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Contents

Deep Learning for Dialogue Systems: Chit-Chat and Beyond

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ABSTRACT

With the rapid progress of deep neural models and the explosion of available data resources, dialogue systems that supports extensive topics and chit-chat conversations are emerging as a research hot-spot for many communities, e.g., natural language processing (NLP), information retrieval (IR), and machine learning (ML). Building a chit-chat system with retrieval techniques is an essential task and has achieved great success in the past few years. The advance of chit-chat systems, in turn, can support extensive IR tasks, e.g., conversational search, conversational recommendation. To facilitate the development of both retrieval-based chit-chat systems and IR tasks supported by these systems, we survey chit-chat systems from two perspectives: (1) techniques to build chit-chat systems, i.e., deep retrieval-based models, generative methods, and their ensembles, (2) chit-chat components in completing IR tasks. In each aspect, we present cutting-edge neural methods and summarize the core challenges encountered and possible research directions.

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1

Introduction

Starting from the 1960s, conversational artificial intelligence has become a crucial research field and has grabbed much more attention in recent years. Empowered by deep neural models, dialogue systems have demonstrated very impressive and appealing performance in virtual assistants and social bots. In viewing its potential and values, mainstream NLP, IR, and even ML communities have started contributing to dialogue systems. Dialogue systems can be roughly grouped into two classess, i.e., task-oriented and chit-chat systems. The former group focuses on completing predefined tasks with task-specific constraints and goals, e.g., restaurant booking and making calls. The later systems are mainly designed for modeling the 'chats' characteristic of human-human conversations (Daniel and James, 2020) without specific goals and constraints, i.e., the topics of the conversation could be any. Given predefined constraints and goals, task-oriented systems can achieve impressive performance with limited data and computational resources. In contrast, chit-chat systems require massive training conversations to mimic human chatting with extensive topics. Unlike task-oriented systems that have achieved great success for decades, learning-based chit-chat systems have not made great strides until recent years with the explosion of both data resources, model capacity (data modeling capability of deep neural networks), and computational power. To facilitate the development of chit-chat systems and their supported IR tasks and bridge the gap between different research communities, especially for the NLP and IR fields, we propose to systematically review state-of-the-art chit-chat systems and draw the connections between chit-chat and tasks, from being supporting tasks and the unified modeling framework in the paradigm of pre-trained language models.

Specifically, our work has a deep concentration on deep neural chit-chat systems using IR techniques and NLP methods, i.e., this paper presents lessons and experiences of how to establish relevant, coherent, diverse, knowledgeable, and human-like chit-chat systems. Besides, we also discuss the connections between chit-chat systems and tasks, ranging from the perspectives of treating chit-chat components as supporting tasks to make task completion more natural (e.g., recommendation) to the trend of leveraging unified framework for various downstream tasks in the era of pre-trained language models. To the best of our knowledge, it is the first survey paper to cover these topics and features.

The main contributions of this survey are as follows:

- We thoroughly survey the deep neural models in recent years for chit-chat systems, ranging from retrieval-based methods to generation-based approaches and ensemble of retrieval-based and generation-based models.

  We provide the connections between the recently resurgent chit-chat systems and task-oriented systems, e.g., conversational recommendation and conversational search, which enables us to explore more possibilities of building either better chit-chat systems or improving user experience in constructing IR systems.

- We introduce various solutions for addressing or mitigating the confronted challenges (e.g., context modeling, one-to-diversity, human factors learning) from different perspectives, including data-side and model-side solutions and utilization of extra resources.

- We present necessary data resources and evaluation methods for building retrieval-based and generation-based chit-chat systems.

We also analyze the main challenges that we are facing and give the possible exploration directions and the rising trends, which will shed light on building human-like systems.

1.1 Intended Audience and Scope

This survey is intended to bridge the researchers of IR and the NLP community to move chit-chat systems forward and support more IR tasks. Our target audience includes, but is not limited to, IR or NLP researchers who want to study chit-chat from different perspectives, e.g., compensating retrieval-based models with the generation or vice versa, IR researchers who need to complete their tasks with the assistance of chit-chat systems, engineers with hands-on experience in building chit-chat systems to leverage advanced chit-chat modeling techniques, anyone who intends to quickly keep up with the frontier of chit-chat systems, anyone who want to learn how to build chit-chat systems with deep neural architectures.

The main scope of this paper is based on the tutorial of SIGIR 2019 and WWW 2019 (Wu and Yan, 2019b; Wu and Yan, 2019a). We expand the tutorial contents with up-to-date techniques for building chit-chat systems, covering retrieval-based methods, generation components, and their ensembles. Besides the above contents, we also discuss the role of chit-chat systems in completing tasks, especially for some emerging IR tasks, e.g., conversational search and conversational recommendation. Considering the new trend of utilizing a unified self-supervised pre-training framework for both chit-chat and IR tasks, we further review a few recent works in this line and point out the possible future direction.

The rest of this survey is structured as follows:

- The remainder of this chapter summarizes the importance of chit-chat systems and presents the core problems of chit-chat systems. Besides, the landscape of chit-chat systems is also introduced. At the end of this chapter, we clarify the relationship and discrepancy between this survey and recent papers.

- Chapter 2 briefly reviews classic chit-chat systems before the neural age, including rule-based, template-based, and learning-based methods, and summarizes the characteristics of these methods.

- Chapter 3 sorts out and elaborates retrieval-based dialogue systems in recent years. This chapter starts with the pre-processing of conversation data and then discusses the core problems of retrieval-based chit-chat systems in detail (e.g., context modeling, knowledge utilization, human factors learning), which ends with necessary data resources and evaluation metrics for building retrieval-based chit-chat systems.

- Chapter 4 provides an alternative option for building chit-chat systems, i.e., generation-based methods, focusing on the pros and cons of generation-based methods in building chit-chat systems and their relationships with retrieval-based solutions. The last part of this chapter gives essential data resources, evaluation methods, and current challenges.

- In Chapter 5, we describe the ensemble of retrieval-based and generation-based methods, focusing on the scenarios of integration and re-ranking, template and prototype, and adversarial learning. Chapter 6 connects chit-chat systems with tasks, including vanilla tasks and newly appeared IR tasks like conversational search, and reveals the trend of unifying chit-chat dialogues and tasks with large-scale pre-trained language models.

- Chapter 7 first concludes this survey with the progress of chit-chat systems and the chit-chat component in IR tasks, and then points out the ongoing struggles and the possible future trends.

1.2 The Importance of Chit-Chat Systems

Chit-chat systems have become more and more popular and important in both academia and industry. Studying chit-chat systems have various benefits, including providing helpful services to human users, promoting the development of artificial intelligence technologies, holding tremendous potential and commercial values in the future.

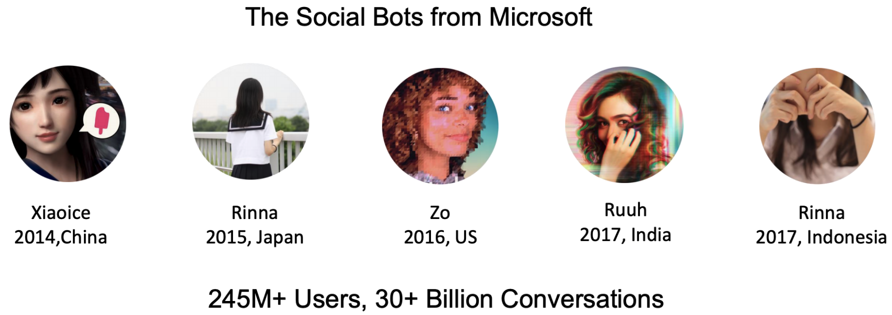

Figure 1.1: User size of social bots from Microsoft (Wu and Yan, 2019b).

To human users, chit-chat systems can satisfy a myriad of human needs, such as communication, social belongings, emotional engagement, etc (Huang *et al.*, 2020b). On account of these merits, various applications, including but not limited to virtual assistants, smart speakers, social bots, and virtual customer services, are developed. As shown in Figure 1.1, chit-chat systems from the Microsoft corporation alone attracted over 245 million users and achieved over 30 billion conversations by 2019.

As for the connections between chit-chat systems and technology development, it is an indicator to calibrate the progress of artificial intelligence by launching the Turing test which is designed to test whether a machine can exhibit intelligent behaviours equivalent or indistinguishable from a human.[1]. Building chit-chat systems also poses various unique challenges to state-of-the-art deep neural models, e.g., one-to-diversity, long-range context modeling, topic shift, long-term engagement computation, human factors learning, and the settlement of these problems, in turn, facilitates the progress of deep learning methods and encourages technical development.

Except for contributing to technology development and human needs, chit-chat systems also connect to various online commercial services. As demonstrated in Figure 1.2, chit-chat conversation might mix with goal-oriented demands, such as question answering, image search, and recommendation. Exploring chit-chat conversations could

[1] https://en.wikipedia.org/wiki/Turing_test

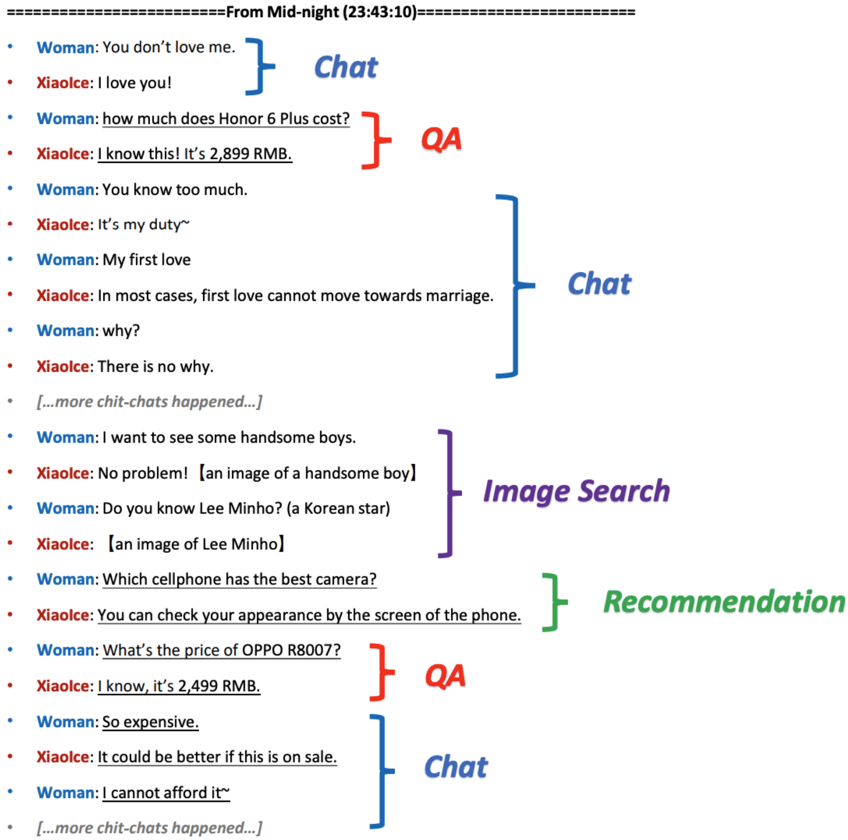

Figure 1.2: A case study that demonstrates the connections between chatbots and goal-oriented applications (Wu and Yan, 2019b).

seamlessly find the demands of users and complete different tasks in a more efficient manner accordingly, i.e., without introducing multiple task-specific systems. It also serves an essential role in intelligent entities and devices by providing the human-machine interface. The progress of chatbots could assist the development of robotics.

With the rapid progress of conversational AI techniques that support human-like interactions between computers and humans, it can be imaged that chit-chat systems are likely to have more industrial applications and broad market prospects. We believe that the potential of these systems is far more than we have seen in recent few years on social bots, virtual assistants, information seeking systems. In the far future, conversational AI systems might change almost everything in our daily life, e.g., the games will be more immersive, robotics are more intelligent that is able to sing, talk and even make friends with humans.

1.3 The Core Problems of Chit-Chat Systems

One of the main goals of chit-chat systems is to pass the Turing test so as to prove that an artificial program can chat like humans. Thus, the properties of human conversations should be considered and modeled in chit-chat systems. Seeing that human conversations are intricate and difficult to formulate, we utilize the qualitative analysis results of human conversation properties in Daniel and James, 2020 to divide and shape the core problems of chit-chat systems. There are mainly six basic properties for human conversations: (1) **turns**, (2) **speech acts**, (3) **grounding**, (4) **sub-dialogues and dialogue structure**, (5) **initiative**, and (6) **inference and implicature**. For deep neural models trained on massive conversation data, **speech acts** and **dialogue structure** are implicitly modelled by neural networks. As for **initiative**, **user-initiative** and **system-initiative** frameworks are more common for task-specific systems while **mixed initiative** are very difficult to achieve. Thus, researchers mainly focus on the following problems in deep neural chit-chat systems.

Context Modeling. One of the main challenges we encountered is the long-range context modeling. Unlike task-oriented conversations that mainly consist of task-specific contents and usually complete a user demand in no more than a few dozens of conversation turns, chit-chat conversation is tied up with over hundreds of turns in usual, owing to the non-goal-oriented nature of chit-chat. In view of this, long-range context modeling has become a crucial issue for chit-chat dialogues to make conversations more consistent and coherent.

One-to-Diversity. In addition to multi-turn context modeling, one-to-diversity has also hindered the development of chit-chat systems. Unlike task-oriented conversations that take task completion as the evaluation metric, chit-chat further needs to mimic human-like conversations. Among various characteristics of human conversations, modeling expression diversity and one-to-many correlations bear the brunt.

Knowledge and Grounding. Beyond learning statistical patterns from existing human conversations, advanced chit-chat systems are expected to master and leverage knowledge like human beings. Besides commonsense knowledge, chit-chat conversations often correlate with noncontextual information, i.e., information and content that are not in context. Hereafter, we denote these extra information as grounding.

Human Factors. For chit-chat systems, user experience and engagement are always the core. To build a better chit-chat system, we have to consider the influence of various human factors, such as personalized expression preference, emotional changes, and beyond.

1.4 Landscape of Chit-Chat Systems and Beyond

A View from Chit-Chat. Advanced chit-chat systems mainly utilize cutting-edge deep neural techniques to automatically obtain responses for any newly given query or dialogue contexts. We group existing chit-chat models into three categories, i.e., retrieval-based frameworks, generation-based models, and the ensemble of retrieval-based and generation-based solutions. Retrieval-based frameworks mainly study how to automatically select feasible response candidates, covering the multi-turn context matching, extra resource utilization, human factors constraining, and pre-trained context-aware representation usages. Generation-based researches focus on the limitations of sequence to sequence networks, exploring from the perspective of data manipulation, generation pipelines, training objectives, large-scale pre-trained language models, and aforementioned context modeling, as well as human factors. Ensemble solutions investigate how to compensate retrieval-based dialogue systems with the merits of generation models and vice versa.

Linking Chit-Chat with Tasks. The connections between chit-chat and tasks can be categorized into three different directions. One is to discover and complete specific goals from chit-chat human-machine conversations to achieve better user engagement. The second is to enhance downstream tasks with chit-chat components, e.g., it can make it easier for users to accept recommended items from commercial recommendation systems. Another possible direction is to utilize a unified large-scale pre-training framework to complete chit-chat conversations and tasks.

1.5 Comparisons with Existing Surveys

Recently, there has been several tutorials and survey papers on deep learning for dialogue systems. Yih *et al.*, 2015, Yih *et al.*, 2016 and Gao, 2017 reviewed a wide range of IR and NLP tasks driven by deep learning techniques, including question and answering (QA) and dialogue systems. Li and Yan, 2018 presented an overview of the multi-turn human-computer conversations shared task on NLPCC 2018. Chen *et al.*, 2018b provided a tutorial on spoken dialogue systems, which is mainly about traditional task-oriented dialogue systems. Serban *et al.*, 2018 offered a thorough investigation about the public data available for building dialogue systems. Gao *et al.*, 2019a covered a myriad of topics in dialogue systems, including question answering, reading comprehension, task-oriented systems, social bots and industrial applications. Huang *et al.*, 2020b comprehensively studied three challenges that researchers are facing at present in building intelligent dialogue systems. Yan and Wu, 2021 briefly summarized the progress and future of chit-chat dialogues with limited coverage and insufficient in-depth study. Zamani *et al.*, 2022 recently provided an overview of existing research related to conversational information seeking. Gao *et al.*, 2022 also wrote a book about conversational information seeking but focused on recent advances and technical details for building the main modules of conversational information retrieval systems. Considering that deep neural-based systems are the mainstream and are still in the process of development, we mainly compare this paper with recent surveys in closely related fields. More concretely, we conduct comparisons with two recent papers presented by Gao *et al.*, 2019a and Huang *et al.*, 2020b, respectively.

This survey differs with Gao *et al.*, 2019a from the following aspects:

- We mainly focus on chit-chat systems rather than focus on task-oriented systems, question answering, and machine reading comprehension.
- We group recent researches from the view of chit-chat, a specific type of conversation system that has attracted millions of users, instead of connecting goal-oriented dialogues and fully data-driven social bots from a unified perspective of optimal decision making.
- We mainly survey end-to-end methods built upon deep learning methods, instead of presenting task-oriented pipeline models or connecting traditional machine learning methods with modern neural models.
- We expose the recently explosive progress of completing tasks with the assistance of chit-chat systems, e.g., conversational recommendation (Lei *et al.*, 2020). We review the new paradigm of building chit-chat systems and completing tasks in recent large-scale pre-trained language models.

Compared with the short survey written by Huang *et al.*, 2020b, we further present the following contents.

- Instead of focusing on surveying researches that relate to specific challenges of chit-chat systems, we present a comprehensive study of modern chit-chat systems based on deep neural models.
- Except for discussing the main challenges that we are facing, this survey presents various solutions for addressing a myriad of challenges in the chit-chat conversations, which can provide guidance for anyone who wants to build chit-chat systems.
- This paper also has a border coverage, which draws the connection between chit-chat and goal-oriented systems, and emerging tasks of the IR community.

2

Classic Dialogue Systems before Neural Age

This chapter briefly reviews the representative dialogue systems before the neural age, including rule/template-based systems and learning-based solutions.

2.1 Rule-Based Methods

Starting from ELIZA (Weizenbaum, 1966), the chatbot has become one of the important branches of building intelligent programs. Among various solutions, rule(template)-based methods take the dominant role from the era of ELIZA and the ensuing decades. This section takes ELIZA as the representative to demonstrate how to utilize limited rules to construct a program that can have certain types of natural language conversation with humans. Figure 2.1 presents a part of the conversation example in Weizenbaum, 1966 for simplicity. We take the user-issued utterance "You don't argue with me." as an illustration to explain how ELIZA responds. The first step is to detect the target keyword "you" from the user-issued utterance, where each word in the utterance is looked up in a dictionary of keywords, and the highest-ranked one of the identified

TELL ME MORE ABOUT YOUR FAMILY

My mother takes care of me.

WHO ELSE IN YOUR FAMILY TAKES CARE OF YOU

My father.

YOUR FATHER

You are like my father in some ways.

WHAT RESEMBLANCE DO YOU SEE

You are not very aggressive but I think you don't want me to notice that.

WHAT MAKES YOU THINK I AM NOT VERY AGGRESSIVE

You don't argue with me.

WHY DO YOU THINK I DON'T ARGUE WITH YOU

You are afraid of me.

DOES IT PLEASE YOU TO BELIEVE I AM AFRAID OF YOU

My father is afraid of everybody.

WHAT ELSE COMES TO YOUR MIND WHEN YOU THINK OF YOUR FATHER

Bullies.

DOES THAT HAVE ANYTHING TO DO WITH THE FACT THAT YOUR BOYFRIEND MADE YOU COME HERE

Figure 2.1: A typical conversation between chatbot ELIZA and human user, where the capitalized lines are the machine responses (Weizenbaum, 1966).

keywords is selected as the target [1]. Then, each decomposition rule that contains the target keyword "you" is tried. For example, a specific template associated with the keyword "you" decomposes the utterance

`You don't argue with me.`

into:

`You 0 me.`

where "`0`" stands for indefinite number of words. Certain transformation rule is then involved to translate (`You 0 me.`) as:

`I 0 you.`

with the reassemble rule (tacking with a prefix "Why do you think"):

`Why do you think I 0 you`

Finally, ELIZA outputs "WHY DO YOU THINK I DON'T ARGUE WITH YOU" for the user-issued utterance. Through analyzing the

[1] If there is no matched keyword in the dictionary, the system will output non-committal responses.

above conversation, typical rule-based techniques in ELIZA can be summarized as:

- The identification of the target keyword (in the keyword vocabulary and with the highest-ranked score) from the given utterance.
- Linking keyword with associated decomposition rules.
- Choosing proper transformation rule.
- Selecting reassemble rule utilized for creating response to the user-issued utterance.
- Designing provision mechanisms that can deal with unexpected cases, e.g., responding utterance without matched keyword with non-committal responses such as "I see" (Daniel and James, 2020).

As pointed out by Weizenbaum, 1966, the success of such chatbot to simulate a Rogerian psychologist is owing to the rare dyadic natural language communication in which one of the participating pair is free to assume the pose of knowing almost nothing of the real world. For example, if the chatbot (as the psychiatrist) responds "Tell me about boats" to the user-issued utterance "I went for a long boat ride", one would not assume the chatbot didn't know what a boat is but assume that the psychiatrist has specific conversation goals.

Later on, Colby *et al.*, 1971 utilize a chatbot, namely PARRY, to behave a paranoid person. On the basis of ELIZA's chatting capability, PARRY further models agent-level affections, i.e., fear and anger. Some conversation topics might make PARRY accumulate anger, while other topics will cause more fear. With two variables to present the degree of fear and anger, PARRY can respond with different affection states. Since chatting like a paranoid resembles ELIZA as a Rogerian psychologist and with more capabilities, PARRY is the first chatbot known to pass the Turing Test. Most of the following chatbots trying to pass the Turing test choose similar and more favorable settings. Even some modern chatbots are still based on the influential architecture of ELIZA.

After ELIZA and PARRY, many efforts have been devoted to optimize the techniques of rule-based chatbots (Bradeško and Mladenić, 2012). Weintraub, 1986 introduces parsing to augment keyword identification and propose to improve pattern matching and word vocabulary, which won the Loebner Prize Competition from 1991 to 1993. Other strategies of better parser, pattern matching, extra databases (Hutchens, 1996; Wallace, 2003; Copple, 2008). More rule-based methods can be found in Thorat and Jadhav, 2020.

2.2 Learning-Based Methods

Since writing rules is very tedious and it is also difficult to cover most conversation situations, learning-based methods have been widely explored (Shawar and Atwell, 2005; Schatzmann *et al.*, 2006; Thorat and Jadhav, 2020). Note that this section only quickly reviews a few representative learning-based dialogue systems before the deep neural age. Litman *et al.*, 2000 use the formalism of Markov decision processes and reinforcement learning (RL) algorithms to learn dialogue policy. Williams, 2007 model a spoken dialog system as a partially observable Markov decision process that can unify and extend multiple techniques to form a single principled framework. Ritter *et al.*, 2011 use phrase-based Statistical Machine Translation method to generate a response for a linguistic stimulus. Misu *et al.*, 2012 also utilize reinforcement learning to build dialogue policy but focus on a specific application.

Compared with rule-based solutions, the merits of learning-based methods are two-folds. For one thing, learning-based methods can automatically complete conversation procedures without much hand-crafted efforts like ELIZA by capturing matching patterns and correlations between user-issued utterances and possible responses, generating responses with learned assemble strategies, and editing or creating responses as the provision mechanism. Thus, learning-based methods can be directly adapted to new scenarios with training corpora in short time as it does not take too much time to write various types of rules. For another, learning-based methods can scale up to large size data to capture more patterns, as a result of which they can handle more conversation situations failed in rule-based systems in which there are no matched rules.

2.3 Reconsider the Problem

Compared with rule-based methods and learning-based solutions, the former category is more efficient for data-scarce situations and can efficiently deal with straightforward queries from users, while the latter one has the merits of dealing with uncovered rules/patterns well without much hand-crafted efforts and is easier to transplant to new domains.

On the one hand, with the explosion of online available conversation-like data (e.g., posts on Twitter, Weibo) and the demands of chatbot from millions of netizens, it is very costly and even unlikely to manually write conversation rules for specific types of dialogue with myriads of topics, domains, and users. On the other hand, learning-based methods are not mature yet, which usually outputs irrelevant responses for user-issued queries, leading to low trust and user experience. Another challenge of learning-based methods is figuring out what to optimize because simply mimicking human responses is insufficient in many scenarios and applications. In view of this, rule-based methods are still the mainstream of commercial and industry dialogue systems, while researchers are never ceased to address the limitations of learning-based methods. One of the most important directions of learning-based methods is to learn more from explosive data with a powerful model to capture sophisticated correlations, conversation patterns, and also representations, e.g., using deep models rather than shallow learning-based methods in previous studies. To make the best use of the merits of learning-based methods, another possible aspect is to study fully end-to-end chatbot framework. Most progress of chatbots in recent few years mainly concentrates on these two aspects, i.e., deep learning-based end-to-end models, which will be elaborated in the following chapters of this survey.

3

Retrieval-Based Chit-Chat Systems

This chapter presents the essential and widely used paradigm in real-world applications, i.e., retrieval-based chit-chat systems. The success of these systems correlates with the social attribute of human beings and the availability of massive human conversation data. That is, different people might pursue similar needs from chit-chat systems, such as emotional engagement, counselling, personal assistant, etc. Owing to the convenient access of web information, e.g., Twitter, Facebook, TikTok, people also have similar hotspot topics to converse with. Besides, human beings can share commonsense knowledge with others. Based on these phenomena and observations, it is feasible to retrieve a proper response from existing conversations for a given user query and corresponding dialogue context. With the ubiquitously available resources and powerful retrieval engine, building a retrieval-based chit-chat system has gained increasing interest in recent years.

