.

e. ADEM (Automatic Dialogue Evaluation Model) [76]:

ADEM is a trained model which takes user input, context, system response and produces a qualitative score between 1 to 5. This metric co-relates well with human judge. It captures semantic similarity beyond word overlap statistics, and also exploits both the context and the reference response to calculate its score for the model response.

VII) Research directions:

1. **Dialogue System for mental health [77]:**

   Day to day life has become very hectic and stressful, there is a rising need of evaluating mental health of people and providing them mental support for making their life happy and easy. Chatbot can serve as a emerging solution for the same as this solution can be cost effective, scalable and made available for broader community.

2. Proactive Dialogue System [83]:

Lot of research has been done in dialogue system, but less explored area is proactive dialogue system where the target to be included in final result discussion is already known but chatbots has to drive the conversation slowly and smoothly towards the target.

3. Dialogue System for toxity reduction and guiding pro-social behavior [81][82]:

Today lot of pre-trained models are available for building chatbots. These pre-trained models are trained with huge amount of data freely available on the internet. Many times the response generated by these models can have toxic data. There is a need to design a system which can reduce toxic behavior if present in dialogue system. Guiding user for pro-social behavior is another vertical which can be explored for human wellbeing.

4. Group users Dialogue Systems:

Generally chatbots are designed for one-to-one communication. Many times users communicate in groups. There is need of chatbot which can be used for group discussions or for various tasks like calendar setting for all members of family, meetings at work or even for class of student in some university.

5. Recommendation Dialogue System ensuring ethics and privacy system [37]:

Chatbots can be used to extract specific need and preference of user and accordingly recommend marriage councilors, doctor or any other requirement of user which will make a perfect vertical for future research. Conversation AL system built should be able to set trust among its users so that users share their personal and sensitive information during conversation with system is another area of upcoming research.

	BLEU	Human Evaluatiom	METEOR	Perplexity	Distinct-N	Accuracy	Phoneme Recognition Rate	Precision	Recall	F-score	Dialogue-Act Match	Cosine distance	Dialogue Length	Diversity	Success rate	Average rewards	Avg. turns per dialogue	Classification error rate	Word error rate	Hits @1	correlations	Joint goal accuracy	Inform and success	ROUGE	Mean reciprocal rank
WMT'14 English to French dataset	[3] [6] [20] [21]			[6]																					
IT Helpdesk Troubleshooting dataset		[4]																							
OpenSubtitles dataset		[4][28]											[28]	[28]											
Twitter	[5]		[5]																						
WMT 2014 English-German	[6]			[6]																					
Chinese dataset from Baidu Tieba		[7]		[7]	[7]																				
ImageNet ,						[11]																			
CIFAR10 , C						[11]																			
IFAR100						[11]																			
TIMIT acoustic-phonetic corpus							[12]																		
Twitter dataset						[13]		[13]	[13]	[13]															
Movie Review dataset						[13]		[13]	[13]	[13]															
STC-SeFun dataset						[14]				[14]															
WMT 2015 English-German	[22]			[22]																					
Switchboard (SW) 1 Release 2 Corpus	[26]										[26]	[26]													
Ubuntu Dialogue Corpus		[27]																							
Twitter dialogue corpus		[27]																							
Frames		[30]													[30]	[30]	[30]								
The MovieTriples dataset	[33] [48]	[33] [48]		[48]	[33]														[48]						

	BLEU	Human Evaluatiom	METEOR	Perplexity	Distinct-N	Accuracy	Phoneme Recognition Rate	Precision	Recall	F-score	Dialogue-Act Match	Cosine distance	Dialogue Length	Diversity	Success rate	Average rewards	Avg. turns per dialogue	Classification error rate	Word error rate	Hits @1	correlations	Joint goal accuracy	Inform and success	ROUGE	Mean reciprocal rank
SMD	[39] [49] [56] [57] [58] [59] [68]	[58]	[49]			[49] [57]				[39] [49] [56] [57] [58] [59] [68]	[68]												[68]		
MultiWoz	[39] [55] [59] [68]									[39] [59] [68]	[68]											[55]	[55] [68]		
ATIS Corpus																		[41]	[41]						
Twitter Persona Dataset	[44]	[44]		[44]																					
Twitter Sordoni Dataset	[44]	[44]		[44]																					
Television Series Transcripts	[44]	[44]		[44]																					
Personal Dialog		[45]		[45]	[45]	[45]																			
PERSONA-CHAT dataset				[46]						[46]										[46]					
Emotional STC conversation dataset		[47]		[47]		[47]																			
Stanford Politeness Corpus																									
Soccer dialogue dataset	[49] [58]	[58]	[49]			[49]				[49] [58]															
GLUE benchmark						[53] [54]				[53] [54]											[54]				
the SNLI Corpus						[53]				[53]															
SQuAD v1.1 QA dataset						[53]				[53]															
Camrest	[55] [59] [68] [70]	[70]								[59] [68] [70]	[68]											[55]	[55] [68]		
The bAbI dialog	[57] [68]					[57]				[57] [68]	[68]												[68]		
DSTC2	[57]					[57]				[57]															
Wizard of Wikipedia	[61]				[61]				[61]															[61]	
REDIAL	[61] [67]			[67]	[61] [67]				[61] [67]															[61] [67]	

	BLEU	Human Evaluatiom	METEOR	Perplexity	Distinct-N	Accuracy	Phoneme Recognition Rate	Precision	Recall	F-score	Dialogue-Act Match	Cosine distance	Dialogue Length	Diversity	Success rate	Average rewards	Avg. turns per dialogue	Classification error rate	Word error rate	Hits @1	correlations	Joint goal accuracy	Inform and success	ROUGE	Mean reciprocal rank
Reddit dataset	[62] [66]	[62] [66]		[62]										[66]											
DSTC9	[65]	[65]	[65]					[65]	[65]	[65]														[65]	[65]
OpenDialKg	[68]									[68]	[68]												[68]		
SODA		[69]																							
KETOD									[71]	[71]												[71]			
Empathetic Dialogues dataset	[82]	[82]		[82]																				[82]	
Prosocial Dialog	[82]	[82]		[82]																				[82]	

Table II: Metrics used for evaluation of Dialogue System

6. Multilingual Chatbots:

Most of the chatbots are generally designed for single language and majority English, chatbots handling multiple language and avoiding language biasing is a need of hour so that facility can be made available to broader class of audience.

Conclusion:

Thus we have consolidated review on knowledge enhanced dialogue system to facilitate improved text generation. We have reviewed different ways of implementing dialogue system, extracting internal knowledge and external knowledge, response generation methods, various dialogue corpora's available along with different metrics used for evaluation of different tasks of dialogue system and finally conclude the paper with upcoming research challenges which will facilitate various researchers aspiring to work in this domain.

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