Recent advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP), particularly the latest developments of OpenAI products such as ChatGPT and GPT-4, have highlighted the importance of research on dialogue systems. These rapid improvements have also emphasized the importance of human-like dialogue systems and demonstrated the potential benefits they could bring to our daily lives. Existing work on this topic is divided into two main categories: task-oriented and open-domain dialogue systems. Task-oriented dialogue systems are designed to assist users in performing various daily tasks (e.g., searching for information, booking a train ticket, or reserving a hotel room). Apple's Siri, Amazon's Alexa, and ChatGPT, to a degree, are noteworthy examples of such systems. Therefore, dialogue systems follow a set of pre-defined conversational topics in the task-oriented setting. In addition, these systems have clear goals and objectives at each stage of the conversation. Therefore, their performance on these defined tasks is measurable and can be assessed through standard evaluation metrics such as accuracy and precision.

On the other hand, open-domain dialogue systems, also known as conversational agents or chatbots, are designed to converse with users about various topics. The main goal of chatbots is to model human behavior in their daily conversations, imitate these behaviors in a natural and engaging manner, and accommodate users' needs by providing companionship and entertainment. Contrary to the task-oriented setting, conversations with conversational agents are not about specific pre-defined topics and could contain subjects of all backgrounds. In addition, there are no boundaries for the discussed topics in the open-domain setting. Hence, due to the open-ended nature of conversations with such systems, they are beneficial across various essential services, such as emotional and mental health support. However, there are no clearly defined goals or objectives for open-domain dialogue systems, making the data collection, model design, and evaluation process highly challenging.

A vital trait of human behavior in daily conversations is our ability to empathize with others. Through our conversations, we can acquire the different perspectives of others, observe the world from their point of view, realize the implications regarding their situation and feelings, and respond in a manner that makes them feel heard and understood. Therefore, empathy enables us to feel emotions and experiences through others, even in situations we might not have encountered before. In addition, empathy is an important ability in human conversations that creates trust and rapport between individuals [1]. It is essential for human-like dialogue systems to possess such traits, particularly in applications that support individuals. In these applications, empathetic systems could also appear more engaging as they could be perceived as caring and understanding agents [2]. This highly desired feature enables users to perceive chatbots as potential companions.

Empathy is a considerably new concept in psychology, adopted from the German word Einfühlung, first proposed in 1986 [3]. Given the relative recency of this term in English and its abstract nature, there is no well-established and globally accepted definition of this concept in the literature [4], and many scholars have proposed their interpretations [1]. However, the mutual ground between these interpretations considers empathy as a complicated construct with various dimensions that could be broadly defined through two aspects: affective and cognitive empathy [5], [6]. Affective empathy enables us to simulate the emotions of others, which facilities the understanding of their feelings [7]. In contrast, cognitive empathy focuses on understanding the implications and constraints regarding the situation of others and their cognitive states [8]. Therefore, as empathy's affective and cognitive aspects are complementary and essential for realizing empathy, they should be considered when developing an empathetic dialogue system.

Research on empathetic dialogue systems has received growing attention in the NLP community to their potential benefits. However, most existing work defines empathy as the ability to understand the emotion of others and respond appropriately [9]. Thus, they only focused on implementing the affective aspect of empathy. For instance, the most widely-used dataset for this task, EmpatheticDialogues [10], has 32 emotion labels for each conversation and proposes generating empathetic responses according to these labels. In addition, Lin et al. proposed a mixture of experts model that would learn each available emotion type (e.g., sadness, happiness, and anger) separately [11], while Majumder et al. analyzed and designed when, how, and to what intensity does an empathetic dialogue system needs to mimic the user's emotions [12]. There have also been efforts to incorporate external knowledge bases, such as conceptual knowledge from ConceptNet [13], to understand the user's emotions better and respond empathetically [14]. However, the literature has yet to explore implementing cognitive empathy in empathetic dialogue systems.

In many situations, individuals do not explicitly state every detail about their situation, as most of the required information is expected to be understood by both parties. Therefore, such information is implied. As humans, we leverage our commonsense knowledge (i.e., the ability to assess, judge, and understand the world in a logical and practical manner) to draw these implications about a person's situation. For instance, if a person tells us that they have lost much weight, although not explicitly mentioned, we could imply that they must have worked hard and followed a diet. On the contrary, dialogue systems only have access to what the user has mentioned in the conversation (i.e., no access to commonsense knowledge), which prevents them from understanding the relative implications of the user's situation and, in turn, makes them unable to express cognitive empathy.

In this thesis, we hypothesize that by leveraging commonsense knowledge for understanding situational implications and realizing cognitive empathy, we could enable dialogue systems to generate more empathetic responses. These systems would need access to external commonsense knowledge about world facts and daily events and learn to consider empathy's affective and cognitive aspects to generate responses. To this end, we propose the **c**ommonsense-aware **em**pathetic dialogue system (CEM). Accordingly, we conduct substantial experiments, including automatic mathematical metrics and human annotations, to evaluate our model's performance and analyze its improvements compared to previous work. Our experimental results demonstrate that the proposed model outperforms existing approaches, generating more empathetic responses and higher user satisfaction rates.

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