We start this chapter with an introduction to the paradigm of retrieval. We then present the essential indexing and pre-retrieval process before retrieving and ranking the response candidates with a matching neural model. Later on, we discuss the common challenges and advanced solutions of retrieval, including history modeling, extra information

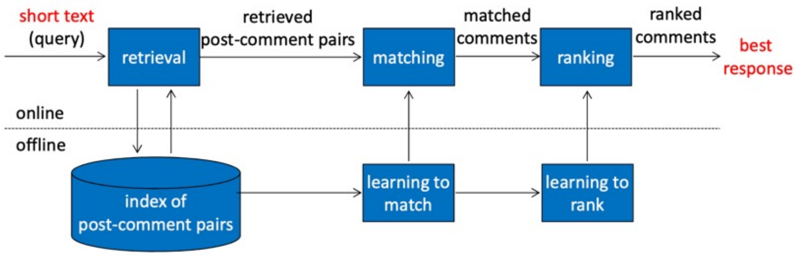

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Figure 3.1: System architecture of retrieval-based short text conversation (Ji *et al.*, 2014).

utilization, human factors learning, and pre-trained language models. We end this chapter with evaluation metrics for building a retrieval-based dialogue system.

3.1 The Paradigm of Retrieval

In most cases, we can obtain a correlated response from existing conversation data by powerful retrieval engine and matching models. These retrieved responses are created by human beings, which are grammatically fluent and contain informative content. Leveraging these existing conversations as system outputs makes dialogue systems perform like humans.

For each query, the retrieval system needs to select a proper response from millions of conversation utterances. It is natural to launch a coarse-to-fine retrieval pipeline. That is, the system first conducts pre-retrieval from existing conversations with a powerful engine and then utilizes a deep neural model to perform a fine-grained selection from the retrieved candidates. In other words, most of the existing retrieval-based dialogue systems can be decomposed into two stages, i.e., the simple and fast pre-retrieval and the sophisticated candidate ranking.

3.1.1 Indexing and Pre-Retrieval

The primary retrieval-based methods respond to human input by selecting a response from a pre-built index (Ji *et al.*, 2014). Specifically, Ji *et al.*, 2014 break down the retrieval-based short text conversation

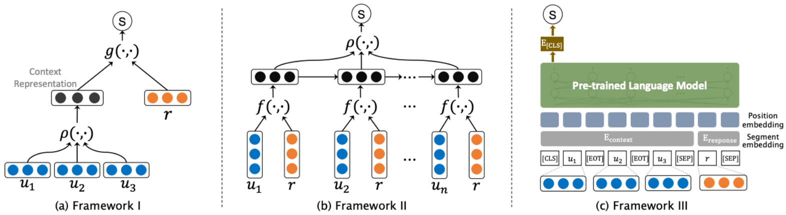


Figure 3.2: Three typical context-response matching frameworks: (1) representation-based framework, (2) interaction-based framework, (3) PLM (Pre-trained Language Model)-based framework (Tao *et al.*, 2021b).

into three stages, namely retrieval, matching and ranking. Figure 3.1 illustrates the overall architecture of the system. In a nutshell, (1) in retrieval-stage, the system employs three fast basic linear matching models (i.e., *Query-Response Similarity*, *Query-Message Similarity* and *Query-Response Matching in Latent Space*) to retrieve a number of candidate message-response (post-comment) pairs for the given query q, forming a reduced candidate set C_q^{reduced}; (2) in the matching stage, the system utilizes more matching models (i.e., *Translation-based Language Model*, *Deep Matching Model* and *Topic-Word Model*) to further evaluate all the comments in C_q^{reduced}, returning a matching feature set $\{\Phi_i(q,(p,r), i \in \Omega\}$ for each candidate post-comment pair. The matching models are learned offline with techniques referred as learning to match; and (3) in the ranking stage, the system uses a linear ranking function $\text{score}(q,(p,r)) = \sum_{i\in\Omega} \omega_i \Phi_i(q,(p,r))$ with the matching models as features to further evaluate all the comments (responses) in C_q^{reduced}, and assigns a ranking score to each candidate comment. Then, the system ranks the candidate comments based on their scores and selects the comment with the highest score to respond. The linear ranking function is learned offline with learning to rank techniques.

3.1.2 Response Selection Frameworks

For deep neural retrieval-based chit-chat systems, learning to match and rank is essential, and researchers usually formulate matching and ranking as a response selection task (Tao *et al.*, 2021b). The core of response selection is to learn a context-response matching model $f(\cdot)$

from training data to compute the matching score between a dialogue context c_i and a given response candidate r_i. The training objective of a context-response matching model is

$$\mathcal{L} = -\sum_{i=1}^{N} y_i log(f(c_i, r_i)) + (1 - y_i) log(1 - f(c_i, r_i)) \tag{3.1}$$

where y_i is the label to indicate whether a response candidate is suitable for the given dialogue context. As presented in Figure 3.2, there are mainly three types of context-response matching frameworks. Different with Tao *et al.*, 2021b that group existing neural context-response matching methods based on their frameworks, we structure existing literature from the type of context information to be processed. In this survey, we refer dialogue context to dialogue history, user profile, and extra resources (e.g., document, image caption, video). The modeling of each type of dialogue context is elaborated in detail in the following sections. At the end of this chapter, we give a brief review of pre-trained language models (PLMs) for context-response selection. Since PLMs are developing rapidly, and current methods will get outdated quickly, we mainly discuss the role of PLMs in retrieval-based dialogue systems.

3.2 Dialogue History Modeling

A long-term and core problem of the retrieval-based dialogue system is the modeling of the multi-turn dialogue history. Earlier studies pay attention to constructing single-turn history-response matching models where only a single utterance is considered, or multiple utterances in the history are concatenated into a long sequence for response selection. Recently, most studies have focused on the multi-turn scenario where each utterance in the history first interacts with the response candidate, and then the matching features are aggregated according to the sequential dependencies of the multi-turn history.

3.2.1 Single-turn Dialogue History Modeling

Early studies of retrieval-based chit-chat systems mainly focus on response selection for single-turn conversation, where the last turn of dialogue history (i.e., the dialogue query) is used to select a proper response. Many efforts have been devoted to learning good representations for query and response candidates independently, and then the matching score is computed based on these two types of encoded representation vectors. The essence of most retrieval-based natural language processing problems is text matching, and we first introduce some classic text matching methods.

Lu and Li, 2013 propose a DNN (Deep Neural Network)-based matching model, namely DeepMatch$_{topic}$, for short texts response selection, which combines both the localness and hierarchy intrinsic in the structure, where localness corresponds to salient local structure in the semantic space of parallel text objects, hierarchy refers to different levels of abstraction in matching. Hu *et al.*, 2014 propose ARC-I/ARC-II, which further improves the model by utilizing a deep convolutional neural network architecture to learn the representation of message and response, or directly learn the interacted representation of two sentences, followed by a multi-layer perceptron to compute the matching score. Wu *et al.*, 2018b propose KEHNN to exploit a knowledge gate to fuse the semantic information carried by the prior knowledge into each word representation. The knowledge gate is a nonlinear unit and controls how much information from the word is kept in the new representation and how much information from the prior knowledge flows into the representation. By this means, noise from the irrelevant words is filtered out, and useful information from the relevant words is highlighted. The model then forms three channels to perform matching from multiple perspectives. Each channel models the interaction of two pieces of text in a pair by a similarity matrix. Tay *et al.*, 2018a propose the Hermitian Co-Attention Recurrent Network (HCRN) for text matching. The authors leverage attractive properties of the complex vector space and propose a co-attention mechanism based on the complex-valued inner product (Hermitian products). Unlike the real dot product, the dot product in complex space is asymmetric because the first item is conjugated. Aside from modeling and encoding directionality, the proposed approach also enhances the representation learning process. Moreover, Tay *et al.*, 2018b further propose MACN as a new paradigm of utilizing attention not as a pooling operator but as a form of feature

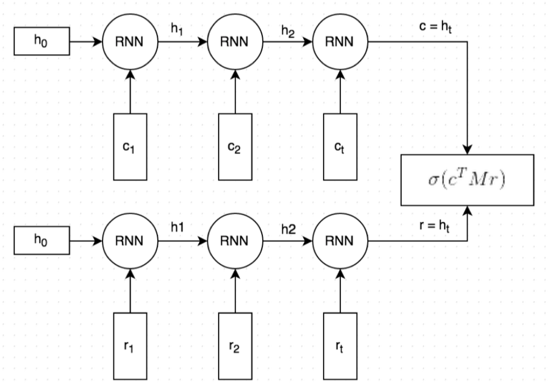


Figure 3.3: Diagram of dual-LSTM. The RNNs have tied weights. c, r are the last hidden states from the RNNs. c_i, r_i are word vectors for the dialogue history and response, $i < t$ (Lowe *et al.*, 2015).

augmentation. Chen and Wang, 2019 introduce ESIM to demonstrate that a sequential matching model based only on chain sequence can outperform all previous models, including hierarchy-based methods, suggesting that the potential of such sequential matching approaches have not been fully exploited in the past.

However, dialogue datasets often contain several turns of dialogue utterances. Thus, researchers try to utilize this helpful information based on such single-turn history modeling. Lowe *et al.*, 2015 introduce the Ubuntu Dialogue Corpus, a dataset containing almost 1 million multi-turn dialogues, and propose the dual LSTM model to encode multi-turn dialogue history and response respectively, which is depicted in Figure 3.3. To model multi-turn dialogue history, the authors choose to concatenate multiple utterances in the history into a long sequence, which is similar to single-turn dialogue history modeling.

3.2.2 Multi-turn Dialogue History Modeling

Apart from the above single-turn modeling strategies, many researchers have begun to emphasize the hierarchical structure of multi-turn dialogue history as shown in Figure 3.4.

Beyond directly concatenating all turns of utterances, many multi-

	Context
utterance 1	*Human*: How are you doing?
utterance 2	*ChatBot*: I am going to **hold a drum class** in Shanghai. Anyone wants to join? The location is near Lujiazui.
utterance 3	*Human*: Interesting! Do you have coaches who can help me practice **drum**?
utterance 4	*ChatBot*: Of course.
utterance 5	*Human*: Can I have a free first lesson?
	Response Candidates
response 1	Sure. Have you ever played drum before? ✓
response 2	What lessons do you want? ✗

Figure 3.4: A multi-turn conversation sample from Wu *et al.*, 2017.

turn dialogue history modeling methods have been proposed. For example, Zhou *et al.*, 2016 use RNN to read history and response and use the last hidden states to represent history and response as two semantic vectors. The obtained semantic vectors are utilized to measure their relevance. Yan *et al.*, 2016 propose DL2R, which first reformulates input query and then combines matching scores computed based on the reformulated and the original queries, as well as the retrieved queries and responses, respectively. Since then, most researches in the literature have adopted the "representation-matching-aggregation" paradigm to build the matching models.

Wu *et al.*, 2017 propose a novel sequential matching network (SMN) for multi-turn history where each history utterance is encoded conditioned on the response candidate, and these utterances are connected sequentially by GRUs. The matching score is computed on top of the weighted sum of the GRUs' states. The paradigm is depicted in Figure 3.5. Zhang *et al.*, 2018e then propose a Deep Utterance Aggregation model (DUA) that shares a similar structure with SMN. The difference lies in that a gated self-attention is used to obtain the representations of the query and a response candidate, and the subsequent operations are almost the same to SMN. Moreover, Zhou *et al.*, 2018d propose a deep attention matching network (DAM). The query and its candidate response are first represented with self-attention inspired by the transformer network, and then the interactions between them were made with cross-attention to obtain word-by-word matching matrices, and

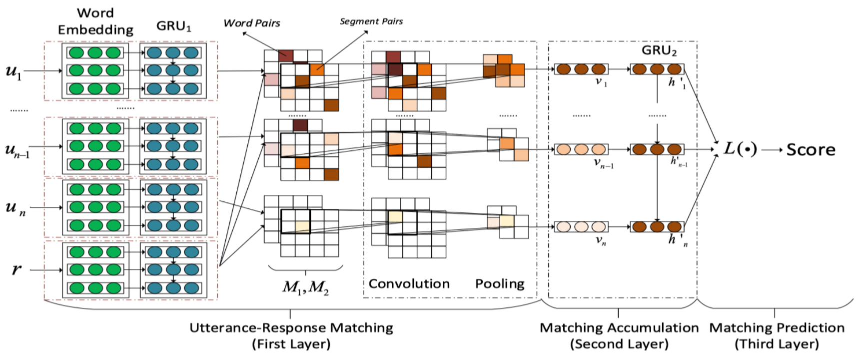


Figure 3.5: Architecture of SMN, a representative model of "representation-matching-aggregation" paradigm (Wu *et al.*, 2017).

finally, the matching score is computed by aggregating all the matching information with a 3D matching tensor. Wang *et al.*, 2019a propose the Iterated Attentive Convolution Matching Network (IACMN) for response selection. The authors argue that most existing works employ Recurrent Neural Networks (RNNs), which are often time-costly due to the limitation of parallelism. As an alternative, IACMN constructs multi-grained representations of history utterances and response candidates by stacking a refined combination of dilated-convolution (Yu and Koltun, 2015) and self-attention, namely the Attentive Gated Dilated Residual (AGDR) block. Tao *et al.*, 2019a perform history-response matching with multiple types of representations in a Multi-Representation Fusion Network (MRFN). The representations encode the semantics of words, n-grams, and sub-sequences and capture both short-term and long-term dependencies among words. In the model, the representations can be fused into matching at an early stage, intermediate stage, and last stage. Evaluation results show that late fusion is always better than early fusion, i.e., fusing the representations at the last stage can achieve the best performance.

Tao *et al.*, 2019b argue that single interaction is not enough and present an interaction-over-interaction network (IOI) that lets utterance-response interaction in history-response matching go deep. Depth of the model comes from stacking multiple interaction blocks that execute

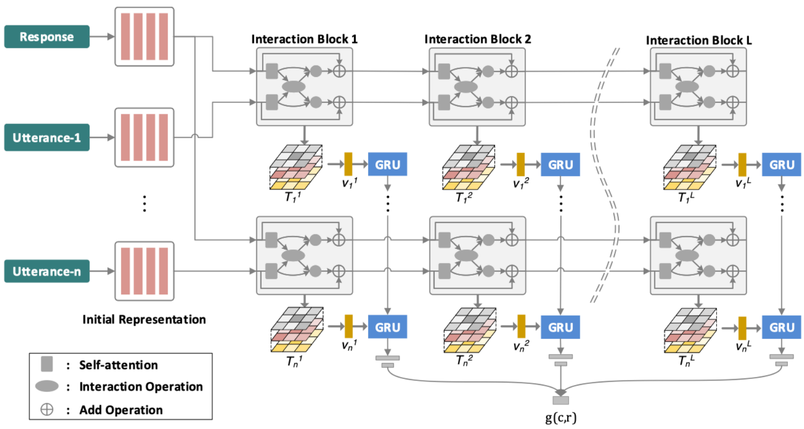


Figure 3.6: Architecture of interaction-over-interaction network (Tao *et al.*, 2019b).

"representation-interaction-representation" in an iterative manner. As shown in Figure 3.6, each history utterance i interacts with the candidate response over L times with the same interaction block, where the t-th interaction is based on the $t-1$-th interaction. All interaction results of each utterance and block are aggregated to compute the final history-response matching score $g(c, r)$, where c and r refer to history utterances and response candidate. Moreover, Deng *et al.*, 2020 propose Intra-/InterInteraction Network (I^3) with latent interaction modeling to comprehensively model multi-level interactions between the history utterance and the response. In specific, they first encode the intra- and inter-utterance interaction with the given response from both individual utterance and the overall utterance history. They then develop a latent multi-view subspace clustering module to model the latent interaction between the utterance and response. Yuan *et al.*, 2019 analyze the side effect of using unnecessary history utterances and verify matching-based models are very sensitive to the history. Then, the authors propose a Multi-hop Selector Network (MSN) to alleviate this problem. Specifically, MSN utilizes a multi-hop selector based on attentive module (Zhou *et al.*, 2018d), word selector, utterance selector, and hop-k selector to select the relevant history utterances for calculating history-response matching score.

3.3 Grounding with Extra Information

There are many types of grounding information in response selection. We group these works from the modality of extra information, i.e., text, image, and video. To better understand how grounding information is utilized in chit-chat response selection, we also include response-selection researches for specific chatting tasks in this section, e.g., question answering based on given images and videos.

3.3.1 Document-Grounded Response Selection

Human conversations, in reality, are often grounded in external knowledge. For example, in Reddit, discussion among users is usually along the document posted at the beginning of a thread which provides topics and basic facts for the following conversation. Lack of knowledge grounding has become one of the major gaps between the current chit-chat systems and real human conversations. As a step toward bridging the gap, Zhao *et al.*, 2019b investigate knowledge-grounded response selection and specify the knowledge as unstructured documents that are common sources in practice. Figure 3.7 shows an example from PERSONA-CHAT, a dataset released by Zhang *et al.*, 2018b. Formally, given two speakers' profiles as documents and a conversation context, one is required to distinguish the true response from the false ones.

The challenges include (1) how to ground conversation contexts with documents given that utterances in the contexts are not always related to the documents due to the casual nature of chit-chat conversation (e.g., the greetings in Figure 3.7); (2) how to comprehend documents with conversation contexts when information in the documents are rather redundant for proper response recognition (e.g., the description regarding B's hobby in her profile in Figure 3.7); and (3) how to effectively leverage both information sources to perform matching. Zhao *et al.*, 2019b propose a document-grounded matching network (DGMN) which breaks down the matching process into four stages, namely encoding, fusion, matching, and aggregation. In the encoding stage, DGMN encodes sentences in a document, utterances in a conversation context, and a response candidate through self-attention. Then DGMN con-

A's profile	trying new recipes makes me happy. i feel like i need to exercise more. i am an early bird , while my significant other is a night owl. i am a kitty owner.
B's profile	i might actually be a mermaid. i use all of my time for my education. i am very sociable and love those close to me. i enjoy swimming in the ocean , i feel in tune with its inhabitants.
Context	**A**: hi how are you today **B**: i am good . how are you ? **A**: pretty good where do you work ?
True response	i do not work , i am a full time student . what about you?
False response	i have been working as a salesman for more than 10 years.

Figure 3.7: An example of document-grounded dialogue (Zhao *et al.*, 2019b).

structs a document-aware context representation and a context-aware document representation via an attention mechanism to model context grounding and document comprehension. With the rich representations, DGMN distills matching information from each utterance-response pair and each sentence-response pair, where whether an utterance needs grounding, which parts of the document are crucial for grounding and matching, and which parts of the context are useful for representing the document are dynamically determined by a hierarchical interaction mechanism. The final matching score is defined as an aggregation of matching signals from all pairs.

Different parts of the context and knowledge are differently important for recognizing the proper response candidate as many utterances are useless due to the topic shift. That excessive useless information in the context and knowledge can affect the matching process and lead to inferior performance. To address this problem, Hua *et al.*, 2020 propose a multi-turn Response Selection Model that can Detect the relevant parts of the Context and Knowledge collection (RSM-DCK). Specifically, the model first uses the latest utterances of the dialogue context as a query to pre-select relevant parts of the dialogue context and document. Then the selected dialogue context and document interact with the response candidate individually by cross-attention, and a BiLSTM is employed to aggregate the matching features of the context, document, and response candidate, respectively. Due to the inter-dependency and temporal relationship among utterances in the dialogue context, another

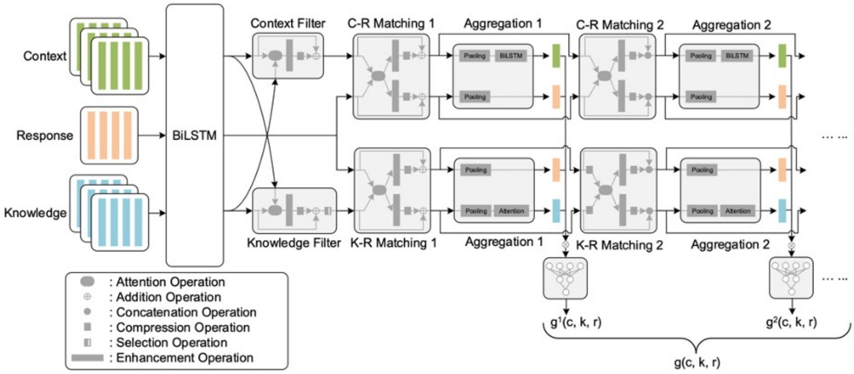


Figure 3.8: Structure of the Filtering before Iteratively Referring (FIRE) framework (Gu *et al.*, 2020b).

BiLSTM is adopted to accumulate the dialogue context. To select the most relevant sentences in the knowledge collection, the fused representation of the pre-selected dialogue context and response candidate is utilized as the query to post-select the document with the attention mechanism for the reason that sentences in the document are relatively independent and the true response tends to be solely related to one of them.

A similar idea of detecting relevant contexts and knowledge for response selection can also be found in Gu *et al.*, 2020b. The model architecture is shown in Figure 3.8. The major difference between DGMN and FIRE is the design of a context filter and a knowledge filter at the encoding stage. Specifically, the context filter makes the context refer to the knowledge and derives knowledge-aware context representations. On the other hand, the knowledge filter derives context-aware knowledge representations utilizing the same global attention mechanism.

3.3.2 Image-Grounded Retrieval-Based Dialogue

Recently, lots of researchers have considered bringing the vision and language together, such as image caption (Xu *et al.*, 2015; Hendricks *et al.*, 2016) and visual question answering (Antol *et al.*, 2015; Noh *et al.*, 2016; Yang *et al.*, 2016). However, it is still far away from the goal of

Caption: The skiers stood on top of the mountain.
Person A (1): how many skiers are there
Person B (1): hundreds
Person A (2): are they getting ready to go downhill
Person B (2): i think so my view is at end of line
Person A (3): is it snowing
Person B (3): no, there is lot of snow though
Person A (4): can you see anybody going downhill
Person B (4): no my view shows people going up small hill on skis i can't see what's going on from there
Person A (5): do you see lift
Person B (5): no
Person A (6): can you tell if they are male or female
Person B (6): skiers closest to me are male
Person A (7): are there any children
Person B (7): i don't see any but there could be it's huge crowd
Person A (8): does anybody have hat on
Person B (8): they all have winter hat of some sort on
Person A (9): is sun shining
Person B (9): yes, all blue sky
Person A (10): do you see any clouds
Person B (10): no clouds

Figure 3.9: An example of visual dialogue (Das *et al.*, 2017a).

developing general AI agents that can "see" (e.g., understanding their surroundings or social media content) and "communicate" (e.g., share their opinions with humans). Das *et al.*, 2017a make a step towards conversational visual AI and extend the scenario of visual question answering to visual dialogue. In visual dialogue, given an image, a history of dialogue consisting of a sequence of question-answer pairs, and a natural language follow-up question, the machine is required to answer in free-form natural language. Specifically, the machine should understand the dialogue context and extract essential clues from the image to pick a proper answer from a set of candidate answers. Figure 3.9 gives an example of the visual dialogue. The main challenges of visual dialogue include: (1) how to fuse multi-modal representations since the textual and visual features are always represented with different methods. For example, ResNet (He *et al.*, 2016), VGG Net (Simonyan and Zisserman, 2014) and Faster RCNN (Ren *et al.*, 2015) are widely used to extract the visual features of an image while the textual features are usually represented by word2vec (Mikolov *et al.*, 2013), Glove (Pennington *et al.*, 2014) and pre-trained language models (Devlin *et al.*, 2018); (2) how to model the complex interactions between image and dialog; and (3) how to perform visual co-reference resolution. For example, when encountering the word "they" in the second turn in Figure 3.9, the model needs to know that this refers to skiers in the previous turn and locate the skiers in the image to answer the question.

Most researchers build the model on the basis of encoder-decoder architecture, and these works can be categorized into three main groups: (1) fusion-based methods; (2) attention-based methods; and (3) visual co-reference resolution methods.

Fusion-based methods. Das *et al.*, 2017a propose three strategies to convert the model inputs (i.e., the dialogue history, the associated image, and the question in the form of natural language) into a joint representation. First, Late Fusion (LF) exploits LSTMs to encode the entire dialogue history and the question, respectively and exploits the L2-normalized activations from the penultimate layer of VGG-16 (Simonyan and Zisserman, 2014) to represent the image. The representations of the three inputs are directly concatenated and transformed through a linear layer. Second, Hierarchical Recurrent Encoder (HRE) captures the intuition that there is a hierarchical structure in a dialogue history. Specifically, the question/answer is composed of a sequence of words, and the dialogue history consists of a sequence of question-answer pairs. To this end, HRE uses a recurrent block to embed the question at each turn and image jointly. The joint representation, together with the embedding of the current turn, are then fed to a dialogue-RNN to encode the global information. Third, Memory Network (MN) Encoder utilizes a memory bank to store each previous question and the answer as "fact" and learns to refer to the stored facts and image to answer the question. Guo *et al.*, 2019a propose an image-question-answer synergistic network, which serves as a new paradigm to perform the multi-modal fusion. This method extends the conventional one-stage fusion into a two-stage problem. In the first stage, candidate answers are coarsely scored according to their relevance to the image and question pair. Then in the second stage, answers with a high probability of being correct are re-ranked by synergizing with image and question.

Attention-based methods. Recently, researchers have proposed various attention mechanisms which significantly promote the development

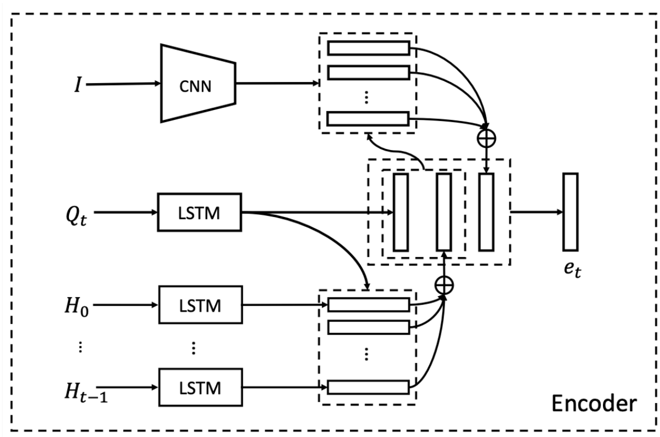


Figure 3.10: Structure of History-Conditioned Image Attentive Encoder (HCIAE) (Lu *et al.*, 2017).

of this field. Lu *et al.*, 2017 propose a History-Conditioned Image Attentive Encoder (HCIAE), which utilizes an attention mechanism that implicitly performs co-reference resolution through focusing on the important part of the dialogue history that can help in answering the current question. The overall architecture is shown in Figure 3.10. In a nutshell, the final encoding is obtained through two steps, i.e., the encoder first uses the current question to attend to the exchanges in the history and then uses the question and attended history to attend to the image. Specifically, given the spatial image features $\mathbf{V} \in \mathcal{R}^{d \times k}$, the embedding of question $\mathbf{m}_t^q \in \mathcal{R}^d$, and the contextual representations of dialogue history $\mathbf{M}_t^h \in \mathcal{R}^{d \times t}$, the first step attention is implemented as:

$$\begin{aligned} \mathbf{z}_t^h &= \mathbf{w}_a^T \tanh(\mathbf{W}_h \mathbf{M}_t^h + (\mathbf{W}_q \mathbf{m}_t^q) \nVdash^T) \\ \alpha_t^h &= \operatorname{softmax}\left(\mathbf{z}_t^h\right) \end{aligned} \tag{3.2}$$

where $\nVdash \in \mathcal{R}^t$ is a vector with all elements set to 1. $\mathbf{W}_h, \mathbf{W}_q \in \mathcal{R}^{t \times d}$ and $\mathbf{w}_a \in \mathcal{R}^k$ are parameters to be learned. $\alpha \in \mathcal{R}^k$ is the attention weight over dialogue history. The attended history feature $\hat{\mathbf{m}}_t^h$ is then defined as the convex combination of columns of $\mathbf{M}_t$, weighted by α_t^h. The second step attention is implemented as:

$$e_t = \tanh\left(\mathbf{W}_e \left[\mathbf{m}_t^q, \hat{\mathbf{m}}_t^h, \hat{\mathbf{v}}_t\right]\right) \tag{3.3}$$

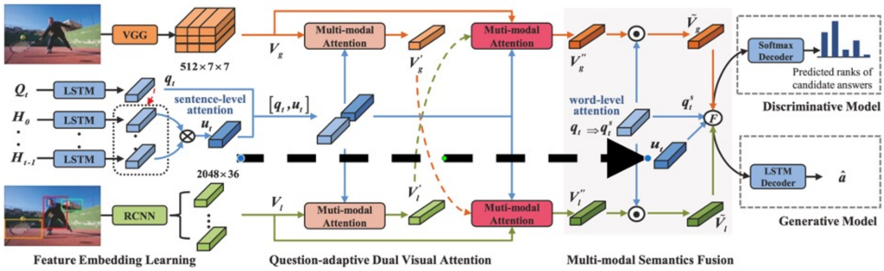


Figure 3.11: Structure of Dual Visual Attention Network (DVAN) for visual dialogue (Guo *et al.*, 2019b).

where $\mathbf{W}_e \in \mathcal{R}^{d\times 3d}$ is weight parameters and $[\cdot]$ is the concatenation operation.

To let the model selectively focus on regions of the image and segments of the dialogue history according to the question, Wu *et al.*, 2018a propose a sequential co-attention mechanism (CoAtt). Given the encoded image V, dialogue history representations U and question representations Q, CoAtt exploits a co-attention mechanism to generate attention weights for each feature type using the other two as the guidance in a sequential style. This process is defined as $\tilde{x} = \text{CoAtten}(X, g_1, g_2)$ and implemented as follows:

$$\begin{aligned} H_i &= \tanh(\mathbf{W}_x x_i + \mathbf{W}_{g_1} g_1 + \mathbf{W}_{g_2} g_2), \\ \alpha_i &= \text{softmax}(\mathbf{W}^T H_i), \quad i = 1, \ldots, M, \\ \tilde{x} &= \sum_{i=1}^{M} \alpha_i x_i, \end{aligned} \tag{3.4}$$

where X is the input feature sequence (i.e., V , U or Q), and $g^1, g^2 \in \mathbb{R}^d$ represent guidances that are outputs of previous attention modules. $\mathbf{W}_x, \mathbf{W}_{g_1}, \mathbf{W}_{g_2} \in \mathbb{R}^{h\times d}$ are learnable parameters, where d and h are the feature dimension and the size of hidden layers respectively. M is the length of input sequences.

To address cross-modal semantic correlation for visual dialogue, Guo *et al.*, 2019b propose a Dual Visual Attention Network (DVAN) which explores visual cues from different views related to the current question. As shown in Figure 3.11. First, DVAN imposes the current question on history to acquire the attended history feature (sentence-level attention). Next, the attended history and question features are used to refer to the related image regions and detected bounding boxes (question-adaptive dual visual attention). Finally, an answer is inferred through a multi-model semantic fusion scheme.

Since the single-step reasoning approach has an inherent limitation in taking only a first glimpse of the image and the dialogue history, Gan *et al.*, 2019 propose a Recurrent Dual Attention Network (ReDAN) that exploits multi-step reasoning for visual dialogue. In each question-answering turn of a dialogue, ReDAN infers the answer progressively through multiple reasoning steps. In each step of the reasoning process, the semantic representation of the question is updated based on the image and the previous dialogue history, and the recurrently refined representation is used for further reasoning in the subsequent step.

To further explore the effectiveness of attention mechanisms in visual dialogue, Park *et al.*, 2020 propose a multi-view attention network, which breaks down the visual dialogue task into two sub-problems. First, the model constructs the question-guided contextual representation and collects the topic-related clues from the dialogue history. Second, the model performs multi-modal alignment between visual and textual representations through the sequential alignment process. To alleviate the modality-imbalanced problem, Kim *et al.*, 2020 propose various consensus-dropout and ensemble methods to integrate the image-only and the image-history-joint model and achieve more balanced performance on all metrics. Suganuma, Okatani, *et al.*, 2020 propose a Light-weight Transformer for Many Inputs (LTMI) to cope with the expensive computational cost of directly applying the vanilla Transformer to model the many-to-many utility interactions.

Visual co-reference resolution methods. Due to the sequential and inter-dependent property of questions in dialogue, visual reference resolution is the key component required to localize attention accurately in the presence of ambiguous expressions. Seo *et al.*, 2017 propose a novel attention mechanism that exploits an associative memory to perform visual reference resolution (AMEM). As shown in Figure 3.12, the proposed model employs two types of intermediate attention, namely

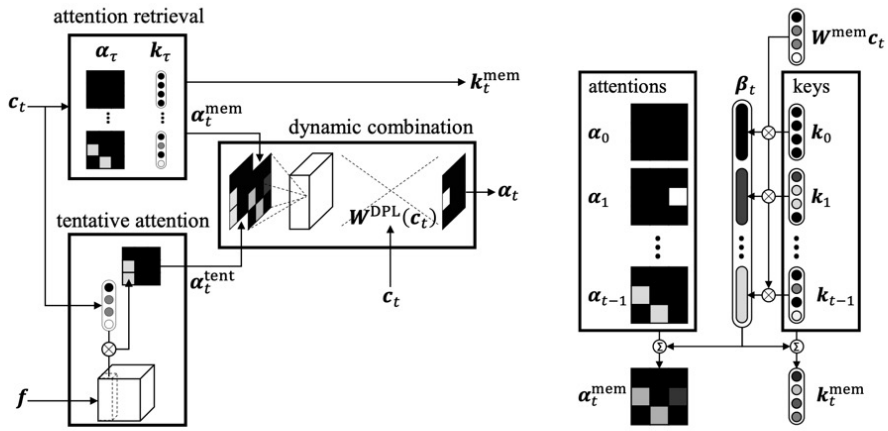


Figure 3.12: Structure of the AMEM framework (Seo *et al.*, 2017).

tentative attention, and retrieved attention. Specifically, tentative attention is implemented by computing the similarity of the encoding of the question and history, $\mathbf{c}_t$, and each feature vector, $\mathbf{f}_n$ as follows:

$$\begin{aligned} s_{t,n} &= (\mathbf{W}_c^{\text{tent}}\mathbf{c}_t)^\top(\mathbf{W}_f^{\text{tent}}\mathbf{f}_n) \\ \alpha_t^{\text{tent}} &= \text{softmax}(\{s_{t,n}, 1 < n < N\}), \end{aligned} \tag{3.5}$$

where $\mathbf{W}_c^{\text{tent}}$ and $\mathbf{W}_f^{\text{tent}}$ are learnable parameters, and $s_{t,n}$ is an attention score for a feature at the spatial location n. AMEM also obtains the most relevant previous attention using an attention memory for visual reference resolution. Given the attention memory $\mathbf{M}_t = \{(\alpha_0, \mathbf{k}_0), (\alpha_1, \mathbf{k}_1), \ldots, (\alpha_{t-1}, \mathbf{k}_{t-1})\}$ with α_τ, the previous attention map and the keys for associative addressing $\mathbf{k}_\tau$, the most relevant previous attention is retrieved based on the key comparison as follows:

$$\begin{aligned} m_{t,\tau} &= (\mathbf{W}^{\text{mem}}\mathbf{c}_t)^\top\mathbf{k}_\tau, \\ \beta_t &= \text{softmax}(\{m_{t,\tau}, 0 < \tau < t-1\}), \end{aligned} \tag{3.6}$$

where $\mathbf{W}^{\text{mem}}$ are learnable parameters. The relevant attention α_t^{mem} is defined as $\alpha_t^{\text{mem}} = \sum_{\tau=0}^{t-1}\beta_{t,\tau}\alpha_\tau$. The tentative and relevant attentions are first obtained independently and then dynamically combined depending on the question embedding.

To make the visual co-reference resolution process more interpretable, Kottur *et al.*, 2018 propose to incorporate neural module networks

(NMNs) into the visual dialogue framework. In addition to the neural modules designed for Visual Question Answering, the authors also introduce three modules to handle visual dialogue, including *Not*, *Refer* and *Exclude*. The goal of *Refer* module is to resolve references in the question Q_t and ground them in the conversation history H. Specifically, given the reference pool $P_{\text{ref}} = \{(x_p^{(i)}, a_p^{(i)})\}_i$ which keeps track of entities seen so far in the dialogue, the *Refer* module uses the text embedding x_{txt} to attend to the reference pool, and this procedure is implemented as follows:

$$\begin{aligned} s_i &= \text{MLP}([x_{\text{txt}}, x_p^{(i)}, \Delta_i t]), \\ \tilde{s}_i &= \text{Softmax}(s_i), \\ a_{\text{out}} &= \sum_{i=1}^{|P_{\text{ref}}|} \tilde{s}_i a_p^{(i)}, \end{aligned} \tag{3.7}$$

where $\Delta_i t$ denotes the absolute difference between the round of x_{txt} and the round when $x_p^{(i)}$ was first mentioned. The *Not* module is designed to focus on regions of the image that are not attended by the attention map a generated by the last module. The *Exclude* is designed to handle the question like "What other red things are present?". Specifically, *Exclude* module invokes *Find*, *Not* and *And* modules to complete this action:

$$y = \text{And}[\text{Find}[x_{\text{txt}}, x_{\text{vis}}], \text{Not}[a]], \tag{3.8}$$

where the *Find* module localizes all objects instances in the image, the *Not* module focuses on regions other than those specified by the attention map a. *And* module is used to combine the outputs of the aforementioned two modules.

Inspired by how humans make the co-reference resolution, Niu *et al.*, 2019 propose a Recursive Visual Attention (RvA) architecture that can recursively review the topic-related dialogue history and refine the visual attention. As illustrated in Figure 3.13, when the dialogue agent encounters a question that is expressed with ambiguity (e.g., "Are they on or off?"), it will recursively review the dialogue history and refine the visual attention until it can resolve the visual co-reference (e.g., "How many lamps are there?").

Similarly, Kang *et al.*, 2019a assume that humans break down the visual reference resolution into two steps: (1) linguistically resolve the

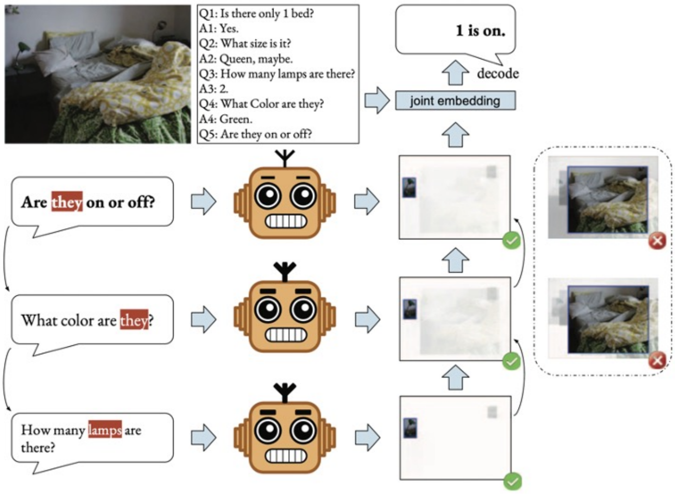


Figure 3.13: The intuition of the Recursive Visual Attention (RvA) in visual dialogue (Niu *et al.*, 2019).

ambiguous questions by recalling the dialogue history from one's memory and (2) find a local region of a given image for the resolved questions. The authors further propose the Dual Attention Networks (DAN), which consists of two kinds of attention modules, namely *REFER* and *FIND*, corresponding to the aforementioned two steps. First, the *REFER* module aims to attend to the most relevant proportion of dialogue history with respect to the given question. Given the encoding of question q_t and the representations of dialogue history $M_t = \{h_i\}_{t=0}^{t-1}$, DAN utilizes multi-head attention to calculate the importance of different proportions:

$$\begin{aligned}\text{head}_n &= \text{Attention}(q_t W_n^q, M_t W_n^m),\\ \text{Attention}(a, b) &= \text{softmax}\left(\frac{ab^\top}{\sqrt{d_{\text{ref}}}}\right)b,\end{aligned} \tag{3.9}$$

where $W_n^q \in \mathbb{R}^{L \times d_{\text{ref}}}$ and $W_n^m \in \mathbb{R}^{L \times d_{\text{ref}}}$ are learnable parameters, d_{ref} denotes the dimension of the latent space. The multi-head representation x_t is defined as $x_t = (\text{head}_1 \oplus \cdots \oplus \text{head}_h)W^o$, where W^o is the learnable parameters and $\oplus$ is the concatenation operation. The output of the

REFER module e_t^{ref} is then defined as:

$$\begin{aligned} c_t &= \text{ReLU}(\hat{x}_t W_1^f + b_1^f) W_2^f + b_2^f, \\ \hat{c}_t &= \text{LayerNorm}(c_t + \hat{x}_t), \\ e_t^{\text{ref}} &= \hat{c}_t \oplus q_t, \end{aligned} \tag{3.10}$$

where $\hat{x}_t = \text{LayerNorm}(x_t + q_t)$, W_1^f, b_1^f, W_2^f, and b_2^f are learnable parameters. The *FIND* module employs the bottom-up attention mechanism to obtain the visual attention weights:

$$\begin{aligned} r_t &= f_v(v) \odot f_{\text{ref}}(e_t^{\text{ref}}), \\ \alpha_t &= \text{softmax}(r_t W^r + b^r) \end{aligned} \tag{3.11}$$

where W^r and b^r are learnable parameters, $f_v(\cdot)$ and $f_{\text{ref}}(\cdot)$ are MLPs. The attention weights will be further used to compute the vision-language joint representations as follows:

$$\begin{aligned} \hat{v}_t &= \sum_{j=1}^{K} \alpha_{t,j} v_j \\ z_t &= f'_v(\hat{v}_t) \odot f'_{\text{ref}}(e_t^{\text{ref}}) \\ e_t^{\text{find}} &= z_t W^z + b^z, \end{aligned} \tag{3.12}$$

where W^z and b^z are learnable parameters, $f'_v(\cdot)$ and $f'_{\text{ref}}(\cdot)$ are MLPs. The output e_t^{find} is then used to score the candidate answers.

Other approaches. In this section, we briefly summarize other approaches used to solve the visual dialogue problem. These methods can be roughly grouped into the following categories: (1) employing the graph neural networks (Schwartz *et al.*, 2019; Zheng *et al.*, 2019b; Guo *et al.*, 2020) to have a better comprehension of the semantic dependencies among implicit visual and textual contexts; (2) optimizing the dialogue policy with reinforcement learning methods (Das *et al.*, 2017b; Yang *et al.*, 2019b); (3) pre-training the vision-language transformer on a large multi-modal corpus and transferring to visual dialogue (Murahari *et al.*, 2020); and (4) initializing the encoder with BERT and adopt visually grounded masked language modeling (MLM) and next sentence prediction (NSP) objectives to optimize the model (Wang *et al.*, 2020b).

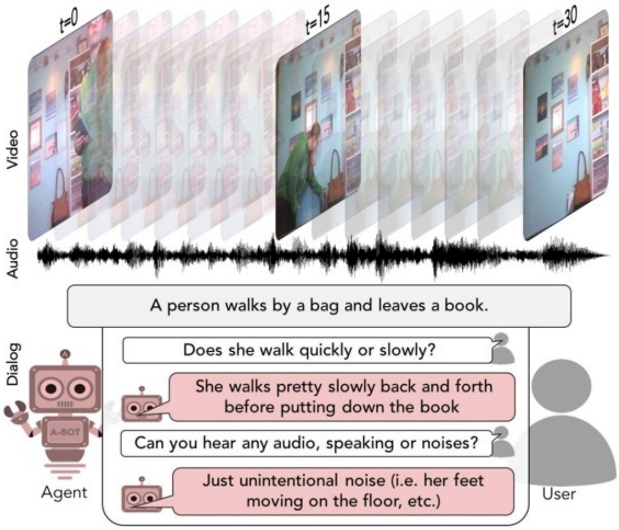


Figure 3.14: An example of Audio Visual Scene-Aware Dialogue (AVSD) (Alamri *et al.*, 2019).

Mostafazadeh *et al.*, 2017 also propose a new task where a question is first asked according to an image, and then a response is generated following the image and the question.

3.3.3 Video-Grounded Retrieval-Based Dialogue

Many potential applications for conversational agents would benefit significantly from comprehending the scene where the agent is operating. However, visual dialogue only involves conversing about a static image which is inherently limited. To this end, Alamri *et al.*, 2019 make one step further by proposing the task of scene-aware dialogue. Figure 3.14 depicts a conversation about a temporally varying scene that is carried on between an agent and a human. To answer such questions, the agent not only needs to understand the visual scene holistically but also be aware of the audio information.

Formally, given an input video, the history of a dialogue about the video, which is composed of a short script plus the first $t-1$ QA pairs, and a follow-up question (the t-th question in the dialogue), the goal of the system is to select a proper response from a set of 100 candidate

Persona 1	**Persona 2**
I like to ski	I am an artist
My wife does not like me anymore	I have four children
I have went to Mexico 4 times this year	I recently got a cat
I hate Mexican food	I enjoy walking for exercise
I like to eat cheetos	I love watching Game of Thrones

[PERSON 1:] Hi
[PERSON 2:] Hello ! How are you today ?
[PERSON 1:] I am good thank you , how are you.
[PERSON 2:] Great, thanks ! My children and I were just about to watch Game of Thrones.
[PERSON 1:] Nice ! How old are your children?
[PERSON 2:] I have four that range in age from 10 to 21. You?
[PERSON 1:] I do not have children at the moment.
[PERSON 2:] That just means you get to keep all the popcorn for yourself.
[PERSON 1:] And Cheetos at the moment!
[PERSON 2:] Good choice. Do you watch Game of Thrones?
[PERSON 1:] No, I do not have much time for TV.
[PERSON 2:] I usually spend my time painting: but, I love the show.

Figure 3.15: An example of persona-based dialogue (Zhang *et al.*, 2018b).

answers. To have a more intuitive observation about the impact of different input information, Alamri *et al.*, 2019 propose a late-fusion approach for video-grounded dialogue. The video frames and the audio track are independently transformed into a fixed-sized vector through convolutional neural networks (CNNs). The words in the dialogue history of the current turn are concatenated to form a long sequence, which is then fed to an LSTM to generate the contextual representation. The encoding of the question is implemented in analogy to the encoding of the dialogue history. The four vectors are then concatenated to rank the candidate answers. Intuitively, increases or decreases in performance from input ablation are directly linked to the usefulness of the input.

3.4 Human Factors: Emotion, Persona and Beyond

With the development of dialogue systems, more attention has been paid to building empathetic and more human-like chit-chat systems through explicitly modeling human factors such as persona and emotion, where persona refers to various user profile information e.g., name, age, knowledge or expertise, wording behaviours. Though more attempts were made in generative-based dialogue systems as will be discussed in the next chapter, there are various works that incorporate human factors into retrieval-based chit-chat systems.

Naturally, a human-like chit-chat systems should display a consistent personality during its chatting with humans. Recently, an increasing number of works pursue to design retrieval-based chit-chat systems grounding on persona information. Zhang *et al.*, 2018b proposed to grounding dialogue systems on persona information to make chit-chat more engaging. They firstly constructed a new dataset named PERSONA-CHAT, where each human-human dialogue is paired with several sentences that describe the persona information of both speakers. They further designed the profile memory network, which considers the dialogue history as input and then performs attention over the persona to combine with the dialogue history. Mazare *et al.*, 2018 collected a much larger personalized dialogue corpus from Reddit [1] and implemented a persona-based response selection network similar to Zhang *et al.*, 2018b. Gu *et al.*, 2019a then proposed the dually interactive matching network which can better incorporate persona descriptions into multi-turn response selection. Specifically, they adopted a dual matching architecture, which performs interactive matching between responses and contexts and between responses and personas respectively, for ranking response candidates. Li *et al.*, 2021a highlighted the effectiveness of user dialogue histories and constructed two personalized dialogue corpora where each dialogue case is paired with the dialogue histories of both users. They further design a personalized hybrid matching network which incorporated user dialogue histories into hybrid representation matching between dialogue context and the response by personalized attention and wording behavior modeling. Zhong *et al.*, 2020 collected a dialogue corpus from two subreddits whose conversations are considered more empathetic than that of others. They proposed a BERT-based response selection model which employed co-attention between the candidate response and the persona information as well as the dialogue context based on the representations calculated by BERT.

Beyond persona information, researchers have been starting to explore the effect of emotion in response selection to build more empathetic chatbots recently. Lubis *et al.*, 2019 pointed out the necessity of positive emotion in responding to humans. Stepping from this point, they firstly

[1] https://www.reddit.com/r/datasets/comments/3bxlg7/

proposed a response retrieval approach for positive emotion elicitation by utilizing examples of emotion appraisal from a dialogue corpus. Then with the help of the retrieval model, they constructed a corpus by replacing responses in dialogue with those that elicit more positive emotion. Qiu *et al.*, 2020 incorporated emotional factors into context-response matching from two aspects: 1) they modeled the dynamic emotional flow and utilized the learned intrinsic emotion features to enhance context-response matching through a multi-task learning framework, 2) they designed flexible controlling ways to customize social bots in terms of emotion.

3.5 Pre-Training in Dialogue Retrieval Models

Recent years have witnessed a growing number of large-scaled pre-trained language models such as BERT (Devlin *et al.*, 2018), RoBERTa (Liu *et al.*, 2019b), XLNet (Yang *et al.*, 2019c). Based on the deeply-stacked self-attention architecture (Vaswani *et al.*, 2017), these models are trained with self-supervised objectives on large-scale open data to become powerful feature extractors that can not only provide contextual representations but also be fine-tuned to specific down-stream tasks without additional parameters except an MLP layer. The idea of self-supervised pre-training inspired a growing number of studies of retrieval dialogue systems. The core motivation of works in this section is to find the nature of human dialogues, which makes dialogue modeling distinctive from other NLP tasks that can guide the design of model architectures, input formulations, and self-supervised objectives. Among them, some works share the spirits of pre-training and develop their own model architecture (Tao *et al.*, 2021a) and training objectives (Tao *et al.*, 2020), while others build response selection models upon some released pre-trained language models and even move a step further to exploit dialogue specific self-supervised objectives to pre-train or post-train a dialogue model that is tailored for multi-turn response selection.

Tao *et al.*, 2020 introduced ECMo (i.e., Embedding from a Conversation Model) to provide contextualized representations that are tailored for dialogue modeling for the multi-turn response selection task. They pre-trained a large hierarchical encoder-decoder dialogue generation model on a large dialogue corpus to better model the multi-turn context of human dialogues. The generation model can provide word-level and sentence-level contextualized dialogue representations that are blended into the input and the output layer of the matching model, respectively, which is similar to ELMo (Peters *et al.*, 2018).

Wolf *et al.*, 2019 borrow the idea of transfer learning and adapt GPT (Radford *et al.*, 2018b) to response generation and response selection tasks through fine-tuning with the language modeling loss and the next utterance classification loss. The proposed model achieved remarkable results in the response selection.

More recently, researchers mainly adopt BERT (Devlin *et al.*, 2018) as the backbone of their response selection model. There are several obstacles that prevent the direct adaptation of BERT to the multi-turn response selection task. Firstly, although BERT is skilled at performing text pair classification tasks, the input formulation of multi-turn response selection is a bit different from that of typical text-pair classification tasks such as NLI, where the inputs are two sentences that are concatenated together with a special separator token. In fact, the inputs of the multi-turn response selection task consist of two parts, one is the dialogue context which is comprised of multiple utterances, and a candidate response which is an individual utterance. Next, the domain of the pre-training corpora (i.e., English Wikipedia and Book Corpus) is usually quite distant from the downstream dialogue corpus, especially when the dialogue is domain-specific (i.e., the Ubuntu Corpus (Lowe *et al.*, 2015)). Moreover, the pre-training objectives (i.e., masked language modeling and next sentence prediction used in BERT) are not tailored for multi-turn response selection. In this research line, various works explore to introduce dialogue-specific features or design training objectives that are tailored for multi-turn response selection to tackle the aforementioned problems.

As for the incorporation of dialogue-specific features, Whang *et al.*, 2019 firstly adopted BERT to multi-turn response selection task and proposed an effective domain adaptive post-training method to improve the model performance. The proposed BERT-VFT model was firstly post-trained on the task-specific corpora using masked language modeling and next sentence prediction to equip the model with specific

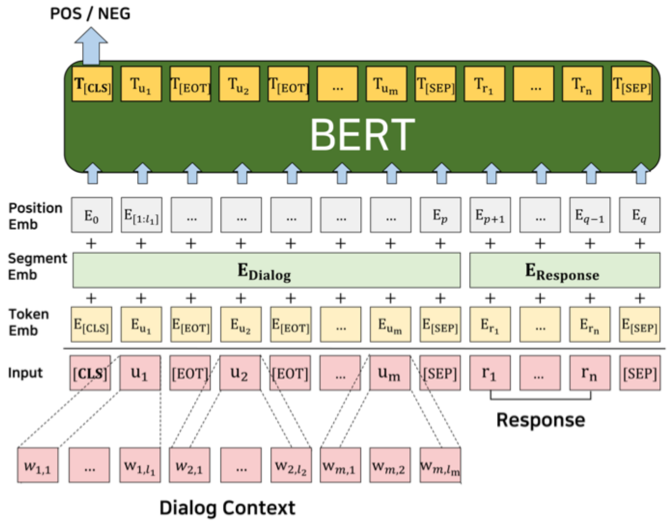


Figure 3.16: An example of BERT-based response selection (Whang *et al.*, 2019).

domain knowledge. Moreover, to mitigate the gap of input formulation between typical sentence-pair matching and multi-turn response selection, BERT-VFT made some modifications on BERT, as illustrated in Fig 3.16. Specifically, as the dialogue contexts are comprised of multiple utterances, they injected an additional special token EOT (i.e., end of turn) between dialogue utterances in the input context. The two proposed techniques were followed by most of the works along this line. Similarly, Gu *et al.*, 2020a proposed SA-BERT, which additionally introduces the speaker embedding that models the speaker changes information in a dialogue flow. Moreover, SA-BERT also employs a speaker-aware disentanglement strategy which selects a small number of the most important utterances as the filtered context according to the speakers' information in them.

Meanwhile, in addition to the original objectives (i.e., masked language modeling and next sentence prediction) used in Whang *et al.*, 2019; Gu *et al.*, 2020a during post-training, various works concentrate on designing new self-supervised objectives (which can also be considered as data augmentation strategies) that are tailored for multi-turn response selection to post train the pre-trained language model. Whang *et al.*, 2020 propose three utterance manipulation strategies (i.e., insertion, deletion, and search) to aid the response selection model towards maintaining dialogue coherence. In insertion, an utterance is randomly extracted from consecutive utterances in the context, and the model is trained to predict the insertion position. In deletion, the goal for the model is to find the irrelevant utterance that is inserted into the original context. As for search, the model learns to select the true previous utterances from the shuffled context utterances. Lu *et al.*, 2020 propose to augment the dialogue corpus for fine-tuning the pre-trained language models by treating the last utterance of consecutive utterances in a session as the positive response while considering a randomly chosen utterance in the same session as the negative response. Xu *et al.*, 2020c proposed a more systematic method to incorporate the self-supervised objectives. Specifically, they introduced four self-supervised tasks, which include next session prediction, utterance restoration, incoherence detection, and consistency discrimination, to post-train a pre-trained language model for multi-turn response selection in a multi-task manner. Li *et al.*, 2020a introduced task-specific pre-training on in-domain task-related corpora with task-specific objectives. They constructed the dialogue-related corpora based on four medium-sized prevailing dialogue corpora. They generated three negative examples through utterance ordering, utterance insertion, and utterance replacement for each positive example, which aims to provide negative examples lacking readability, fluency, and coherence. They further scored examples with n-gram Normalized Inverse Document Frequency (n-NIDF) and trained the model using the mean-square error (MSE) objective.

3.6 Evaluation

Most of the researches reviewed in this chapter focus on the task of response selection (context-response matching). Thus, the model performance evaluation lies on how to automatically calibrate the model capability of retrieving a suitable response, i.e., the ground-truth response is expected to be selected or obtain a higher matching score. There are four metrics that are widely used (Zhang *et al.*, 2018b; Zhao *et al.*, 2019b; Alamri *et al.*, 2019): (1) **mean rank (MR)** of the ground truth human response, which is sensitive to overall tendencies to rank ground-truth higher—important in the context as other candidate answers may be equally plausible, (2) **recall@k** that measures how often the ground truth is ranked in the top k choices, (3) **mean reciprocal rank (MRR)**, which values placing ground truth in higher ranks more heavily, and (4) **normalized discounted cumulative gain (NDCG)** (Das *et al.*, 2017a), where NDCG takes into account all relevant answers from the ranked list and penalizes the lower rank of the candidate answers with high relevance scores. Except for these straight-forward evaluation metrics, retrieval-based chit-chat systems also requires more evaluation methods to measure the **efficiency of the response selection system**.

3.7 Summary

This chapter presents most of the representative deep neural response selection model for building chit-chat systems, which is categorized from the types of context information utilized in calculating context-response matching scores, including multi-turn history modeling, document-grounding, visual information utilization, persona, and emotion. We also briefly review some typical approaches based on pre-trained language models. We can conclude that most of recent neural response retrieval methods focus on (1) **the utilization of context information**, (2) **how to effectively model context information**, and (3)**how to efficiently model context information**. With the prevalence of large-scale PLMs, the model efficiency of retrieval-based chit-chat systems will become the core challenge in the near future.

4

Generation-Based Chit-Chat Systems

Unlike retrieval-based chit-chat systems, generation-based methods can create new responses for a specific query given the correlated dialogue context. From the perspective of IR, generation-based methods can be alternative solutions when retrieval-based models fail. For instance, there is no related response in previous conversations, or the users prefer a personalized response. Moreover, generation methods also serve a vital role in the ensemble-based chit-chat system, which will be discussed in the next chapter. This chapter presents necessary information for the IR community to either build an ensemble chit-chat system or construct an alternative model when retrieval-based systems fail.

We start this chapter with a brief overview that mainly clarifies the difference between generation-based methods and previously mentioned retrieval-based models and reveals the development trend of chit-chat systems. We then summarize and simply introduce the widely utilized sequence to sequence generation frameworks in the age of deep learning. After this, we explore several essential challenges and research topics, including tackling the one-to-diversity issue, context modeling, knowledge and grounding in response generation, human factors, and response generation methods based on the booming pre-trained language models.

At the end of this chapter, we give a preliminary study about the most challenging problem of chit-chat conversation generation, i.e., performance evaluation, and provide some open available data resources for building generation-based chit-chat systems.

4.1 The Paradigm of Generation: A Rising Trend

As stated in Chapter 3, retrieval-based conversation systems can obtain real-world responses from existing conversation records, which is more accessible for humans. For dialogue context that resembles existing data, it is cheap and safe to retrieve a proper response since deep neural networks can capture the correlations and matching degree between dialogue context and pre-retrieved response candidates. Besides, training a deep model that can perform context-response matching is more data-efficient than estimating the joint probability distribution in conditional language models in generation-based conversation systems, which is more applicable for scarce data scenarios such as task-oriented systems. However, retrieval-based methods still have their limitations, one of which is that there is no existing conversation history that can accord with the given dialogue context. Another shortage is that retrieving responses from existing conversations cannot handle the notable problem of chit-chat conversations, i.e., one-to-diversity modeling, where the response for a specific conversation context varies according to many extra conditions such as persona, expression behaviors, emotion change, etc. Besides, it is also challenging to fuse multiple resources and extra information in the obtained response.

In contrast, generation-based models, by virtue of their encoder-decoder framework and capabilities in estimating the joint probability distribution of languages, can create new responses for unseen dialogue context in historical conversation data. Beyond that, encoder-decoder frameworks are more efficient for fusing different information to generate better responses. It is also feasible to achieve controllable response generation based on different conditions, e.g., persona, emotion preference, by modifying the conditional probability distribution objective, and thus generation-based methods can handle the one-to-diversity problem well for chit-chat conversations. The downside is that generation-based methods require large-scale conversation history for model training, especially for the chit-chat conversations, and more computational resources to build commensurate models are desirable accordingly. Another possible risk is caused by the widely-used generation training objective of maximizing the log-likelihood of utterances in the training data, which will encourage generation-based chit-chat systems to produce either short responses or responses with commonly co-occurred wordings, and none of which is rational for real-world chit-chat systems.

Although generation-based chit-chat systems exist various kinds of problems, learning to converse by generating response shows a clear ascending trend. This upward trend is due to many different reasons. One of the critical reasons is the explosion of open-available conversation records. Another contributing factor is the rapid growth of computing capacity, and it is even applicable to run models such as BERT-base on mobile devices. With massive data and powerful GPUs as well as parallel algorithms, it is not brain surgery to train a large-size response generation model that performs well for chit-chat conversations. It is even favorable to pre-train large-scale language models for building chit-chat systems, e.g., DialogGPT. These pre-trained models, by virtue of their great fitting capability and impressive model capability, can not only generalize well across different topics, domains, and even languages but also have a certain degree of ability to handle few-shot/zero-shot problems. Besides, these pre-trained models can learn commonsense knowledge with language modeling jointly. Thus, building chit-chat systems on these pre-trained language models can create informative and fluent responses for new topics or unseen dialogue contexts, which will prevent some negative issues, e.g., resulting in dialogue breakdown and poor user experience. Another character is that it is convenient to jointly learn language generation and other influence factors, e.g., commonsense knowledge, grounding information, personalized demand.

As for the IR community, more powerful generated-based methods can also facilitate retrieval-based chit-chat systems. For one thing, generation-based methods could produce multiple alternatives for a user-issued query to enhance the response matching process. For another, generation-based methods could fuse multiple retrieved response candidates and edit obtained response candidates with different requirements, e.g., polishing irrelevant information, injecting personalized factors. Based on the above situation, generation-based methods are not only popular for other research communities but also for the IR field.

4.2 Overall Framework: Architecture and Challenges

One of the important reasons for the flourishing of chit-chat systems is the significant progress of sequence to sequence neural frameworks. Starting from Sutskever *et al.*, 2014, various sequence to sequence models are proposed. Bahdanau *et al.*, 2015 further enhance the original sequence to sequence model based on the recurrent neural network with a context attention mechanism. Gehring *et al.*, 2017 propose a novel sequence to sequence framework entirely based on convolutional sequence to sequence model, which allows high effective parallel training and long-context modeling. Shortly afterward, Vaswani *et al.*, 2017 propose the Transformer model fully based on attention computation, which has the merits of both parallel training and dynamic context window modeling, as well as long-range correlations capturing. Since then, Transformer has become the most popular and widely acknowledged framework for sequence to sequence modeling.

Generation-based chit-chat systems formulate conversation as a sequence to sequence task to leverage the powerful sequence to sequence modeling capabilities of these frameworks. Given a conversation input $\boldsymbol{x}$ which is an user-issued query with/without dialogue context, target output response $\boldsymbol{y}$, and other conditions ($\boldsymbol{C}$) such as knowledge ($\boldsymbol{k}$), persona ($\boldsymbol{p}$), grounding ($\boldsymbol{g}$), the generation-based chit-chat task can be formulated as learning the mapping function $f(\cdot)$ to capture the corrections between input $\boldsymbol{x}$, conversation condition $\boldsymbol{C}$, and output $\boldsymbol{y}$, which is implemented as maximizing the following objective:

$$p(\boldsymbol{y}|\boldsymbol{x}, \boldsymbol{C}) = \prod_{t=1}^{T_y} p(y_t|c, y_1, \cdots, y_{t-1}) \tag{4.1}$$

where T_y is the length of the target response y, and $\boldsymbol{C} = (\boldsymbol{k}, \boldsymbol{p}, \boldsymbol{g})$ [1]. $p(\cdot)$

[1]Other conditions that can affect model outputs or alter the target response are also desirable.

can be parameterized as deep neural networks. In doing so, it can be achieved to automatically create a response for given dialogue context and other conditional information.

4.3 Tackling the One-to-Diversity Issue

In modeling chit-chat conversation generation, one of the notorious challenges is "one-to-diversity". For a given dialogue history or context, there might be many feasible responses to fill the requirement and change the direction of the conversation, e.g., responding from different aspects of the given conversation history, starting a new topic along with a dialogue breakdown, conversing with the same semantic but different language expressions. The reasons behind this problem are in various aspects. For one thing, the open-available data is still limited compared with all possible conversations and one-to-diversity correlations, as a result of which data-driven methods built upon these data, not surprisingly, fail to model the one-to-diversity problem. For another, existing widely-used sequence to sequence mapping frameworks, e.g., aforementioned Seq2seq model, ConvSeq2seq, and Transformer along with the cross-entropy training objective, are insufficient to address the one-to-diversity correlation learning. Moreover, typical generation-based conversation systems ignore conversational behaviors of humans in producing one-to-diversity dialogues, where individuals will respond by combing dialogue context, commonsense, human factors, and other extra information.

Figure 4.1 presents a few examples that reflect the one-to-diversity challenge for chat-driven conversations. Take the user input "What are you doing?" for example, there are multiple feasible responses, and these responses consist of diversified words.

To address these challenges, existing work mainly explore data manipulation, new generation framework and pipeline, effective training objective, and leveraging extra resources. Since data serves as the core of building conversation systems in the era of the deep neural network, we will first elaborate on recent findings on data manipulation, including data augmentation and data selection. In the after part, we present the representative framework and pipeline as well as effective objectives

Input: What are you doing?	
1. I've been looking for you.	4. I told you to shut up.
2. I want to talk to you.	5. Get out of here.
3. Just making sure you're OK.	6. I'm looking for a doctor.
Input: What is your name?	
1. Blue!	4. Daniel.
2. Peter.	5. My name is John.
3. Tyler.	6. My name is Robert.
Input: How old are you?	
1. Twenty-eight.	4. Five.
2. Twenty-four.	5. 15.
3. Long.	6. Eight.

Figure 4.1: Conversation cases that illustrate the one-to-diversity problem (Li *et al.*, 2016a).

designed for addressing the one-to-diversity problem, respectively. In the end, we discuss how to leverage extra resources in mitigating the one-to-diversity problem. Note that this section mainly focuses on the pros and cons of existing researches from the one-to-diversity aspect. For instance, modeling human factors and commonsense knowledge are two essential topics of conversation systems, but we only focus on their characteristics in addressing the one-to-diversity issue in this section, where more researches of knowledge grounding and human factors will be discussed in Section 4.5 and 4.6. In this section, we refer to one-to-diversity as both the expression diversity and one-to-many correlations.

4.3.1 Data Manipulation: Augmentation and Selection

It is widely acknowledged that data is the King during the time of deep neural networks, i.e., the performance of chit-chat systems based on deep neural networks is bounded by the given training data. In other words, most problems of existing models can be directly addressed or mitigated from the perspective of data manipulation. Herein, data manipulation mainly refers to widely-used data augmentation and selection methods. Recall that our target of introducing data manipulation is to address the one-to-diversity problem in chit-chat dialogues, including expression diversity and one-to-many modeling. In the following part, we will elaborate on how to utilize data manipulation to solve the above-mentioned two challenges, respectively.

Among which, expression diversity calibrates the word frequency and co-occurrences, where low expression diversity means the generated responses consist of high-frequency and commonly co-occurred words, and in turn, high expression diversity correlates with more informative words and in-context contents. In most cases, the expression diversity of automatically generated responses is well below human beings, e.g., the ground-truth conversations, and thus data manipulation methods that can improve expressions diversity are sorely needed. For low-resource scenarios, it is more preferable to perform data augmentation by creating more data with low-frequency and rarely co-occurred words so that the augmented data could prevent the deep neural models from trapping into some high-frequency words and lexical combinations. For the high-resource setting, various data selection strategies are commonly utilized by filtrating out most of the data samples with high-frequent and non-informative words to re-balance the data distribution. In doing so, we can improve both the expression diversity of neural chit-chat systems and the data efficiency of model training. In real-world applications, it would be better to simultaneously introduce both data augmentation and selection strategies, either by first augmenting and then selecting or augmenting one part and selecting another part.

For the one-to-many diversity issue, the most straightforward solution is to conduct data augmentation by creating multiple responses for each given conversation context. Another possible direction of obtaining more one-to-many labeled data is to correlate each dialogue context with multiple responses that have similar context information. Moreover, it is also worth considering the many-to-one problem in existing data, i.e., one response can fit multiple dialogue contexts. Filtering out these labeled data with common responses can also mitigate the challenge of one-to-many modeling. Same as data manipulation for expression diversity, these methods are mixed-used in practice.

Following the data manipulation line, Csáky *et al.*, 2019 propose to improve the neural conversational model with entropy-based data filtering to output more diverse responses. Li *et al.*, 2019a introduce a CVAE-GAN framework to perform data augmentation for chit-chat

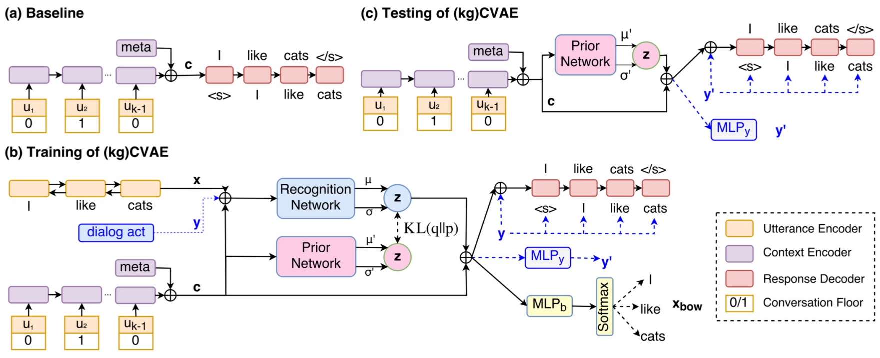


Figure 4.2: Representative neural network architecture of CVAE for chit-chat conversations (Zhao *et al.*, 2017).

conversations, and experimental results indicate that the proposed method can improve the expression diversity of generated responses. Zhang *et al.*, 2020c provide a new framework of data augmentation for chit-chat conversation systems. Through designing a data-level distillation process, a ranking module, and a model-level distillation process, the proposed solution can better utilize massive unpaired data and eventually can create dialogues with diversified contents. Cai *et al.*, 2020b conduct data manipulation to achieve effective instance learning for neural dialogue generation via learning to augment and re-weight, and the model effectiveness of improving response diversity is confirmed in experiments.

In short, data manipulation methods aim at changing the distribution of training data along with the powerful fitting capability of deep neural networks to alter the model outputs from the data side. Below, we will review existing researches on designing new generation frameworks, training with effective objectives, and leveraging extra resources to achieve expression diversity and one-to-many modeling.

4.3.2 Generation Framework and Pipeline

One of the commonly used frameworks for improving expression diversity in chit-chat systems is Conditional Variational Auto-Encoder(CVAE). Through introducing a latent variable, these models can capture sentence-level or session-level global information and thus can prevent them from trapping into local language model (decoder) with high-frequency co-occurred words generated. For chit-chat systems, Cao and Clark (2017), Zhao *et al.* (2017), and Shen *et al.* (2017) first leverage the merits of CVAE models to generate responses with expression diversity. We take the CVAE architecture of Zhao *et al.*, 2017 for illustration, as shown in Figure 4.2. Meta information and context utterances (u_1, u_2, u_{k-1}) are combined as the condition c. Given the condition c, the training target of this model is to re-construct the target response x, which resembles with Auto-Encoder. During testing, the CVAE model takes condition c as input and can produce multiple different responses for the same condition.

By virtue of its strength of generating multiple different responses for a given context, i.e., one-to-many diversity, many variants of CVAE models for chit-chat conversation are proposed later on. Park *et al.*, 2018 propose two strategies to solve the degeneration problem of VAE-based conversation models, including using a hierarchical structure of latent variables and exploiting an utterance drop regularization. Xu *et al.*, 2018a incorporates the CVAE model with the measure of coherence and a context gate to achieve better conversations. Du *et al.*, 2018 enhance CVAE-based conversation models with a sequence of latent variables to achieve high variability in responses and further introduce a backward recurrent neural network to augment the approximate posteriors for capturing long-term dependencies of future tokens in the generation. Unlike the vanilla CVAE model that only uses a latent variable, the proposed method sequentially introduces a series of latent variables as the condition to generate each word of the response sequence. Gao *et al.*, 2019d leverage novel regularization terms to enhance the CVAE model with relevance and meanwhile maintain diversity. Gao *et al.*, 2019c present a discrete latent variable with explicit semantic meaning to enhance CVAE models on the short-text conversation. Zhang and Zhang, 2019 leverage the CVAE model to construct a hierarchical response generation model that can capture different levels of diversity (i.e., word-level and discourse-level). Zeng *et al.*, 2019 change the conventional Gaussian priors of the latent variable in CVAEs as the Dirichlet distribution with flexible structures to effectively represent complex latent variables. Cui *et al.*, 2020 compensate CVAE-based conversation models with a focus-constrained attention mechanism to mitigate the scarce of discourse-level information. Ko *et al.*, 2020 alternatively introduce a regression task on a latent space to integrate information from multiple semantically similar valid responses of a prompt and accordingly improve the diversity of generated response. Khan *et al.*, 2020 conduct adversarial learning on the latent space for diverse dialogue generation. Chen *et al.*, 2018a incorporate hierarchical structure and variational memory network into an encoder-decoder neural network.

Besides CVAE-based models, multi-pass encoder-decoder and multi-stage encoder-decoder can also change the outputs of generation-based chit-chat systems. Zou *et al.*, 2018 propose a multi-encoder to multi-decoder (MEMD) framework to promote diversity of shot-text conversation. Kong *et al.*, 2020 propose a content-aware model with a two-stage decoding process to generate more low-frequency content words (words which have substantive lexical content) with more semantic information rather than high-frequency function words (words which essentially serve to make grammatical properties).

In addition to the above categories, there are also other efforts to optimize generation models. Tian *et al.*, 2019 propose a memory-augmented generative model for conversational response generation by abstracting useful information from the training corpus and then saving this information in the memory. With the assistance of the memorized information, the generation model can output more informative and diverse responses.

4.3.3 Training with Effective Objectives

Apart from data manipulation and generation framework, training objectives also serve as the key component of deep neural networks. To address the expression diversity problem, many researchers attempt to introduce frequency-aware training objectives to encourage generating informative words and penalizing high-frequency words. Li *et al.*, 2016a propose using Maximum Mutual Information (MMI) as the objective function of the neural conversation model to produce more diverse responses. Li *et al.*, 2016c also bring reinforcement learning to neural conversation systems. Song *et al.*, 2017 introduce the maximum marginal relevance ranking algorithm in the beam search process to prevent decoding universal responses. Jiang and Rijke, 2018 review previous approaches to the low-diversity problem of chit-chat systems and linked it with model over-confidence. Besides, they sketch several directions for tackling model over-confidence by confidence penalties and label smoothing. Du and Black, 2019 design an iterative training process and ensemble method based on boosting and combine their method with different training and decoding paradigms, including mutual-information-based decoding and reward-augmented maximum likelihood to improve the diversity of generated responses. Jiang *et al.*, 2019 propose a frequency-aware cross-entropy (FACE) loss function to improve neural response diversity by linking token frequency with a weighting mechanism.

Alternatively, unlikelihood training shows competitive performance in solving the expression diversity problem. To address the limitations of likelihood-based decoding objectives, Baheti *et al.*, 2018 introduce two distributional constraints to encourage semantic similarity, and the distribution over topics and syntax in the response resembles user input. Liu *et al.*, 2018b introduce a statistical re-weighting method to different weights for the multiple responses of the same query to break the dominant sequence-to-sequence loss terms. Gao *et al.*, 2019b design a reinforcement learning algorithm to generate multiple diverse responses simultaneously for short-text conversation. Khayrallah and Sedoc, 2020 apply simulated multiple reference training to model one-to-diversity of non-task-oriented dialogues. Cai *et al.*, 2020a introduce contrastive learning into dialogue generation to solve the low-diversity issue of maximum likelihood estimation (MLE) objective in chit-chat conversations. Ueyama and Kano, 2020 propose an inverse n-gram frequency (INF) loss that can incorporate contextual fluency and diversity at the same time to generate diverse conversations. Li *et al.*, 2020c extend the recently introduced unlikelihood loss to address the low-diversity limitation caused by maximum likelihood training. Besides, He and Glass, 2020 propose negative training by first finding generated samples of a trained model that exhibit undesirable behaviors and then using them to feed negative training signals for fine-tuning the model.

4.3.4 Leveraging Extra Resources

Except for the aforementioned methods, other strategies that can encourage diverse expression and model one-to-many diversity are investigated. The most popular pointcut is leveraging extra resources. Qiu *et al.*, 2019 propose to utilize multiple valid references, which is not always available, and further considering the correlation of different responses to model the one-to-many mapping of chat-driven conversations. Ko *et al.*, 2019 use linguistically motivated specificity and semantic plausibility reranking to generate diverse and informative responses. Su *et al.*, 2020a propose to diversify dialogue generation from the perspective of leveraging non-conversational text, which covers a much broader range of topics.

4.4 Context Modeling: Single-Turn and Multi-Turn

Context modeling is also an essential problem for chit-chat conversations. For real-world conversations, it is not rare to converse in over hundreds turns, and thus mimicking human conversations involves modeling long-range dialogue context. Early research of neural-based response generation system mainly consider single-turn context to verify whether fully data-driven methods can generate human-like responses. Later on, various methods are proposed to model multi-turn context in chit-chat conversations. The below part first presents a few representative researches that only consider single-turn context and then elaborates the more actual setting, e.g., learning to generate response with multi-turn context.

4.4.1 Single-Turn Context Modeling

As shown in Figure 4.3, early-stage of deep neural conversation systems (Vinyals and Le, 2015; Xu *et al.*, 2017) mainly consider single-turn conversations, i.e., the first person utters "ABC", and the second person responds "WXYZ". These methods are built upon recurrent neural networks with the encoder-decoder framework, where encoder is responsible for capturing and aggregating context information while the decoder auto-regressively generates the target response.

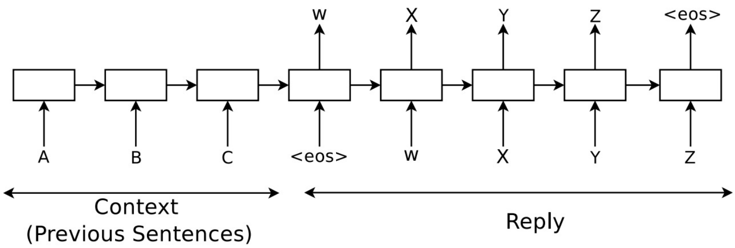


Figure 4.3: Conversation model with sequence to sequence learning and single-turn context, where <eos> is a special token to indicate the beginning and ending of a sequence (Vinyals and Le, 2015).

4.4.2 Multi-Turn Context Modeling

A more realistic setting is to consider multi-turn context information in chit-chat dialogues so that the systems can chat with consistent content and other characteristics and provide more accurate response. With the increase of data size and computing power, learning to chat with multi-turn context utterances has become the main stream of this field, and existing researches can be roughly grouped into the following two lines.

One is to study context modeling and utilization method. Tian *et al.*, 2017 propose weighted sequence integration to explicitly weight the context vector by calculating the correlation between context and query, which can introduce more related context and reduce adverse effects of irrelevant noises. In order to capture important information in the context and generate highly relevant responses, an attention mechanism is used in the encoder. Xing *et al.*, 2018 introduce HRAN, which uses word-level attention within utterances and utterance-level attention among utterances, to dynamically model important parts of a context. Considering the advantage of sequence integration, Zhang *et al.*, 2018c use static and dynamic attention mechanisms for each utterance in one conversation and weight them to obtain contextual representation.

Although traditional attention mechanism or cosine similarity method has been applied to solve the problem of long-distance between response and relevant context information, these methods may lead to insufficient correlation hypothesis. Therefore, the model called ReCoSa is proposed by Zhang *et al.*, 2019a to solve the long-distance dependence problem, initializing representation of each context with LSTM and leveraging multi-layer multi-head self-attention mechanism to computed attention weights for the decoder between updated context and masked response representation. Dziri *et al.*, 2019 introduce THRED. This hybrid model combines conversation history from previous utterances and topic words from a Latent Dirichlet Allocation model using message attention, context-level attention, and topic attention, which generates consistent and topic-related responses. Since RNN-based models cannot perform parallel computing, Mangrulkar *et al.*, 2018 propose a CNN-based hierarchical structure. In this architecture, CNNs are utilized to build encoder and decoder generating n-best responses. Then the proposed CNN re-ranker and N-gram match re-ranker are combined to determine the final rank of each hypothesis.

Most hierarchical models focus on representing the context from the word level and utterance level. However, they do not explicitly model the meaning and relationship of utterances. Therefore, in light of the relationship between the query and response under a background, Shen *et al.*, 2019a propose the CSRR model. In this model, hierarchical latent variables based on VAEs are utilized to represent the utterance meaning. Three hierarchies, namely discourse level, pair level, and utterance level, are built to learn the dependency between query and response. Shen *et al.*, 2018 point out that a good response should be able to smoothly connect previous and future conversations. They introduce the NEXUS model to enhance the connection through maximizing mutual information. With the proposal of the transformer, many researchers applied it to conversation generation.

Cai *et al.*, 2020c propose BCTCE structure. Different from previous hierarchical models, this model directly uses a bi-channel transformer to realize the parallel encoding of dialogue utterances and the document for document-driven conversation. Although transformer-based models can have better performance on long-term dependence, according to the empirical study conducted by Sankar *et al.*, 2019, both recurrent and transformer-based seq2seq models are not significantly sensitive to drastic and unnatural changes to the dialog history. In addition to modifying the model structure, many studies also introduce new tasks to improve the performance of multi-turn response generation. Zhou *et al.*, 2019 propose a context rewriting network(CRN), rewriting the last utterance according to the context history and original last utterance. This unsupervised method generates a self-contained utterance and makes context modeling explainable and controllable. Zhao *et al.*, 2020c introduce a model with a simple structure for response generation, together with order recovery and masked content recovery tasks. This method reduces the complexity of the model, makes context understanding learnable, and improves conversation generation.

Another is to leverage more context information and correlated dialogue history. Wu *et al.*, 2019b propose a new response generation pattern, prototype-then-edit. First, a prototype selector retrieves a context-response pair according to the current context and then rewrites the prototype response by taking differences between prototype context and current context into consideration. Feng *et al.*, 2020 believe that a good response is generally related to the potential context knowledge in the specific scenario. They propose to combine the dialogue history and future dialogue to build scenario knowledge, enhancing the conversation generation system. To incorporate scenario knowledge without future dialogue, an imitation learning framework is introduced to imitate the scenario-based teacher model. As to E-Commerce, Zhang *et al.*, 2020e incorporate the seller's historical dialogue information into response generation through finding out the most relevant seller's historical responses for the customer's question and fusing information from the generation module and copy module. In terms of multi-party dialogue, it is challenging to extract relevant context information due to complex interaction among the interlocutors' roles. Liu *et al.*, 2019a propose a new model, incorporating interlocutor-aware contexts into recurrent encoder-decoder frameworks and predicting the speaker and the addressee when generation responses. For VQA tasks, the MAC network shows strong performance on single-turn VQA tasks, in order to adapt this network to tasks that need reasoning over the dialog history, Shah *et al.*, 2020 augment MAC networks with Context-aware Attention and Memory(CAM), attending over the MAC control states of past dialog turns. This structure makes the conversation characterized with history dependency and coherence.

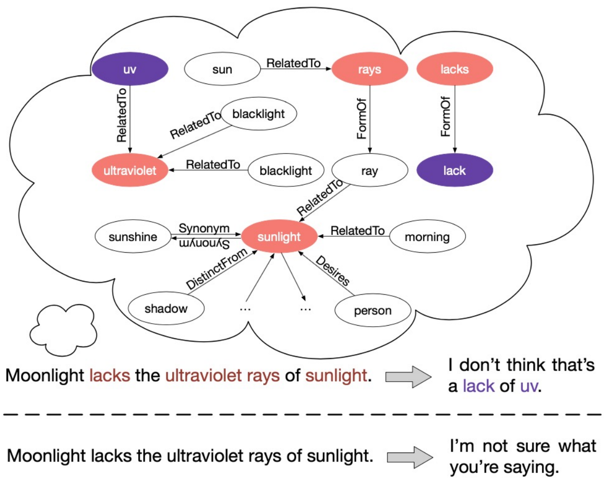


Figure 4.4: Chit-chat response generation with/without (the first/second line) the enhancement of structured commonsense knowledge (Zhou *et al.*, 2018b).

4.5 Knowledge and Grounding in Response Generation

In real-world conversations, a feasible response is not only correlated to the current context information well but also constrained by commonsense knowledge. For chit-chat systems, many researchers have investigated incorporating extra knowledge into the response generation process in recent years. Basically, there are two main types of knowledge that are utilized in neural response generation models, including structured knowledge bases that support logical reasoning and unstructured grounding information such as Wikipedia passage, document, and other background information. In this section, we first introduce representative works that utilize structured knowledge in response generation and then present some typical researches that leverage unstructured information. At the end of this part, we give a few response generation methods that can incorporate structured and unstructured knowledge simultaneously.

4.5.1 Structured Knowledge

Structured knowledge in existing response generation solutions mainly represents entities and their relationships. Liu *et al.*, 2018a employ a knowledge base to mitigate the problem of generating short, general, and meaningless responses. Through matching the relevant facts for the input utterance and diffusing them with similar entities, the proposed method has the ability of convergent and divergent thinking over the knowledge base, and thus it can generate more diverse and informative responses with accurate entities. Zhou *et al.*, 2018b introduce large-scare structured commonsense knowledge[2] in chit-chat conversation generation to augment both language understanding and generation, in which the detailed setting is presented in Figure 4.4. For a given post, the proposed model first retrieves relevant knowledge graphs from a knowledge base and then utilizes a static graph attention mechanism to encode the retrieved graphs. During the generation process, a dynamic graph attention mechanism is proposed to fuse retrieved knowledge graphs and triples for generating commonsense-aware responses. Wu *et al.*, 2020e not only ground response generation on commonsense knowledge graphs but also introduce topic facts from a neural recommender to achieve controllable and interpretable response generation[3]. Zhang *et al.*, 2020a leverage commonsense knowledge graphs to explicitly model conversation flows by representing the potential conversation flow as traverses in the concept space along with relations. Based on the formulation that knowledge selection problem is as a path traversal over knowledge graphs, Jung *et al.*, 2020 further study the utilization of rich structural information in knowledge graph based on the in-and-out attention flow. Wu *et al.*, 2020d focus on the problem of grounding response generation on context-specific knowledge. The authors design a felicitous fact mechanism to let the model focus on the context-relevant knowledge facts and utilize two fusion techniques, context-knowledge fusion, and flexible mode fusion, to integrate knowledge. Xu *et al.*, 2020b divide multi-turn response generation into two sub-tasks, i.e., explicit goal-planning grounded on knowledge graph and goal completion by topic elaboration. To complete the task, the authors present a three-layer hierarchical

[2] https://conceptnet.io/
[3] https://github.com/pku-sixing/IJCAI2020-TopicKA

Topic	Reddit Sequence of Comments	Wikipedia Sentences
Noam Chomsky	<start> Noam Chomsky: Bernie Sanders is Not a Radical. He has Mass Support for Positions on Health-care & Taxes <end> <start> Funny, because Bernie Sanders's idol Eugene Debs ran against FDR <end> <start> Maybe Clinton will be FDR <end> <start> Watch out, Japanese. <end> <start> Japanese You misspelled Syrians <end>	For Chomsky, there are minimalist questions but the answers can be framed in any theory.
		⋮
		Minimalism in structured writing or topic-based authoring is based on the ideas of John Millar Carroll.
		Minimalism is about reducing the interference of the information with the users sense-making process.
		An error, in fact, is the teachable moment that the content can exploit.

Figure 4.5: An example that aligns Reddit utterances and Wikipedia sentences (Vougiouklis *et al.*, 2016).

reinforcement learning model, where the upper-layer policy learns to traverse a knowledge graph to complete the goal planning sub-task, while the lower two layers produce conversation about a specific topic conditioned on the goal-planning.

4.5.2 Unstructured Knowledge and Grounding

Vougiouklis *et al.*, 2016 treat correlated Wikipedia sentences as extra background knowledge to augment the multi-turn response generation task. As shown in Figure 4.5, each sequence of Reddit utterances is paired with 20 Wikipedia summary sentences. Accordingly, the chat-driven response generation task is formulated as generating a response conditioned on previous context utterances and the corresponded background knowledge sentence wherein these two different types of information are modeled by an RNN and a CNN module, respectively. To train a neural chit-chat systems that can generate coherent and content rich response on the Reddit news dataset, Parthasarathi and Pineau, 2018 also introduce unstructured knowledge from Wikipedia summaries and further incorporate the NELL knowledge base. Ghazvininejad *et al.*, 2018 extend neural response generation to a more useful conversational application by producing more contentful responses grounding extra knowledge. They propose a fully data-driven model to complete the task of knowledge-grounded conversation task, which consists of a facts encoder, dialogue encoder, and dialogue decoder. To train the proposed model, they extracted a dataset from the Foursquare dataset with comments about restaurants and Twitter, in which each conversation contains entities that tie to Foursquare.

Lian *et al.*, 2019 explore unstructured knowledge selection (e.g., user profiles, Wikipedia) in response generation to better leverage external knowledge. The authors propose a knowledge selection mechanism in an end-to-end neural model, where both prior and posterior distributions over knowledge are utilized to perform knowledge selection. Lin *et al.*, 2020a further explore the problem of jointly utilizing different types of knowledge in response generation. Specifically, a recurrent knowledge interaction method and a knowledge-copy mechanism that uses a pointer network to copy words from external knowledge are introduced in the decoding steps.

Tian *et al.*, 2020 propose a memory model to capture on-demand knowledge from both conversational contexts, document, and part of anticipated responses in response generation. Chen *et al.*, 2020a concentrate on the gap between prior and posterior knowledge selection of latent variable models in knowledge-aware response generation. Concretely, the authors propose to enhance the prior selection module with the necessary posterior information and design a knowledge distillation training strategy to train the decoder with selected knowledge from the prior distribution. Zheng *et al.*, 2020a study the difference of the selected knowledge between the current turn and previous turns. To enhance the performance of knowledge selection in knowledge-grounded dialogue generation, Wu *et al.*, 2020c propose to first retrieve relevant prototype dialogues and then utilize these dialogues to extract knowledge facts.

As mentioned above, there are mainly two types of extra knowledge, i.e., triples from knowledge graphs and textual documents from corpus. The fusion of the structured knowledge and the non-structured grounding texts has been widely studied. Moghe *et al.*, 2018 argue that formulating response generation as a sequence-to-sequence task is overly simplistic, while human conversations heavily rely on their background knowledge about a specific topic. To mimic human behaviors and study the effect of background knowledge, they create a dataset comprising of movie chats wherein each response is explicitly created by copying or modifying sentences from the given unstructured background knowledge, e.g., plots, comments, fact tables, and reviews about the movies. Liu

message	What did you have for dinner?
baseline	I had fish and chips.
user1	I had spag bol.
user2	Chicken and chips.
user3	Chicken and rice.
user4	Fish and chips.
user5	I had spag bol.
user6	I had Mexican food.
user7	Salad...
user8	I had chicken and chips.
user9	I had spag bol.
user10	Pizza.

Figure 4.6: A case study that reflects the influence of different persona (Li *et al.*, 2016b).

et al., 2019c introduce three components in knowledge-aware chit-chat, including an augmented knowledge graph that contains both triples and texts, knowledge selector, and knowledge aware response generator, to better fuse both knowledge triples and document texts for chit-chat response generation.

Recently, Zhao *et al.*, 2019c explore a more realistic knowledge-grounded dialogue generation setting that only limited labeled examples are available during training. The authors design a disentangled decoder to isolate parameters that rely on knowledge-grounded training examples from the entire generation model. By doing so, the main component of the model can be trained on the cheap and plentiful ungrounded dialogues and unstructured documents, while the rest parameters can be learned with the limited grounded examples. Li *et al.*, 2020b further investigate the setting of zero-resource knowledge-grounded dialogue generation, i.e., context-knowledge-response triples are not required in training. To achieve this goal, the authors propose to leverage latent variables to express the knowledge and devise a variational method to estimate a generation model from two independent corpora, including a dialogue corpus and a knowledge corpus.

4.6 Human Factors: Emotion, Persona, and Beyond

Unlike task-oriented systems, chit-chat systems mainly serve as personal assistants, emotional companions, and the key factors that affect user experience are the long-term engagement and the matching degree between chit-chat systems and users. Thus, human factors, e.g., emotion, persona, play a vital role in real-world conversation systems. Take a very simple case shown in Figure 4.6 for illustration, different users of distinctive persona respond to the same message with diversified contents. This is especially true when we are considering more realistic scenarios. Also, the previous sections of this chapter have concluded that the typical sequence-to-sequence neural networks tend to generate generic responses, and the utilization of extra information such as knowledge graphs, document texts could facilitate creating diverse responses. Similarly, human factors can also serve as strong background information to control the content of generated responses and prevent the conversation model from creating uninformative responses. In view of these merits, many attempts have been made to incorporate human factors in generation-based chit-chat systems, which can be roughly grouped into three categories, i.e., persona, emotion, and beyond.

Persona. As one of the pilot studies, Li *et al.*, 2016b explore both the influence of speaker consistency and speaker-addressee interactions for neural response generation, where the profile of interlocutors are expressed by embeddings (similar to word embeddings) learned from massive training conversations. Kottur *et al.*, 2017 launch an empirical study to investigate the effects of pre-training, embedding training, data cleaning, diversity-based re-ranking, evaluation setting. Based on the trade-offs of different factors, the authors further propose a neural response generation model conditioned on speakers with the enhancement of larger datasets and bootstrapping strategy for speaker embeddings pre-training. Luan *et al.*, 2017 propose a multi-task learning neural conversation model that leverages both conversations across speakers and other types of relative data to the speaker roles to be modeled. Unlike previous works that utilize implicit embeddings as persona, Zhang *et al.*, 2018b crowd-source a dataset that conditions response generation on explicit profile information and the initial personal topics of the conversation partner. In witness to the success of profile information in response generation, Mazare *et al.*, 2018 provide a new dataset that contains 5 million personas and 700 million persona-based dialogues to train a persona-enhanced chit-chat system at scale. Qian *et al.*, 2018 study profile assigning in generating coherent conversations, which is solved by a profile detector to judge whether a profile should be used when responding and a bidirectional decoder to generate personality-coherent responses in a forward-and-backward fashion. Chu *et al.*, 2018 propose a multi-level attention mechanism and a memory module to learn persona representations. Hu *et al.*, 2018 focus on the adaptation of linguistic cues and personality traits to control the system output at each step of the dialogue. Engonopoulos *et al.*, 2018 concentrate on how user groups affect utterance generation in chit-chat systems.

There are also many works in recent years, which mainly enhance personalized chit-chat systems from persona information modeling and incorporation in response generation, including but not limited to, modeling personalization in continuous space via augmented Wasserstein Autoencoders (Chan *et al.*, 2019), variational hierarchical user-based model (Bak and Oh, 2019), adversarial learning (Olabiyi *et al.*, 2019), graph-structured network (Hu *et al.*, 2019), the combination of memory module and conditional variational autoencoder (Song *et al.*, 2019a), persona-guided variational response generator (Wu *et al.*, 2020a), mutual persona perception (Liu *et al.*, 2020), the three-stage framework of generate-delete-rewrite (Song *et al.*, 2020a), persona enhanced dual alternating learning network (Jiang *et al.*, 2020), opinionated dialogue generation with stance-based personas (Scialom *et al.*, 2020), and sketch-filling-ranking framework (Shum *et al.*, 2020). Besides, the investigation of persona-aware response generation with limited resources is non-trivial. Mo *et al.*, 2018 design a transfer reinforcement learning framework to mitigate the problem of insufficient training data. Chang *et al.*, 2019 propose a semi-supervised stable variational model for replier-consistent response generation. Madotto *et al.*, 2019 propose a meta-learning solution to achieve personalized dialogue learning without using any persona description. Moreover, incorporating more useful information in persona-aware response generation is also appealing. Song *et al.*, 2020b introduce natural language inference to generate persona consistent dialogues. Majumder *et al.*, 2020a explore commonsense expansions for persona-grounded dialogue generation.

Emotion. Zhou *et al.*, 2018a first explore large-scale conversation generation conditioned on specific emotion. On the basis of the vanilla sequence-to-sequence dialogue generation model, the authors propose to introduce the high-level abstraction of emotion expressions by embedding emotion categories, the change of implicit internal emotion states captured by internal memory, and explicit emotion expression from external emotion vocabulary modeled by external memory in the response generation process. Li and Sun, 2018 propose a syntactically constrained bidirectional-asynchronous approach for emotional response generation, in which pre-generated emotion keywords and topic keywords are asynchronously introduced in the generation process. Huang *et al.*, 2018 empirically study three different models to restrict generated responses with expressed emotions by introducing emotion constraint in encoder input, encoder output, and decoder. Zhou and Wang, 2018 leverage emoji to convey emotion information to achieve generating emotional responses as scale, where the generation models are implemented as several conditional variational auto-encoder variants. Shi and Yu, 2018 propose to introduce user sentiment from acoustic, dialogic, and textual information to perform sentiment adaptive dialogue generation. Colombo *et al.*, 2019 study emotional response generation in a controlled manner in which emotions in continuous representation are used. Through investigating real-life conversation data, Song *et al.*, 2019b conclude that emotional states are described either by strong emotional words or by implicitly combing neutral words in distinct ways. Based on the observations, the authors propose an emotional chit-chat system that can express the desired emotion explicitly or implicitly in the generated responses with a unified framework. Ma *et al.*, 2020 concentrate on the emotion drift problem, which is referred to the inconsistency of emotion between context and responses, and propose to use a control unit framework to incorporate consistent emotional words during generating responses. Shen and Feng, 2020 further present a curriculum dual learning framework for emotion-controllable response generation.

More recently, empathetic chit-chat conversation systems have attracted growing attention from both academia and industry. To facilitate the development of empathetic dialogue systems, Rashkin *et al.*, 2019 propose a benchmark, which contains 25K conversations grounded in emotional situations. Li *et al.*, 2020e propose a variational model to generate appropriate responses with user emotional reaction awareness. Li *et al.*, 2020d propose a multi-resolution adversarial model to capture the nuances of human emotions and the potential feedback from users, which can generate more empathetic responses. As presented by Zhou *et al.*, 2020c, the popular social chatbot XiaoIce can also output empathetic conversations. In addition, Majumder *et al.*, 2020b consider user emotion in varying degree for empathetic response generation. Specifically, the authors leverage polarity-based emotion clusters and emotional mimicry to improve empathy and context relevance of the generated responses.

Beyond Persona and Emotion. Akama *et al.*, 2017 study the setting of generating stylistically consistent response generation and propose a two-stage training framework that resembles transfer learning accordingly. Gao *et al.*, 2019e introduce a structured latent space to bridge conversation modeling and non-parallel style transfer for stylized response generation. Zhang *et al.*, 2018a attempt to deal with the task of response generation with controlled specificity. To calibrate how controllable attribute affect response generation, See *et al.*, 2019 launch an empirical study to thoroughly test two models, i.e., conditional training and weighted decoding, to control four different attributes, including repetition, specificity, response-relatedness, and question-asking. Takayama and Arase, 2020 introduce the pointwise mutual information (PMI) to measure the co-occurrence degree of an utterance and a response. The co-occurrence degree and a PMI-based word prediction mechanism are introduced in a sequence-to-sequence model to control the specificity of the generated response.

4.7 Pre-Training in Dialogue Generation Models

Starting from BERT (Devlin *et al.*, 2018), pre-trained language models (PLMs) have changed the phase of varied downstream tasks, and many efforts have been devoted to building conversation systems. Bao *et al.*, 2020a propose a representative pre-training framework for dialogue gen-

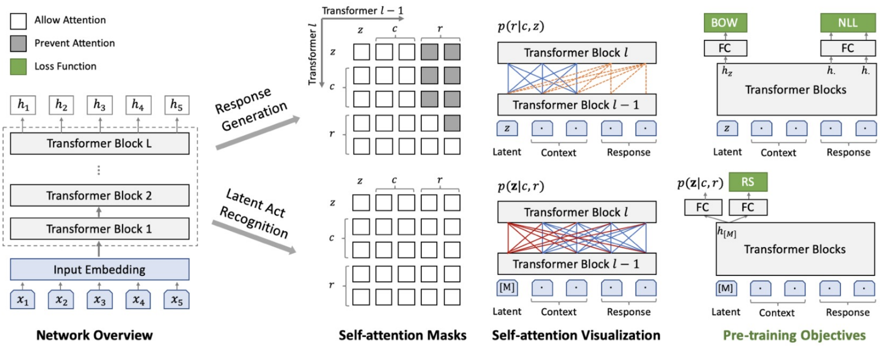


Figure 4.7: A representative pre-training framework designed for dialogue generation (Bao *et al.*, 2020a).

eration. As shown in Figure 4.7, typical pre-training models consist of transformer blocks, and there are some specific modules (e.g., latent variable to address the inherent one-to-diversity challenge) and pre-training tasks (e.g., latent act recognition). Zhang *et al.*, 2020f present a large and tunable neural conversational response generation model, namely DialoGPT (dialogue generative pre-trained transformer). Through training on 147M conversation-like exchanges from Reddit, DialoGPT can generate more relevant, informative, and context-consistent responses. Zhao *et al.*, 2020b study knowledge-grounded response generation with the enhancement of pre-trained language models. Cao *et al.*, 2020 adapt pre-trained language models to response generation with the capability of multiple input sources modeling. Yang *et al.*, 2020 explore stylised response generation on pre-trained language models. Zheng *et al.*, 2020b utilize pre-trained language models as the backbone of the personalized response generation framework.

4.8 Datasets

With the revival of deep neural networks and the simultaneous explosion of open-access web data, many datasets are collected and constructed for neural response generation. We introduce some representative and frequently utilized datasets in the following part.

Context. To train a deep neural response model, researchers explore crawling large-scale chat-like conversations from various social media and forums such as Twitter [4], Weibo [5] and Reddit [6]. These conversations are open-available and cover a myriad of daily topics. Shang *et al.*, 2015 constructed a **S**hort-**T**ext **C**onversation dataset (STC) from Weibo, which contains roughly 4.4 million training pairs. Each pair consists of a user-issued post text and a target response that is supposed to be mimicked by the neural model. This dataset is mainly employed and studied for the single-turn context setting mentioned in Section 4.4.

Sordoni *et al.*, 2015 created a large-scale context-sensitive corpus for chit-chat conversational response generation, which consists of 127M context-message-response triples from Twitter Firehose, covering the period from June 2012 to August 2012. Each triple composes of a context sentence, a message which resembles the post text in STC and a target response. In this setting, a deep neural conversation model is built to create a response conditioned on both the context sentence and massage sentence, which corresponds to the multi-turn context setting in Section 4.4.

Li *et al.*, 2017b developed a high-quality multi-turn conversation dataset by crawling raw data from various websites for English learners to practice spoken language in daily life, namely **DailyDialog**. Compared with the aforementioned two datasets from Weibo and Twitter, Dailydialogue consists of formal language and contains less noise.

Diversity. Xu *et al.*, 2018b built a **L**arge-**S**cale **D**omain-**S**pecific **C**onversational **C**orpus (LSDSCC) to mitigate universal responses and evaluate conversation diversity. They first collected dialogues from the most popular movie discussion board in Reddit, with high-quality and focused domain to alleviate the challenge of producing universal responses. After thorough pre-processing and cleaning procedures, they also created multiple ground-truth responses for each given query and the correlated context in the test set to calibrate the diversity of generated responses.

[4] https://twitter.com/
[5] https://weibo.com/
[6] https://www.reddit.com/

Personalization. To evaluate the influence of human factors, Zhang *et al.*, 2018b collected a **Persona-Chat** dataset via Amazon Mechanical Turk. They crowd-source 1,150 personas with 950 personas for training and 100 personas for validation and testing, respectively, where each persona attaches at least 5 profile sentences. To prevent modeling of trivial overlap, the authors proposed to prepare additional rewritten sets on the 1,150 personas by rephrasing, generalization, or specialization. Then, they assigned each of the two Turkers a persona from the possible set and asked Turkers to chat, resulting in a dataset of 131,438/15,602/15,024 utterances (8,939/1,000/968 dialogues) for training/validation/testing.

Wang *et al.*, 2019c designed an online persuasion task on the Amazon Mechanical Turk platform to study personalized persuasive dialogue systems for social good. They asked one participant to persuade the other to denote a specific charity and collected 1,017 dialogues in total. Then, a persuasion strategy annotation scheme is proposed to label a subset of the collected conversations, where emerging persuasion strategies are annotated. They also linked demographic and psychological backgrounds, i.e., personality traits, morality, value systems, and donation behaviors. Finally, they studied the relationships between personal backgrounds and persuasion strategies.

Zheng *et al.*, 2019a created a large-size multi-turn dialogue dataset from Weibo, named as **PersonalDialog**, which composes of 20.83M conversation sessions and 56.25M utterances of 8.47M speakers. Each utterance belongs to a specific speaker, and each speaker associates with various traits such as age, gender, location interest, etc.

Grounding. Dinan *et al.*, 2018 crowd-sourced a multi-turn dialogue datasets grounding on Wikipedia, named as **Wizard of Wikipedia**. They asked two participants to chat with each other. Unlike previous instruction, the two participants of this setting are asymmetric, i.e., one participant acts as a knowledgeable expert, referred to the **wizard** while another plays the role of a curious learner, denoted as the **apprentice**. When chatting, the wizard has access to related Wikipedia knowledge while the apprentice does not. This dataset covers 1,365 chit-chat dialogue topics such as commuting, Gouda cheese, music festivals, podcasts, and bowling and consists of 22,311 dialogues with 201,999 conversation turns, which is split by 166,787/17,715/17,487 for train/validation/test respectively. The test set contains two subsets, consisting of 533 overlapping topics and 58 unseen topics in train and validation sets.

Zhou *et al.*, 2018c also collected a document-grounded conversation dataset through Amazon Mechanical Turk, where annotators are asked to chat about the given Wikipedia article. To facilitate the dataset collection, the topic of documents is restricted to popular movies and each conversation has more than 12 turns. The final dataset contains 4,112 conversations in total and with an average of over 21 turns. Among which, 2,128 conversations are from the setting that only one of each two-annotator pair has assess to Wikipedia document while the rest 1984 conversations are from the setting that both annotators have access to the same document.

To mimic human conversations that rely on background knowledge about the topic, Moghe *et al.*, 2018 created a dataset consists of movie chats wherein each response is obtained by copying and/or modifying sentences from the background knowledge of the movies, e.g., plots, comments, and reviews. The constructed dataset has 9,071 conversations about 921 movies with 90810 utterances in total, where each utterance contains 15.29 words on average. There are 5,157 unique plots, 1,817 unique reviews, and 12,740 comments about these movies for creating responses.

Rashkin *et al.*, 2018 crowd-sourced the **EmpatheticDialogues** dataset to facilitate the learning of empathetic in chit-chat conversations. Each dialogue is grounded in a specific emotion label and situation that is created by the speaker, with a listener to chat with the speaker. The resulting corpus consists of 24,580 conversations from 810 different annotators, which is split into 19,533/2,770/2,547 for train/valid/test, respectively.

Tuan *et al.*, 2019 designed a task of dialogue generation grounding on dynamic knowledge graphs and created a corresponded corpus from TV series, named as **DyKgChat**. Each input message is paired with a knowledge graph and the ground-truth response. The response generation process is required to correlate with the evolution of the knowledge graph. This corpus contains two subsets, i.e., **HGZHZ** and **Friends**, with 1,247 (17,164 turns) and 3092 (57,757) dialogues respectively. The average lengths of the two sets are 26.95 and 14.52 tokens per turn.

Wu *et al.*, 2019a constructed a dataset named **DuConv** for exploring proactive human-machine conversation under the guidance of explicit conversation goals. In conversation, one plays the role of conversation leader, and the other is the follower, where the leader has access to a knowledge graph and is asked to sequentially alter the conversation topics conditioned on the given conversation goal. The established dataset contains 29,858 dialogues and 270,399 utterances. The average words per utterance and average knowledge per dialogue are 9.1 and 17.1, respectively.

Gopalakrishnan *et al.*, 2019 explore a more general setting of knowledge-grounded chit-chat conversations and accordingly collected a dataset named **Topical-Chat** via Amazon Mechanical Turk. In the process of data collection, every two workers are asked to chat with natural and coherent content grounded in the provided reading sets. Each pair of partners do not have pre-defined roles like in **DuConv** and **Wizard of Wikipedia**. Instead, their conversations could be both symmetric or asymmetric to varying degrees, which is more realistic in human-human conversations. The established dataset covers 8 topics and consists of 9,058/1,131/1,130 conversations as train/valid/test sets. There are 248,014 utterances in total, and each utterance contains roughly 20 words on average.

Moon *et al.*, 2019 manually annotated a open-ended parallel dialogue and knowledge graph corpus named **OpenDialKG**. The corpus is gathered in the Wizard-of-Oz setting Shah *et al.*, 2018 in which two crowd-workers are asked to chat with natural and engaging dialogues. Concretely, the first annotator is asked to initiate a conversation about a given seed entity, and the second one is required to select the most relevant and natural facts from a given list of facts to create a conversational response. Only facts within the 1-hop or 2-hop path of the original conversation topic are considered. Once the second annotator responds to the first annotator, new multi-hop facts from the knowledge graph along with paths from entities introduced in the latest message are retrieved. In the next cycle, the first annotator is instructed to create a new message from the updated facts set, and such a cycle is repeated for each dialogue until a participant ends the conversation. There are two sub-sets in this corpus, including a recommendation task and a chit-chat task. The chit-chat data collection comprises 3,353 dialogues and 19,336 conversation turns. The final knowledge graph consists of 1,190,658 fact triples of 100,813 entities with 1,358 different relationships.

Qin *et al.*, 2019 extracted a large-scale grounded conversational dataset from Reddit. On Reddit, each dialogue correlates with a submission title and a URL linking to a news or background article to start the conversation about the contents of the given URL, which can be utilized to study neural conversation with on-demand machine reading. After multiple steps of filtration and pre-processing, there are 28.4K/1.2K/3.1K dialogues and documents with 2.36M/0.12M/0.34M utterances for train/valid/test, respectively. There are 15.18M/0.58M/1.68M sentences in train/valid/test documents. The average lengths of utterances and document sentences are 18.74/18.84/18.48 and 13.72/14.17/14.15 words for train/valid/test, respectively.

Tang *et al.*, 2019 further extracted a new dataset from **Persona-Chat** (Zhang *et al.*, 2018b) for target-guided chit-chat conversation by maintaining all conversations while discarding the persona information. Then, the extracted data is processed by automatically extracting keywords for each utterance. In doing so, each utterance is paired with a target subject, i.e., extracted keywords to guide the conversation. The final dataset contains 8,939/500/500 conversations for train/valid/test. There are 101,935/5,602/5,317 utterances in train/valid/test sets, respectively. There are 2,678/2,080/1,571 keyword types for train/valid/test, and the corresponded number of keywords are 2.1/2.1/1/1.9 on average.

4.9 Evaluation Metrics

4.9.1 Overlap-based Metrics

Due to the success of the traditional text generation evaluation metrics, researchers often utilize the text generation metrics to assess the dialogue generation task. The most popular metrics in previous work are

BLEU (Papineni *et al.*, 2002), METEOR (Banerjee and Lavie, 2005), and ROUGE (Lin, 2004). Among them, BLEU and METEOR are both proposed to evaluate machine translation tasks, and the ROUGE is the classical evaluation metric in text generation.

BLEU. Papineni *et al.*, 2002 proposed the BLEU metric to improve the n-gram precision calculation by combining the sentence length penalty. First, the brevity penalty BP is shown as

$$\mathrm{BP} = \begin{cases} 1 & \text{if} \quad c > r \\ e^{1-r/c} & \text{if} \quad c \leq r \end{cases} \tag{4.2}$$

Then, BLEU will be calcalated as

$$\mathrm{BLEU} = \mathrm{BP} \cdot \exp(\sum_{n=1}^{N} w_n \log p_n). \tag{4.3}$$

METEOR. METEOR (Banerjee and Lavie, 2005) is also a metric of the machine translation task based on the harmonic mean of unigram precision and recall, with recall weighted higher than precision. The METEOR metric fixes some of the problems found in the BLEU metric and produces a good correlation with human judgment at the sentence or segment level.

ROUGE. Different from Papineni *et al.*, 2002 of utilizing the precision between the n-gram of the candidate and the reference text, Lin, 2004 propose to calculate the recall as follows,

$$\text{ROUGE-N} = \frac{\sum_{S\in\{ReferenceSummaries\}gram_n\in S} \sum Count_{match}(gram_n)}{\sum_{S\in\{ReferenceSummaries\}gram_n\in S} \sum Count(gram_n)}. \tag{4.4}$$

Overall, these word-overlap metrics measure how many words overlap in a given generated response when compared to a reference response. However, Liu *et al.*, 2016; Lowe *et al.*, 2017; Tao *et al.*, 2018 argued that these word-overlap metric scores are weakly correlated to human judgment due to ignoring the notorious one-to-many nature of the chit-chat dialogues.

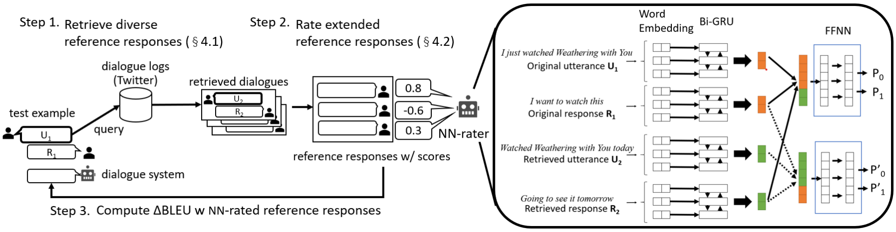


Figure 4.8: The overview of vBLEU (Gupta *et al.*, 2019).

ΔBLEU. Therefore, Galley *et al.*, 2015; Gupta *et al.*, 2019 proposed the improved overlap-based metrics by comparing the generated response with multiple diverse references. For example, Discriminative BLEU (ΔBLEU) (Galley *et al.*, 2015) embeds human judgments concerning the quality of reference sentences directly into the computation of corpus-level multiple-reference BLEU. The calculation process is as follows,

$$\Delta\text{BLEU-N} = \frac{\sum_i \sum_{g \in n-grams(h_i)} \max_{j: g \in r_{i,j}} \{w_{i,j} \cdot \#_g(h_i, r_{i,j})\}}{\sum_i \sum_{g \in n-grams(h_i)} \max_j \{w_{i,j} \cdot \#_g(h_i, r_{i,j})\}}. \tag{4.5}$$

Gupta *et al.*, 2019 also address this problem by carrying out automatic evaluation using multiple reference responses instead of a single-reference in the chit-chat dialogue evaluation. As mentioned in Gupta *et al.*, 2019, the additional information in the multiple reference response improves the evaluation robustness and quality under the one-to-many condition. Meanwhile, the information from multiple references can better express the diversity of the model.

***v*BLEU.** Later on, vBLEU is presented in Yuma *et al.*, 2020. This method first collects diverse reference responses from massive dialogue data and then annotates their quality judgments by using a neural network trained on automatically collected training data. After rating extended reference responses, vBLEU is more similar to human evaluation. More details of vBLEU are illustrated in Figure 4.8. Because of the poor performance of the overlap-based metrics, it seems using n-grams as the representation of the dialogue sentence is not a good choice.

4.9.2 Embedding-based Metrics.

As mentioned before, the overlap-based metrics based on the n-gram overlap calculation show that the n-gram is not a good choice for the utterance representation. Researchers attempt to handle this issue by representing the utterance in hidden space via deep neural networks.

Embedding Average. Mitchell and Lapata, 2008 proposed to calculate the cosine similarity between the averaged word embeddings in the two sentences. Rus and Lintean, 2012 proposed the Greedy Matching, which calculates the greedily matching words in two sentences based on the cosine similarities, and the total scores are then averaged across all words.

Vector Extrema. Forgues *et al.*, 2014 proposed to use the cosine similarity between the largest extreme values among the word embeddings in the two sentences as the embedding metric. In a word, these three metrics, called Embedding Metrics, first convert both the response reference and generated response to the high-dimensional hidden space, then calculate the similarity score between them. Note that there are many choice for the used embeddings, such as word2vec [7], glove [8] and so on. Embedding Metrics have been widely utilized to evaluate the chit-chat dialogue systems (Gu *et al.*, 2019b; Chan *et al.*, 2019; Shen *et al.*, 2018) and have shown their effectiveness in the chit-chat dialogue evaluation.

However, the Embedding Metrics do not show a high correlation with the human judgment limited by the representation of the word-embedding. Recently, with the fantastic development of the large-scale pre-training models (Devlin *et al.*, 2018; Liu *et al.*, 2019b; Radford *et al.*, 2019), researchers proposed to enhance the embedding metrics by converting the dialogue sentences to hidden space via pre-training model (Zhang *et al.*, 2019c; Zhao *et al.*, 2019a; Sellam *et al.*, 2020). The

[7] https://code.google.com/archive/p/word2vec
[8] http://nlp.stanford.edu/data/glove.840B.300d.zip

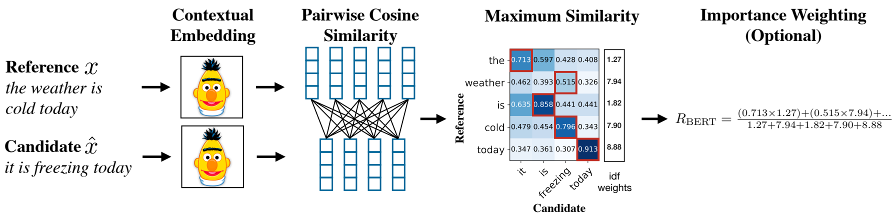


Figure 4.9: The overview of BERTScore (Zhang *et al.*, 2019c).

common idea behind these metrics is that they measure the semantic similarity between a reference response and a generated response, independent of the conversational context.

BERTScore. Specifically, BERTScore (Zhang *et al.*, 2019c) uses strong large-scale pre-training model, i.e., BERT and RoBERTa, to greedily match each word in a reference response with one word in the generated response. By doing so, it computes the recall of the generated sequence. The overview of BERTScore calculation is given in Figure 4.9. BERTScore was shown to have a strong system-level and segment-level correlation with human judgment on several machine translation tasks.

MoverScore. Zhao *et al.*, 2019a proposed to use the Word Mover's Distance, a special case of Earth Mover's Distance, to measures the semantic distance between the reference text and candidate text. MoverScore can better measure the semantic between the text.

BLEURT. BLEURT (Sellam *et al.*, 2020) is based on the BERTScore and fine-tuned on human judgments after pretraining on large-scale synthetic data with multiple automatic metrics as supervision signals. BLEURT has shown its strong correlation with human judgment on machine translation tasks. Meanwhile, due to the training on the supervision signals, BLEURT is more robust than the BERTScore.

However, recent metrics adapted from the text generation tasks are all based on the measure with the reference, i,e., the ground-truth response in chit-chat. Due to the notorious one-to-many nature (Li

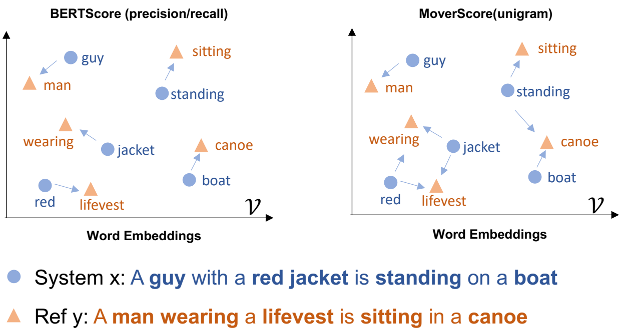


Figure 4.10: An illustration of MoverScore (Zhao *et al.*, 2019a) and BERTScore (Zhang *et al.*, 2019c).

et al., 2016a; Zhao *et al.*, 2017) of chit-chat dialogue, a good response should be related well to its context yet may be largely different from a reference response in semantics.

4.9.3 Learning-based Metrics.

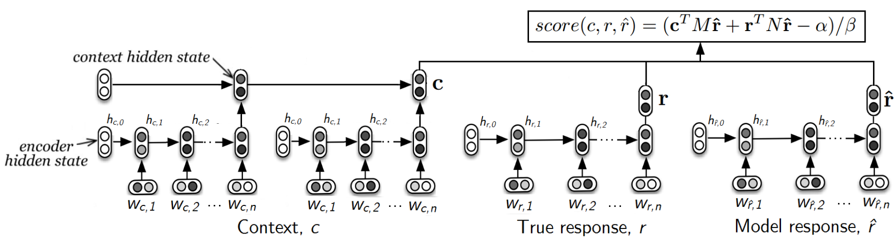


Figure 4.11: An illustration of ADEM (Lowe *et al.*, 2017).

Recent researchers attempt to enhance the dialogue evaluation by learning-based strategy.

ADEM. Lowe *et al.*, 2016 first propose to regard the evaluation as a next utterance prediction task which is based on the context-response manner, the model design is the same as Kannan and Vinyals, 2017. Lowe *et al.*, 2017 proposed the automatic dialogue evaluation model (ADEM),

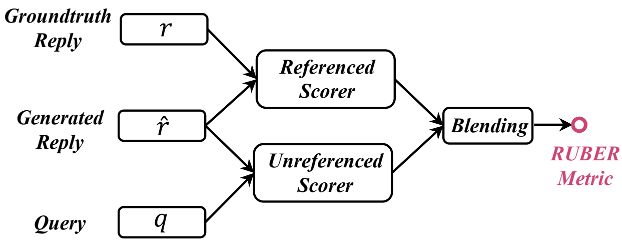


Figure 4.12: An overview of RUBER (Tao *et al.*, 2018).

which is trained in a semi-supervised manner using a hierarchical RNN. ADEM employs a pre-training procedure to learn the parameters of the encoder for the response generation task. Then, ADEM is sequentially trained on few labeled data for the evaluation prediction. The process is shown as

$$score(c, r, \hat{r}) = (c^T M\hat{r} + r^T N\hat{r} - \alpha)/\beta \tag{4.6}$$

where c is the dialogue context. r and $\hat{r}$ indicate the response reference and candidate response, respectively. $M, N \in R^n$ are learned matrices initialized to the identity, and α, β are scalar constants used to initialize the model's predictions in the range [1, 5]. As shown in Eq. 4.6 and Figure 4.11, ADEM predicts the score from two manners. It is not only based on the matching degree between response reference and candidate response but also the dialogue context and candidate response. It is the first work that proposes to use the matching degree of the dialogue context and candidate response. Limit to the lack of the labeled data, Liang *et al.*, 2020 propose to utilize Likert-score based self-reported user rating in social conversational systems, e.g., Alexa.

RUBER. As presented in Figure 4.12 RUBER (Tao *et al.*, 2018) is an unsupervised automatic evaluation metric that considers the similarity of the generated response with conversational context and response reference. Different from the ADEM, RUBER does not use the human-labeled dataset. The prediction score from RUBER is calculated by a designed discriminative model, which learns to evaluate whether a response matches the conversational context well. This metric shows a high correlation with human annotation. Note that RUBER is also based on the context-response matching manner and the reference-response matching manner. Ghazarian *et al.*, 2019 extended the RUBER based on the BERT. Meanwhile, Sinha *et al.*, 2020 argued that most of the automatic dialogue evaluation metrics do not generalize to unseen datasets and/or need a human-generated reference response during inference, making it infeasible for online evaluation. Sinha *et al.*, 2020 proposed an unreferenced automated evaluation metric that uses large pre-trained language models to extract latent representations of utterances and leverages the temporal transitions that exist between them.

Sato *et al.*, 2020 focused on evaluating chit-chat dialogue systems via response selection. This work first proposes to construct response selection datasets with well-chosen false candidates, containing those unrelated to the ground-truth response and those acceptable as appropriate responses. After the response selection, the evaluation system can conduct a better prediction of the matching degree between response reference and candidate response.

However, Sai *et al.*, 2019 revisited the design of the ADEM and proved theoretically that the comparison with reference response in the referenced metric causes ADEM to make conservative predictions where scores have a very low standard deviation. To further improve the robustness, Zhao *et al.*, 2020a proposed to remove the reference-response matching manner and enhance the discriminative model by fine-tuning on a few human-annotated data.

PONE. Meanwhile, researchers found that negative sampling quality is crucial for the model performance when the evaluating model is a discriminative model. However, a random sample can only bring the negative sample, which is much different from the reference, and the discriminative model can easily distinguish the positive and negative sampling. Lan *et al.*, 2020 proposed several sampling strategies called PONE to collect the valuable negative samples for the discriminative training. PONE proposed to use the weighted negative sampler to obtain the valuable negative samples and the positive data generator to

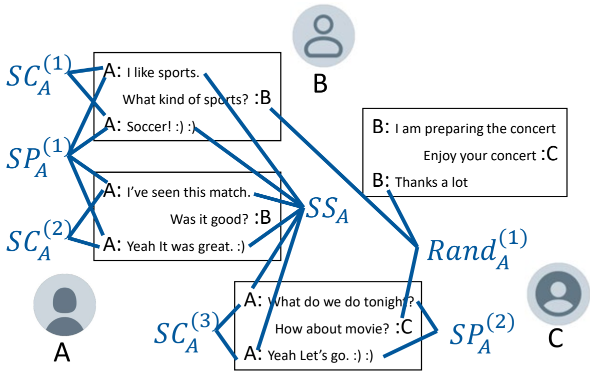


Figure 4.13: An illustration of SSREM (Bak and Oh, 2020).

generate more positive samples.

Bak and Oh, 2020 also argued that the negative sampling is important and proposed to use four kinds of negative samples. The first one is random utterances from speakers who are not the current speaker. The second one is the current speaker's utterances. The third one is the current speaker's utterances in conversations with the same partner. The last one is the current speaker's utterances in a single conversation. Bak and Oh, 2020 improve the response evaluation by conducting these negative sampling from several levels, which is given in Figure 4.13.

Sai *et al.*, 2020 argued that these discriminative metrics should train on multiple relevant responses and multiple irrelevant samples for any given context. Because the adversarial negative samples will be close to the positive samples, multiple relevant responses can handle this issue. Therefore, they collected such a dataset and improved the evaluation performance significantly.

USR. Mehri and Eskenazi, 2020b proposed USR, an UnSupervised and Reference-free evaluation metric for dialogue generation. USR is a reference-free metric that trains unsupervised models to measure several desirable qualities of dialogue and consists of the Masked Language Modelling Metric and dialogue Retrieval Metrics. Then, USR uses a merged score as the prediction result.

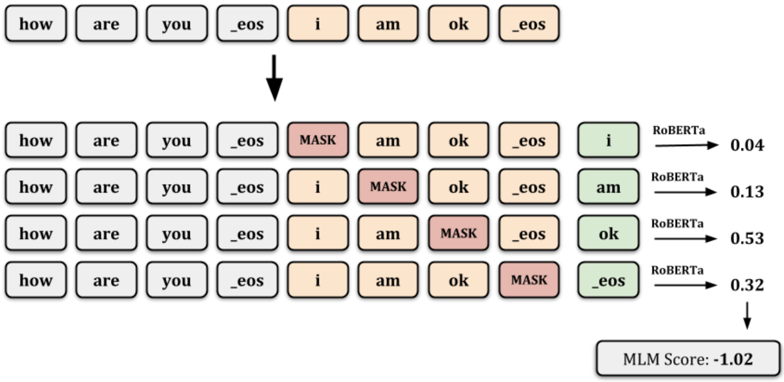


Figure 4.14: An illustration of USR (Mehri and Eskenazi, 2020b).

FED. Mehri and Eskenazi, 2020a introduce the FED metric (fine-grained evaluation of dialog), an automatic evaluation metric which uses DialoGPT, without any fine-tuning or supervision. Deriu and Cieliebak, 2019 propose AutoJudge which is the first method works by first generating dialogues based on self-talk and then uses human ratings on these dialogues to train an automated judgement model.

Others. Li *et al.*, 2019b provide an alternative procedure involving comparing two full dialogues, where a human judge is asked to pay attention to only one speaker within each and make a pairwise judgment. Tong *et al.*, 2018 proposed to joint learning multi-lingual data by adversarial multi-task learning for enhancing the hidden representation of the dialogue utterance. Huang *et al.*, 2020a enhance the evaluation model by the knowledge graph. Chan *et al.*, 2021 introduce a self-supervised evaluation method to enhance one-to-many evaluation in the latent space.

4.10 Summary

This chapter presents typical generation-based chit-chat techniques to address the challenges of diversity, context modeling, knowledge utilization and grounding, human factors learning, and performance evaluation. It can be observed that: (1) many of recent researches still focus on designing better evaluation metrics since there are no reliable and cheap metrics for evaluating chit-chat conversations, (2) expect for consistency between context (dialogue history, extra knowledge), persona, emotion and response in retrieval-based chit-chat systems, generation-based chit-chat systems further encounter the challenge of generating controllable and expected content without ethical issues.

5

Ensemble-Based Chit-Chat Systems

As introduced in the former two chapters, there are mainly two kinds of chit-chat models, i.e., retrieval-based models and generation-based models. The retrieval-based models collect a large number of conversations (query-response pairs). As shown in the upper part of Figure 5.1, they first recall a small response set from the conversations through a fast recalling manner. Then, the retrieval-based models rank the small response set to select the best response utilizing a complex but effective method. Different from retrieval-based methods, generation-based models trained on conversations can create a response in the fashion of word by word. To make full use of the advantages of both the retrieval-based and generation-based models, the ensemble methods construct candidate responses from the two kinds of models in which the best response from the candidate responses is selected.

As presented in Chapter 3, the retrieval-based models select responses from a large conversation set where the responses in the conversations are written by humans literally. Thus, the obtained responses are fluent, natural, and reliable in practice. However, the retrieval-based models fail when lacking appropriate responses in the conversation set. The merits of these real-world human conversations guarantee the

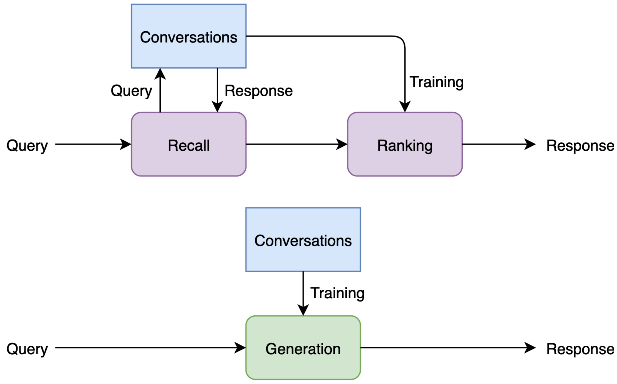


Figure 5.1: Comparison between retrieval and generation based models. The upper part represents retrieval-based methods, while the lower part demonstrates generation-based approaches.

effectiveness of retrieved-based methods, but meanwhile, it constitutes a bottleneck for the line of response-retrieval models.

Generation-based models involve generating responses given the query. Different from simple copy and reuse of existing human utterances, the generation models can learn to "create" responses by sampling words from a pre-defined vocabulary under the constraint of the conditional language model learned by the encoder-decoder framework. The sampled response space is, to some extent, unlimited (Yan, 2018) and thus, the generation-based models can handle more complex queries. However, in real-world applications, the generation models can not always guarantee to generate qualified responses. Sometimes the responses are short and meaningless, and sometimes they are diverse but unrelated to the query.

The pipeline of the two models are drawn in Figure 5.1. The conversations in the retrieval-based models are treated as the searching source for the recall process, and the ranking model is trained using the conversations. As for the generation-based models, the conversations are used to train the generation model only.

Considering the advantages and disadvantages, researchers combine the two kinds of methods into one "model" and name it as "ensemble model". Generally, ensemble models absorb the advantage of both models through reranking the results from retrieval and generation-based models, feeding the retrieved response into generation models, treating the retrieved responses as prototype editing, helping each other through adversarial training. And the results show that the ensemble approach is appealing in performance (Chen *et al.*, 2017).

5.1 Integration and Reranking Based Ensemble

The ensemble model is first introduced by Song *et al.*, 2018, which is an integration and reranking-based model. As shown in Figure 5.2, the pipeline of this kind of model is: 1) retrieving a small candidate response set from a large conversation set, 2) feeding the retrieved response into the generation model, 3) reranking the retrieved and generated responses. The first step to retrieve the candidate response set is the same as the retrieval-based models.

The retrieved response is fed into the generation-based model to decrease the probability of universal replies, owning to the additional condition (retrieved response). Besides, the retrieved responses are written by humans, which makes the response a good guide to the generation model. To feed the retrieved response into the generated model, most of the researchers built a multi-encoder generation model. One encoder encodes the query, and the other encoder encodes the retrieved response. The retrieved responses are diverse and can be utilized to answer the query from different perspectives and in different ways. In viewing of this, Song *et al.*, 2018 and Yang *et al.*, 2019a fed multiple retrieved responses into the generation model, instead of one response (Zhuang *et al.*, 2017). An attention mechanism is applied to weight the retrieved responses. The representations of query and retrieved responses are used to initialize the decoder. The generation model is trained in the same way as the normal response generation models. Besides, Song *et al.*, 2018 utilized a copy mechanism to enrich the generated response with helpful words that appeared in the retrieved response.

After obtaining the responses from the retrieval and generation-based models, the ensemble model reranks the responses to select the most appropriate one as the final response. The generation model may create an excellent response or a meaningless response. So it is necessary to

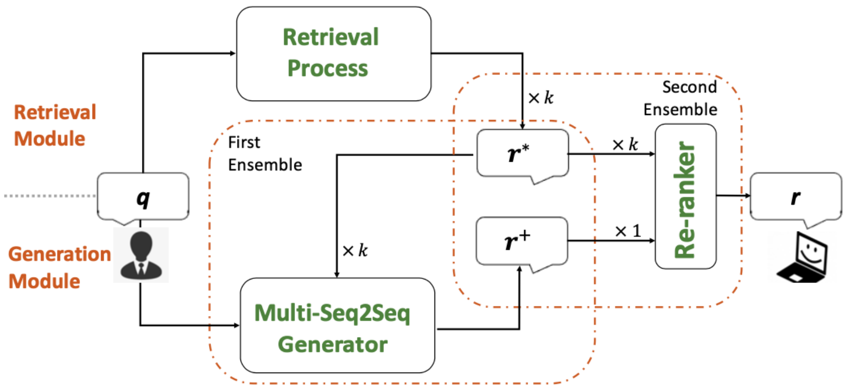


Figure 5.2: An example of integration and reranking-based ensemble model (Song *et al.*, 2018).

design the reranking model to select the final response. There are different ways to rerank the responses: 1) constructing conversation-related features including term similarity, entity similarity, topic similarity, length, fluency (Song *et al.*, 2018) and ranking the response using the gbdt or xgboost classifier. 2) training a neural network-based classifier model to evaluate the responses. For example, Cai *et al.*, 2019b trained an interactive matching model to predict the matching degree between the query and the response. They built an interaction matrix based on the pairwise similarity between words in query and response. Then matrix is fed into a convolutional neural network (CNN) to predict the final ranking score.

This kind of ensemble model mainly helps the generation model with the retrieved response and rerank the responses from both the retrieval and generation-based models. Feeding the retrieved response into the generation model improves the quality of the generated responses. And the reranking process ensures the quality of the final response.

5.2 Template and Prototype-Based Ensemble

Template and prototype-based ensemble can be also categorised as generation-based models. In this survey, we treat chit-chat systems that involves both retrieval and generation components as ensemble methods, leaving pure retrieval-based and generation-based approaches in previous two chapters. When writing a paragraph of text, human tends to find a similar existing text as the template and produce the new text by editing the selected template text. The template helps people to build the skeleton of the paragraph, and it is only needed to incorporate the new contents into the skeleton. In order to facilitate the text generation model to produce fluent dialogue response, researchers propose the prototype-based generation methods, which firstly retrieve a similar dialogue response as the prototype and then edit the prototype by considering the current dialogue context semantics. Different from the prototype editing-based dialogue generation methods, it will be more straightforward to use the retrieved text as the final response to users. It is obvious that the text may have many irrelevant words and facts, which will confuse the user. Thus, the prototype-based model is a trade-off between retrieval-based and generation-based methods, and this method can give fluent and consistent responses.

Guu *et al.*, 2018 firstly propose a prototype editing-based text generation method that improves perplexity on language modeling and generates higher quality outputs according to human evaluation. They model sentence generation as a prototype-then-edit process in two steps. Given a training corpus of sentences, the model randomly samples a prototype sentence from a prototype distribution first. Then, an edit vector is sampled from an edit prior. The obtained edit vector and the previously selected prototype are fed into a neural editor to generate a new sentence. Following this line, Wu *et al.*, 2019b bring the prototype-then-edit paradigm into the dialogue generation task, which first retrieves a prototype response from a pre-defined index and then edits the prototype response according to the differences between the prototype context and current context. They first use a popular information retrieval platform Lucene to construct the index and use its inline algorithm to compute the context similarity between the dialogue contexts. In the language modeling task (Guu *et al.*, 2018), an edit vector is randomly sampled from a distribution because the ways of editing the sentence are not constrained. In contrast, Wu *et al.*, 2019b take both retrieved dialogue context and current dialogue context into consideration when they revise a prototype response.

Previous methods use the latent edit vector to produce the new text. In contrast to these methods, Cai *et al.*, 2019a propose a skeleton-to-response paradigm in which the skeleton is extracted from the retrieved dialogues. However, when the retrieved response is irrelevant to the input query, the performance will drop sharply. A possible reason is that both the useful and useless information are mixed in the dense vector space, which is uninterpretable and uncontrollable. Cai *et al.*, 2019a employ the skeleton generator to extract a response skeleton by detecting and removing unwanted words in a retrieved response, and use the response generator to add query-specific details to the generated skeleton for query-to-response generation. Since the skeleton is produced by extracting and removing words, this method uses the reinforcement learning method to optimize the parameters in the model. However, previous skeleton-and-generation methods encounter the challenge of precisely extracting a skeleton and effectively training a retrieval-guided response generator. Cai *et al.*, 2019b present a novel framework in which an interpretable matching model makes the skeleton extraction, and a separately trained generator accomplishes the following skeleton-guided response generation. One novel characteristic of this model is that the training of the skeleton extractor and the response generator is decoupled, yet they work cooperatively under the help of a retrieval system. Since there is no explicit response skeleton in general query-response pairs for training, they propose to employ an interpretable matching model for matching skeleton extraction.

So far, the introduced methods all concentrate on the chitty-chat without incorporating any knowledge into the dialogue model, resulting in the model generating dull and generic responses like “I don’t know”. However, incorporating knowledge is also a difficult task to dialogue generation, where selecting knowledge facts for the dialogue context remains a challenge. The widely used approach, i.e., Entity Name Matching, always retrieves irrelevant facts from the view of local entity words. Wu *et al.*, 2020c propose a novel knowledge selection approach, Prototype-KR, and a knowledge-aware generative model, Prototype-KRG. When the user gives a query to the chatbot, this method first retrieves a set of prototype utterances relevant to the query. Then, the Prototype-KR ranks such knowledge facts based on the semantic similarity and then selects the most appropriate facts. Next, Prototype-KRG can generate an informative response using the selected knowledge facts. Zhang *et al.*, 2020b argue that the dialogue system still suffers from problems such as lack of diversity and contextual relevance. Inspired by writing articles, Zhang *et al.*, 2020b introduce a polishing process into the generation model to address this issue. Human authors typically write a draft text and then polish it many times. When polishing a sentence, human tends to adopt writing styles and techniques from existing literature. Inspired by this, Zhang *et al.*, 2020b propose a retrieval-polished response generation model for dialogue system. The motivation behind this model is to use the retrieved response to polish the generated response to enhance its information and fluency.

Most previous works usually focus on generating fluent responses using the prototype-based method. However, the ability of a dialogue system to express pre-specified language style during conversations has a direct, positive impact both on its usability and on user satisfaction. Su *et al.*, 2020b introduce a new prototype-to-style framework to tackle the challenge of stylistic dialogue generation. The framework uses an information retrieval system and extracts a response prototype from the retrieved response. A stylistic response generator then takes the prototype and the desired language style as model input to obtain a high-quality and stylistic response.

5.3 Adversarial-Based Methods

Most prior deep learning dialogue models approximate such a goal by predicting the next dialogue utterance given the dialogue history using the maximum likelihood estimation objective. Although these methods achieve success in many generation tasks and some of the methods achieve the state-of-the-art performance in dialogue benchmark datasets, such oversimplified training objectives will lead to some problems, e.g., generating dull, generic, repetitive, and short-sighted responses (Li *et al.*, 2017a).

A good dialogue model should generate sentences indistinguishable from human utterances. This goal suggests a training objective resembling the idea of the Turing test. Researchers borrow the idea

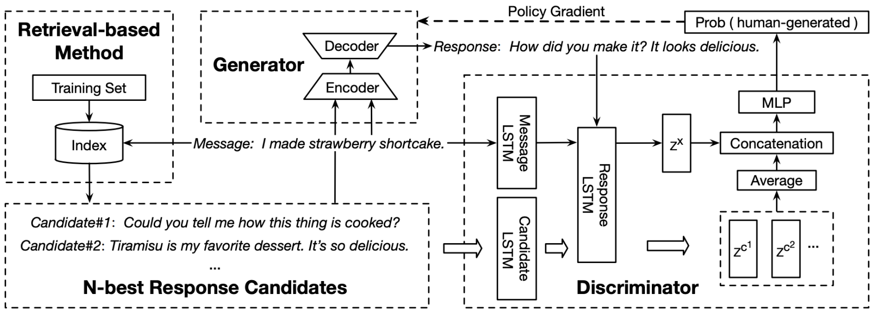


Figure 5.3: An overview of the adversarial based approach (Zhu *et al.*, 2019).

of adversarial training (Goodfellow *et al.*, 2014) in dialogue systems, in which two models are trained in an adversarial fashion, including a generator that defines the probability of generating a dialogue sentence and a discriminator that labels dialogues as human-created or model-generated. Goodfellow *et al.*, 2014 cast the dialogue generation task as a reinforcement learning problem where they jointly train two systems, a generative model to produce response sequences and a discriminator analogous to distinguish between the human-created sentences and the model-generated sentences. Intuitively, the simple idea is to combine the retrieval-based dialogue system and generation-based dialogue system under the generator-discriminator framework. Zhang *et al.*, 2019b propose an adversarial learning framework for enhancing a retrieval-generation ensemble model in the open-domain conversation scenario. This model consists of a language-model-like generator, a ranker generator, and a ranker discriminator. Following this work, Yu *et al.*, 2019a propose a hybrid approach for open-domain dialogue generation. This model combines the advantages of retrieval methods and generative methods. The system aims to produce sequences that are indistinguishable from human-created sentences. Therefore, they employ adversarial training to the generative model and use reinforcement learning to optimize the model that involves non-differential modules. Zhu *et al.*, 2019 propose a retrieval-enhanced adversarial training method for neural response generation, where the overview model architecture is shown in Figure 5.3. Distinct from existing approaches, this method leverages an encoder-decoder framework in terms of an adversarial training paradigm while taking advantage of N-best response candidates from a retrieval-based system to construct the discriminator.

5.4 Summary

By comparing the above three types of "ensemble" chit-chat systems, we can conclude that: (1) **integration and re-ranking based ensemble can achieve better performance than either retrieval-based or generation-based method in the high probability** since these ensemble methods can pick up the best response from both retrieval-based and generation-based methods. The retrieved candidates serve as prototypes for the generation-based component. In turn, generation-based modules can provide more candidates, resembling data augmentation. (2) **Prototype retrieval based ensemble can achieve better performance than only utilizing generation-based module** with the augmentation of related human conversations. However, it is difficult to distinguish good or bad between this kind of ensemble and retrieval-based method, since retrieved response with high-quality might not need revision, while poor retrieved response can deteriorate the generation process. (3) **Adversarial training is an effective add-on for the above-mentioned two types of ensemble** insomuch as adversarial training can propagate back more loss signal of obtaining human-like responses.

6

Connecting Chit-Chat with Tasks

In early years, dialogue systems were designed either for completing specific tasks or serving as entertainment tools with chit-chat conversations and non-limited topics. With the shared back-bone neural models and the evolution of user preferences, the boundary between task-oriented dialogue and chit-chat has been much more blurred in recent years. The task-oriented system can output task-independent content while chit-chat conversation can achieve an intended purpose. Since previous chapters have thoroughly discussed and reviewed most of the representative chit-chat model framework in the research community and industry applications, we further discuss the connection between existing chit-chat systems and tasks in this chapter to sketch out the whole landscape of conversational AI. Generally, dialogue systems serve as an interface for users to interact with computers via natural language. For task-oriented dialogues, chit-chat skills are useful in detecting user intent, making recommendations, and improving user experience for better engagement. We start this chapter with a brief review of completing tasks with dialogue systems, which has been systematically studied and compared in previous survey (Gao *et al.*, 2019a), following with the connections between traditional task-specific systems and chit-chat

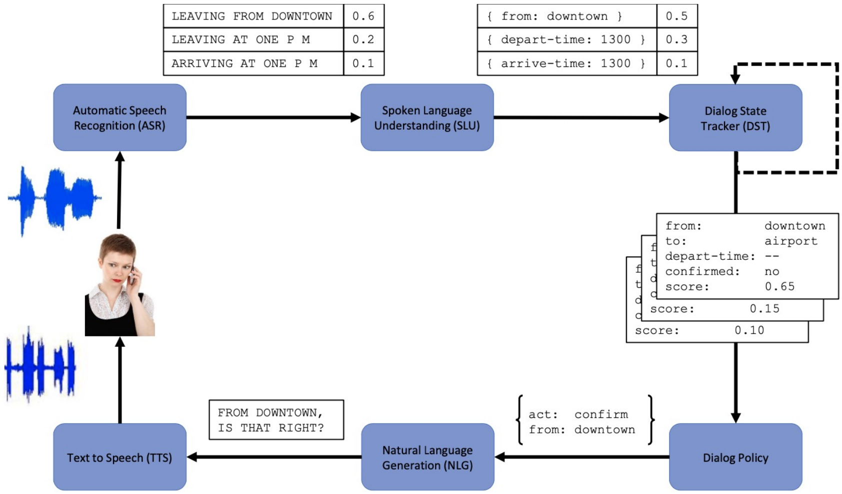


Figure 6.1: A representative framework of task-driven spoken dialogue system (Williams *et al.*, 2016).

ones. We then present the most important and successful combination paradigm of dialogue system and tasks in the IR community, i.e., combing conversation with search and recommendation. Besides, we also briefly review other emerging and representative cases of connecting dialogue systems with tasks, including conversational question answering and conversational machine reading. Moreover, we also discuss the possible research direction that unifies the framework of both chit-chat and task-oriented systems in the paradigm of pre-trained language models. This chapter ends with a discussion of better interleaving of chit-chat and task-oriented dialogues, bottlenecks to overcome, and future applications.

6.1 Linking Task-Driven Systems with Chit-Chat

6.1.1 Overview of Task-Oriented Dialogue Systems

Building task-oriented dialogue systems has been a long-range goal of AI community, and great efforts have been made by researchers from both academia and industry. To promote the development of this field, Gao *et al.*, 2019a sketched out the landscape of conversational AI in the last few years, mainly focusing on task-driven systems and neural approaches. As shown in Figure 6.1, the typical neural architecture of a task-oriented system consists of four modules to process text information, including intent understanding, dialogue state tracking, dialogue policy, and natural language generation. Before discussing the connections between chat-driven dialogue and task-specific systems, we first summarize and review each of the four modules with the notations and conversation examples from Daniel and James, 2020.

Intent Understanding. Intent understanding component mainly involves **slot-filling**, **domain** and **intent classification**. Take the following user utterance for example:

`O`	`O`	`O`	`O`	`O`	`B-DES`	`I-DES`	`O`	`B-DEPTIME`	`B-DEPTIME`	`O`
`I`	`want`	`to`	`fly`	`to`	`San`	`Francisco`	`on`	`Monday`	`afternoon`	`please`

the domain and intent of this utterance are computed as AIRLINE and SHOWFLIGHT, respectively, by a neural classifier that can process utterance, e.g., the combination of the BERT model and a feed-forward layer. The slot filling task normally contains a sequence labelling process with predefined tags, say BIO tags, to predict the slots and conduct filler string extraction for each slot. As shown by the above example, the slot DEPTIME is tagged by the sequence labeler, and the filler string `San Francisco` is extracted for filling the slot.

Dialogue State Tracking. The function of dialogue state tracking is to compute the current dialogue state that includes both fillers of each slot and the most recent user dialogue act. Herein, the dialogue act corresponds to the interactive function of the turn or sentence, which is designed for each particular task. Take the restaurant recommendation system (Young *et al.*, 2010) for instance, the dialogue act `REQUEST(a,b=x,...)` refers to request value for a given `b=x` in which `b` can be a slot name and `x` is the corresponded filler string. The slot-filling and dialogue act detection are launched jointly by the dialogue state tracker to process each user utterance, e.g., the example from Mrkšić *et al.*, 2017 that

`I'm looking for a cheaper restaurant`

is processed as

`inform(price=cheap)`

where `inform` refers to dialogue act, and `price` and `cheap` are slot and filler, respectively. The newly coming user utterance will be converted with the constraints of the entire state of the frame at this point (the fillers of each slot). For instance, the next user utterance following the above-mentioned user turn is to convert

`Thai food, somewhere downtown`

into

`inform(price=cheap, food=Thai, area=centre)`

which is the simplest dialogue state tracker, and more sophisticated models can be found in Gao *et al.*, 2019a.

Dialogue Policy. With the obtained dialogue state, i.e., the most recent dialogue act and slot-fillers, the dialogue policy is to decide what dialogue act should generate. Given the dialogue act sequences from the system (A) and the user (U) before the current turn i of the conversation, the dialogue policy is supposed to predict the next dialogue action A_i, formulated by:

$$\hat{A}_i = \underset{A_i \in A}{\operatorname{argmax}} P(A_i | A_1, U_1, \ldots, A_{i-1}, U_{i-1}) \tag{6.1}$$

If the dialogue state is simplified by merely maintaining the set of slot-fillers, the computation of next dialogue action A_i is to maximize:

$$\hat{A}_i = \underset{A_i \in A}{\operatorname{argmax}} P(A_i | Frame_{i-1}, A_{i-1}, U_{i-1}) \tag{6.2}$$

where $Frame_i$ refers to the current state of the frame with slots filled by current fillers. A_{i-1} and U_{i-1} are the last turn dialogue acts of the system and user, respectively. The probability function of $P(\cdot)$ is parameterized by neural networks.

Low-Resource Setting in Generating Tasks Dialogues. Once the next dialogue action is computed by dialogue policy, the natural language generation component is introduced. Normally, natural language generation (NLG) comprises two stages, i.e., content planning and sentence realization. In application, content planning can be completed by dialogue policy component, and thus the natural language generation part mainly focuses on creating utterance sentences based on the dialogue act and slot fillers, which is exemplified by following (Nayak *et al.*, 2017):

`recommend(restaurant name= Au Midi, neighborhood = midtown, cuisine = french)`

1 Au Midi is in Midtown and serves French food.

2 There is a French restaurant in Midtown called Au Midi.

where the latter two sentences are generated by the NLG module conditioned on the given dialogue action `recommend()` and these slot fillers.

As high-quality training data is expensive and difficult to collect for various sorts of problems, NLG task is usually under the low-resource setting. To address this limitation, the delexicalization strategy is presented, where slot values are replaced by placeholders to represent the correlated slots, as shown in the following:

`recommend(restaurant name= Au Midi, neighborhood = midtown, cuisine = french)`

1) `restaurant_name` is in `neighborhood` and serves `cuisine` food.

2) There is a `cuisine` restaurant in `neighborhood` called `restaurant_name`.

Thus, the NLG process is decomposed by first obtaining the delexicalized sentences for model training and then utilizing these data to train an encoder-decoder neural network for generating delexicalized sentences. These placeholders are replaced by the correlated slot values to output the final utterance.

6.1.2 Completing Tasks and Chit-Chat Dialogues

In real-world applications, chit-chat conversations typically consist of chat-driven contents alternating with task-oriented utterances. As shown in Table 6.1, the given synthetic conversation case represents many realistic conversation situations. The user starts a conversation with a chatbot in the demands of emotional engagement, and then the bot attempts to show empathy and divert the attention of the user, following with the task-oriented sub-dialogue of recommending and obtaining a first-person shooter video game running on an iPad. The

Table 6.1: An illustration of chat-driven conversation case in which the conversation starts with chit-chat and then shifts to goal-oriented dialogue.

Types	Roles	Utterances
Chat	User:	Hi ANONYMOUS-Bot, I feel a little bit depressed today?
	Bot:	What happened? Is anything wrong?
	User:	My SIGIR submission is got rejected. It is five months of hard work.
	Bot:	I am sorry to hear that. Do you know the reason for it?
	User:	Not yet. I just want to escape from this situation right now.
	Bot:	Yeah, you really should take a break.
Task	User:	OK, any recommendations?
	Bot:	How about play games at home, considering the outbreak of COVID-19.
	User:	That sounds okay! I used to play shooter video games.
	Bot:	Do you prefer first-person or third-person?
	User:	I have played first-person a lot. Third-person would be better.
	Bot:	You could try PUBG or PUBG mobile.
	User:	I have never played PUBG mobile before, and I just bought an iPad.
	Bot:	You can download it from App Store, and it's free.
	User:	Thank you! I can't wait to try this game.

task-oriented sub-dialogue will be completed by the aforementioned framework. With both the capabilities of dealing with chat-driven and task-driven situations and not a single one that can be omitted, the chatbot can obtain a better user experience and higher loyalty. Besides the chat-centric scenarios, the chat-driven conversation can, in turn, facilitate task-driven conversations. For instance, introducing more task-irrelevant and chit-chat contents in the iteration turn of goal-oriented user-machine conversation could make the dialogue system appear more intelligent rather than a machine that can merely complete specific tasks, resulting in more user engagement and trust. Many other situations also need chat-driven conversation to assist task-driven dialogues, e.g., recommendation, question answering, which will be illustrated in the next few sections.

Apart from the alternative appearance of task-oriented contents and chat-driven utterances, chit-chat and task-specific systems also encounter some common challenges, including but are not limited to conversational implicature, dialogue structure modeling, grounding, multi-turn and dynamic context modeling, and low-resource text generation. Besides, there is an emerging trend of transmitting from end-to-end neural framework to multi-stage pipeline for chat-driven systems, which resembles main-stream task-oriented systems in many stages, e.g., intend understanding (domain and intent classification, keywords extraction), dialogue analysis (discourse analysis, structure extraction), content planning, natural language generation. In turn, researches that complete task-oriented dialogues with end-to-end models are not rare recently. Furthermore, task-oriented and chat-driven systems share many back-bone models in the deep neural age such as encoder-decoder framework (Sutskever *et al.*, 2014; Vaswani *et al.*, 2017), pre-trained language models (Devlin *et al.*, 2018; Zhang *et al.*, 2020f).

6.2 Conversational Search and Recommendation

Search and recommendation are the two main ways for humans to obtain information from the Internet, and they are also the two areas where AI is most widely used in practice. The purpose of search and recommendation tasks is to find suitable items or websites for users. The only difference is that the task of search is conducted by the user, i.e., the user has a clear query, while the recommendation task is performed by the system, i.e., the user does not have a clear query.

In recent years, with the continuous progress of dialogue technology on the traditional single-round static search and recommendation system, many works on conversational search and recommendation systems have been aroused (Zhang *et al.*, 2021; Yang *et al.*, 2021a; Li *et al.*, 2021b). For example, compared with the traditional recommendation system, the conversational recommendation system can inquire about the user's attribute preferences and the attitude of the product through natural language and understand the user's feedback through natural language. Through multiple rounds of human-computer interaction, it will be more conducive for the system to accurately understand the user's preferences and find more suitable products.

A conversational search/recommendation system not only needs to be able to recommend items based on the context of human-machine conversations but also generate replies as a dialogue system. In order to enable the conversational search/recommendation system to have the above-mentioned functions, in recent years, researchers have explored

Conversation initiated by user `ID=AQGUDK0MSQ95L`
U: Can you find me a `tablet` on Amazon?
S: Sure, any requirement on the `network`?
U: Built-in free wireless data network.
S: Any preference on the `memory`?
U: 2GB of internal memory as well as a microSD expansion slot for additional memory.
S: Any preference on the `battery`?
U: Battery is removable and user-replaceable.
Result: Product `ID=1400532620`.

Figure 6.2: An example of template-based conversational recommendation session (Zhang *et al.*, 2018d).

from two perspectives, where the first is dialogue understanding and item retrieval, and the second is response generation.

6.2.1 Dialogue Understanding and Item Retrieval

In conversational search and recommendation, the system needs to be able to understand the context of the conversation and predict which product the user prefers. Specifically, this task can be defined as: given the dialogue context information $\{d_1, d_2, \cdots, d_n\}$, the task is to predict the user's desired product i_k, where d_k is a round of human-computer interaction dialogue content, in which the content could be a sentence composed of natural language, or a recommended product i_k which belongs to set of all products $\{i_n\}_{n=1}^{N}$.

In early studies, researchers limited the natural language in the interaction process with templates and did not allow users or machines to use free natural language to communicate. For example, Zhang *et al.*, 2018d constrained the natural language interaction between humans and machines as the form shown in Figure 6.2. In the conversation session, the user's inquires and replies to the machine can only be in a given format, and it is the same for the questions and replies of the machine. Although this template-based interactive mode realizes conversational search/recommendation, there are many limitations and inconveniences in practice.

In recent years, researchers have tried to remove the template-based

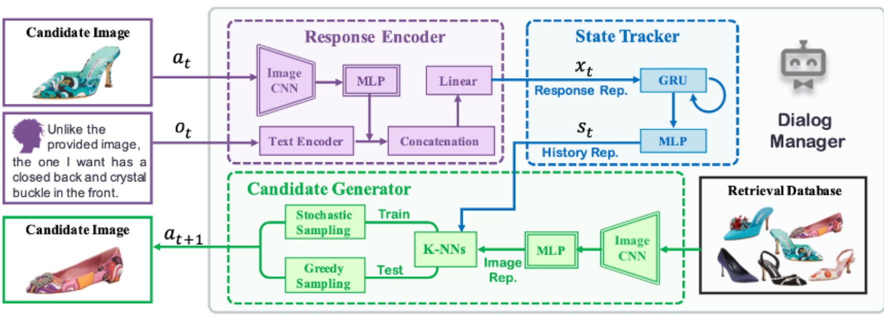


Figure 6.3: The proposed model framework in Guo *et al.*, 2018.

restrictions and allow users to communicate with the system in unrestricted natural language, thereby improving the convenience and user experience of the search/recommendation system during conversations. Guo *et al.*, 2018 consider the conversational recommendation task in the e-commerce shopping scenario. In their setting, each user has one desired item. The system interacts with the user in multiple rounds and recommends an item for the user in each round. Given the recommended item, the user gives feedback to describe the difference between the recommended item and the desired one. Based on the user's feedback, the machine will re-recommend the product until the machine recommends the expected product for the user. Specifically, the model consists of a dialogue encoder module that encodes each round of human-computer interaction dialogue, a state tracking module that integrates the dialogue content of each round, and a candidate generation module that generates candidates and retrieves items based on the dialogue state. As shown in Figure 6.3, for the product a_t recommended by the machine to the user in the t_{th} interaction, and the text feedback information o_t which describes the difference between the product and the product that the user wants, the dialogue encoder module calculates the dialogue representation x_t. After that, the state tracker uses a GRU network to update the current state of the dialogue, which takes the t_{th} round of dialogue representation x_t as input and calculates the updated historical representation s_t up to time t. Taking the historical representation s_t through time t as the query, the candidate generator calculates the similarity between s_t and each product representation and uses the K-NN method to generate a candidate set. According to the similarity calculated by the model, the item with the largest similarity $a_{(t+1)}$ is recommended to the user in round t+1.

In the training process, in order to get the user's text feedback information after each step of product recommendation from the model, the authors pre-train a user simulator with additional data on the correlated image caption task. The related image caption task is to generate descriptions about differences given a target image and a candidate image. The pre-trained image caption model will be fixed during training and used as a user simulator to generate text feedback o_t in each round of dialogue. In addition, since the K-NN operation used to generate the candidate in the candidate generator module and the sampling operation are non-differentiable, the authors adopt a two-stage training method of supervised learning and reinforcement learning. In the supervised learning phase, the randomly initialized model is used to interact with the user simulator for multiple rounds by maximizing the probability of retrieving the user's desired item while minimizing the probability of retrieving a randomly negative item for each interaction turn. In the reinforcement learning phase, the model is initialized with the model obtained in the supervised learning phase. In each round of interaction with the user simulator, the reward is represented by the probability of recommending the desired item predicted by the model. The model is trained with the model-based reinforcement learning algorithm.

During inference, based on the probability distribution calculated by the candidate generator of the model in each round of interaction, the model selects the item with the largest score as the recommendation result until the item that the user desires is correctly recommended.

Although the method proposed by Guo *et al.*, 2018 could interactively recommend items based on the user's natural language feedback in multiple turns and finally find the product that the user desires, there are still some shortcomings. The most important issue in the method proposed by Guo *et al.*, 2018 is that, when the model interacts with users and recommends products in each round, it does not consider whether there is a deviation or a conflict between the products in this round and the content mentioned in the previous rounds of user feedback. In order to solve this problem and try to avoid conflicts between the recommended products and the user's previously mentioned requirements, researchers have improved on the method proposed by Guo *et al.*, 2018 and verified their approaches on the same recommendation data set.

In Yu *et al.*, 2019b, the researchers pre-trained an MLP to predict the similarity between the current round of recommended product and the information related to the item attributes and item features mentioned by users in previous rounds of interaction. In accordance with Guo *et al.*, 2018, Yu *et al.*, 2019b also apply reinforcement learning to train the product recommendation module. For the reward signal, in addition to the reward that measures the accuracy of recommended items, Yu *et al.*, 2019b incorporate the prediction of the pre-trained MLP as the reward. Zhang *et al.*, 2020d adopt the idea of adversarial learning and introduce a discriminator to determine whether the currently recommended product conflicts with what the user has said before. For each iteration in a training step, the model is first updated with the recommendation loss function and then updated with the loss signal calculated by the discriminator, and finally, the parameters of the discriminator are updated. In this way, the model simultaneously finds the products that users want through multiple rounds of interaction, and the recommended products in each round of interaction will not conflict with previous user feedback.

Knowledge Enhanced Approach. To correctly recommend products to users, one important issue of the conversational recommendation system is that the model must have a sufficient understanding of the characteristics of each product itself. Researchers have proposed to incorporate knowledge graphs to model attribute information on items. Meanwhile, knowledge graphs not only allow the model to have an understanding of the product but also can be used to model other entity information mentioned in the interaction between the user and the system so as to help the machine better understand the dialogue context.

Sarkar *et al.*, 2020 proposed to introduce DBpedia as an external knowledge to improve the performance of movie recommendation tasks.

Aiming at the contextual information of the interaction between the user and the machine, this paper uses each entity mentioned in the dialogue to obtain sub-graphs from the knowledge graph through multi-hop propagation or the page-rank algorithm. The model calculates the graph embedding of these entities in the sub-graph and uses the attention mechanism to integrate the embedding to calculate the user representation. Based on the user representation that incorporates knowledge information, the model can effectively recommend items to the user. Experimental results also confirm that the recommendation accuracy is significantly improved by incorporating the knowledge graph compared to only using the training data set.

User Memory Modeling. To improve the accuracy of recommendations, researchers not only consider incorporating external knowledge to learn more strong representations items, but also focus on how to model the user's historical behavior information.

Xu *et al.*, 2020a propose to model each user's historical interaction item-sequences and the attribute information. This information is modeled in a graph structure, which is denoted as a user memory graph. In the process of interacting with users and recommending products, the model first uses the BERT model to encode the chat content information in the current session to obtain a vector representation and then uses an inference module based on R-GCN. The content and preference information in the user memory graph are used to infer user preferences and make product recommendations. In addition to predicting the expected products, the model also predicts information such as slot, dialogue act, and product attributes of the user's chat content and uses multi-objective learning to enhance the model performance further.

PLMs in Conversational Search/Recommendation. In addition to studying how to introduce external resources such as knowledge graphs and user historical behaviors to improve the recommendation accuracy of dialogue recommendation tasks, some researchers also focus on applying pre-trained language models in dialogue recommendation.

Penha and Hauff, 2020 propose to detect whether the pre-trained language model has learned the knowledge to solve the dialogue recommendation task. For BERT and Roberta, they first verify whether the models obtained directly after pre-training without fine-tuning have an understanding of the characteristics and content of the product, as well as the similarity information of products. Then, the product recommendation performance was explored. For understanding the characteristics of a product, i.e., the knowledge of the content, the authors draw on the masked language model task in BERT for probing, i.e., designing a problem similar with Devlin *et al.*, 2018 to evaluate the model performance in terms of product characteristic understanding. As for the ability to recommend similar products based on specific products, i.e., generalization ability, the authors explore from two perspectives. On the one hand, the authors borrow the idea of the next sentence prediction task in BERT model training. A template as "If you liked The Hobbit, [SEP] you will also like Lord of the Rings" is designed, and the probability that the model retrieves the correct sentence correctly is calculated. On the other hand, for sentences such as "It gives a brilliant picture of three bright young people." and "The Brothers Karamazov.", they use the vector representation of the CLS token calculated by the BERT model to compute the similarity for testing whether the model can correctly distinguish these products. Experimental results show that without fine-tuning, BERT has knowledge stored in its parameters about the content of books, movies, and music. Meanwhile, it has more content-based knowledge than collaborative-based knowledge.

In addition, the authors also investigate the performance of BERT when incorporating fine-tuning on the dialogue recommendation data set, thereby constructing a search-style dialogue recommendation model. Experimental results show that the BERT model has significant limitations in the effect of direct fine-tuning. It is easy to be attacked by adversarial samples. The researchers also found that if the masked language model for product features and the next sentence prediction for product relevance are added at the same time for fine-tuning BERT, the introduction of external knowledge to the model can be relieved to a certain extent. The model simply learns to capture the shortcomings of the pattern and significantly improves the accuracy of the recommendation.

6.2.2 Response Generation

In a conversational search/recommendation system, the model not only needs to correctly recommend products according to the content of the conversation but also needs to interact fluently with users, especially in the form of natural language. Interacting with the user in the form of natural language, on the one hand, allows the machine to ask user preferences for a better understanding of user intentions, and on the other hand, brings a better user experience by recommending customized products according to each dialogue sentence. To build a conversational search/recommendation system that can not only interact with users in natural language but also recommend products for users, it is necessary to make the model have the functions of reply generation and item retrieval at the same time, and it must be able to make accurate judgments during the interaction, i.e., whether the response should be generated at present or product recommendation should be made.

Li *et al.*, 2018 explore the field of movie recommendation and builds the first conversational recommendation system that can interact with users in natural language. The model contains an LSTM-based HRED encoder to encode the dialogue context information. In the reply generation part, the model uses an LSTM network as the decoder. In addition, the authors use the movieLens data set to pre-train a recommendation module based on denoising auto-encoder. In order to enable the model to determine whether to output a movie or a word at each step when generating a reply, the model introduces a switch mechanism in the decoder, i.e., a gating mechanism is used to determine the current decoding or recommendation. If the model judges that it is to decode, it will select a word in the vocabulary for output. Otherwise, the model first maps the hidden state in the decoder to a semantic space about all movies, i.e., calculating a vector with the dimension of the number of movies. The value of each dimension is between 0-1, and the vector is used as the input of the recommendation module to predict the recommendation result. In the training process, the model adopts the teacher forcing strategy. During the test, the model determines whether it is to decode or recommend according to the results of the switch gate at each step of the decoding.

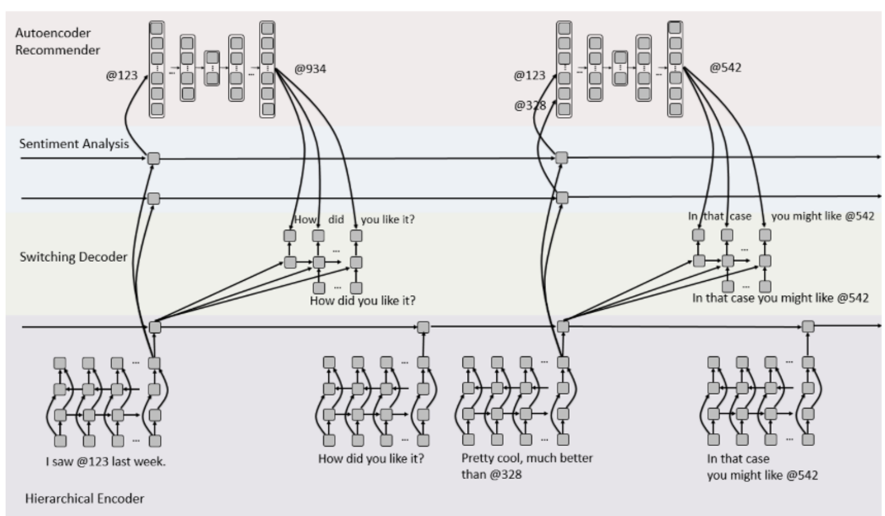


Figure 6.4: The model framework in Li *et al.*, 2018.

Although in Li *et al.*, 2018, the model can generate response and product recommendation at the same time and can automatically determine whether it should be decoding or recommendation during operation, this method is only limited to a given entire context and let the model generate a sentence with the recommended product reply to this mission scenario. However, in a real dialogue recommendation scenario, the machine needs to be able to conduct a complete dialogue with the user from beginning to end and recommend products in the dialogue, so it is not enough to only consider the given context for response generation and product recommendation. Based on this shortcoming, Kang *et al.*, 2019b explored how to allow the machine to conduct a complete dialogue with the user from beginning to end. To achieve this goal, a two-stage training method combining supervised learning and reinforcement learning is adopted in the paper. In the supervised learning stage, the author uses actual corpus to train two symmetrical models in the teacher forcing mode. In the reinforcement learning stage, the author lets the two models chat from beginning to end until they find the desired product. During the training process, the authors introduce rewards related to response quality and recommendation accuracy and use policy gradients to update the model. In this way, after the reinforcement learning stage, the model that plays the role of a machine can interact with multiple rounds of natural language from start to finish and predict the products the user wants during the interaction. Similar to the works in item retrieval, in the area of how to better construct a conversational search/recommendation that can both generate replies and retrieve items, researchers also focus on how to base on external resources such as external knowledge and historical user behavior to improve performance on recommendation accuracy and response quality.

Knowledge Enhanced Approaches. In recent years, many works have been conducted on various forms of external knowledge, including knowledge graphs, knowledge about product characteristics/attributes, and knowledge about text topics.

In the studies based on knowledge graph, Chen *et al.*, 2019 and Liao *et al.*, 2019 use the commodity and other entity information that appear in the chat context to obtain the corresponding sub-graphs from DBPedia, calculate the graph representation of these entities, and use them in the recommendation module of the model. Compared with the representation of the product only learned from the training set, the product graph representation calculated by introducing the knowledge graph is more conducive to capturing the attributes of the product itself and the relationship between products. Therefore, it can bring better recommendation performance. At the same time, when the model is generating a reply, it will also take the vector obtained by integrating the representation of the product in the context through the attention mechanism as part of the input. In this way, the model can also be assisted by the knowledge graph when replying. On this basis, Zhou *et al.*, 2020a not only consider the knowledge graph DBPedia related to commodity attributes and relationships but also consider the knowledge graph of word level. The conceptnet is introduced in the article, from which the sub-graphs corresponding to the words appearing in the context are obtained, and the graph representation of these words is calculated. Through such a modeling method that considers both item-related knowledge and word-related knowledge, the model has been further improved.

Focusing on the relevant knowledge of product attributes and characteristics, Liao *et al.*, 2018 use the category tree of the product and the picture information to pre-train a matching model so as to learn the high-quality representation of each product with attribute and feature information and use these representations. In the recommendation and response generation, the accuracy of the recommendation and the richness of the content of the response generation can be improved.

In terms of topic-related knowledge, Zhou *et al.*, 2020a introduce topic-related information for each sentence in the chat context and cut it into the model training process. In addition to letting the model do response generation and product recommendation tasks, it also adds a topic prediction task. That is, which aspect of the sentence should be said in the current interaction of the prediction model. In this way, the model can be more specific about the current context information, which content should be generated in response to, thereby improving the performance of the model.

Personalized Information Modeling. In addition to incorporating external resources to enhance the conversational search/recommendation system, enhancing conversational search and recommendation by modeling user's personalized information is also a popular research direction. In conversational search and recommendation tasks, the user's personalized information mainly includes two aspects, i.e., user profile and user history behavior. Zhou *et al.*, 2020b model the two aspects of personalized preference information jointly. In this paper, the user's historical review information is represented by the user's profile for the movie recommendation scenario. The user's historically watched movie records are used as the user's profile. For the user profile, the model uses a Profile-Bert module as the encoder. The authors apply the ideas in the sequential recommendation for historical behavior information and use the SASSeq encoder module to encode historical behavior information. With the vector representation encoded from the two parts of personalized information, i.e., the historical behavior and user profile, the response generation and product recommendation performance could be improved.

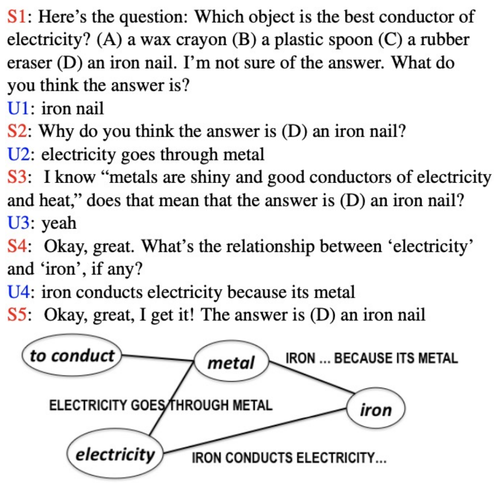


Figure 6.5: A real conversation from Hixon *et al.*, 2015, and the task is formulated as generating the bottom knowledge graph based on the upper conversation utterances.

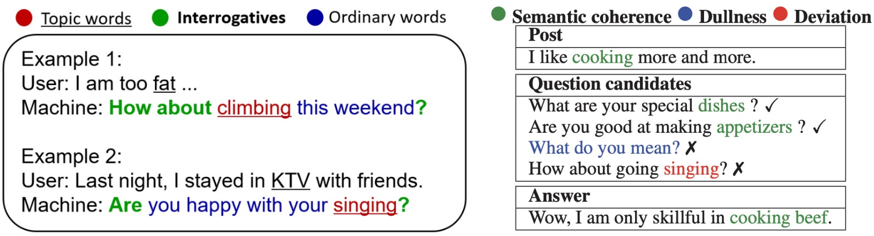
6.3 Conversational Question Answering

Many efforts have also been devoted to combining question answering with chit-chat conversation task (Qu *et al.*, 2020). Most of these researches can be grouped into three groups:1) seeking to leverage extra conversation task to assist question answering (QA), i.e., QA-centric setting; 2) detecting and addressing question answering sub-tasks from chat-driven conversations to enhance user experience of chatbots; 3) completing question answering in an conversation-like manner.

QA-Centric. Hixon *et al.*, 2015 presented a representative system to enhance the question-answering task by introducing an open conversation task. Through chatting with users about specific questions, the system can automatically construct knowledge graphs and, in turn, improve the performance of the QA task. Figure 6.5 presents a typical user dialogue that aligns utterances and knowledge graphs. Specifically, the authors collected 107 science questions from the 4-th grade New York Regents exam (Clark *et al.*, 2014), where each question is paired with four possible answers. The conversation task is initialized to ask users to choose an answer candidate for a specific question and present their explanations for their answers. Then, two different dialogue strategies are introduced to keep the conversation going until a knowledge graph is constructed that can support the answer of the user. There are three types of knowledge graphs at different levels built from dialogues, including utterance-level, dialogue-level, and global knowledge graph. To obtain utterance-level knowledge graph (uKG) whose nodes are all concepts in an utterance, two constraints are used to prune edges, in which only salient relations can be reserved. The obtained uKGs are then merged into a dialogue knowledge graph (dKG) with a sentence alignment strategy. Finally, all dKGs are added to the global knowledge graph with the enhancement of a relation filter.

Conversation-Centric. Wang *et al.*, 2018 study the task of asking questions in chit-chat conversation systems, which is different from the traditional question generation task of question answering, including question patterns, topic scopes, and diversity. The authors find that good questions mainly consist of interrogatives, topic words, and ordinary words, where interrogatives lexicalize questioning patterns, while topic words and ordinary words model topic transition and grammatical constraints, respectively, as shown in Figure 6.6(a). Then, two typed decoders are devised to generate more meaningful questions in the large-scale chit-chat conversation system. Wang *et al.*, 2019b focus on improving the semantic coherence between generated question and the paired post and answer, and meanwhile preventing generating dull questions, as shown in Figure 6.6(b). Laban *et al.*, 2020 further build a chatbot system to create conversations with a user about the news.

Conversation-Like QA. Information seeking and gathering through conversation is essential for humans, which involves a sequence of interconnected questions and answers (Reddy *et al.*, 2019). To study the conversation-like question answering task, the authors introduce a dataset named CoQA for building and evaluating conversational QA systems. Figure 6.7 presents an example conversation from the CoQA dataset. Most works of conversational QA follow a similar setting from then on. Shen *et al.*, 2019b propose a multi-task learning framework, comprising a pointer-equipped semantic parsing model and a type-aware



(a) (b)

Figure 6.6: Conversation examples from chat-centric conversational question answering (Wang *et al.*, 2018; Wang *et al.*, 2019b). The left part illustrates the different composition patterns of questions in large-scale chit-chat conversation systems, while the right shows that question generation in chit-chat conversation requires semantic coherence between generated question and the corresponded post and answer and needs to avoid dull questions.

entity detection model, to achieve conversational question answering over a large-scale knowledge base. Pan *et al.*, 2019 propose a reinforced dynamic reasoning network to address the challenging conversational question generation task, where each question is generated conditioned on a passage and a conversation history. Kaiser *et al.*, 2020 study the setting of conversational question answering over passages by building a word proximity network from large-scale corpora. Baheti *et al.*, 2020 utilize data augmentation to enhance the fluency of generated answer response in conversation QA. Kundu *et al.*, 2020 investigate the sub-task of identifying follow-up questions in conversational QA. Other perspectives of conversation QA such as feedback-weighted learning (Campos *et al.*, 2020), the comparison of learning to reason and exploiting patterns (Verma *et al.*, 2020), informative and specific question generation (Qi *et al.*, 2020), the intricate relationship between question reformulation and answer selection (Vakulenko *et al.*, 2020), and multi-task learning with dynamic task weighting (Kongyoung *et al.*, 2020) have also been studied recently.

As one of the typical conversational QA tasks, many existing works have explored conversational machine reading comprehension (MRC) from different angles (Gupta *et al.*, 2020), including interpretation of natural language rules (Saeidi *et al.*, 2018), entailment-driven extracting

Jessica went to sit in her rocking chair. Today was her birthday and she was turning 80. Her granddaughter Annie was coming over in the afternoon and Jessica was very excited to see her. Her daughter Melanie and Melanie's husband Josh were coming as well. Jessica had . . .

Q_1: Who had a birthday?
A_1: Jessica
R_1: Jessica went to sit in her rocking chair. Today was her birthday and she was turning 80.

Q_2: How old would she be?
A_2: 80
R_2: she was turning 80

Q_3: Did she plan to have any visitors?
A_3: Yes
R_3: Her granddaughter Annie was coming over

Q_4: How many?
A_4: Three
R_4: Her granddaughter Annie was coming over in the afternoon and Jessica was very excited to see her. Her daughter Melanie and Melanie's husband Josh were coming as well.

Q_5: Who?
A_5: Annie, Melanie and Josh
R_5: Her granddaughter Annie was coming over in the afternoon and Jessica was very excited to see her. Her daughter Melanie and Melanie's husband Josh were coming as well.

Figure 6.7: A conversation from CoQA dataset (Reddy *et al.*, 2019), where Q_i, A_i, R_i refer to question, answer, and rationale, respectively.

and editing (Zhong and Zettlemoyer, 2019), the combination of response generation and on-demand machine reading in generating contentful responses (Qin *et al.*, 2019), enhancing conversational MRC with multi-perspective convolutional cube (Zhang, 2019), multiple-choice reading comprehension (Sun *et al.*, 2019), the incorporation of pre-trained language models (Ohsugi *et al.*, 2019), conversation flow utilization via graph neural network (Chen *et al.*, 2020b), and coarse-to-fine reasoning with explicit memory (Gao *et al.*, 2020).

6.4 Connections in the Era of Pre-trained Language Models

In the past few years, with the rapid growth of pre-trained language models (PLMs) (Devlin *et al.*, 2019; Liu *et al.*, 2019b; Lan *et al.*, 2019; Radford *et al.*, 2018a; Radford *et al.*, 2019; Brown *et al.*, 2020; Lewis *et al.*, 2020; Raffel *et al.*, 2020), the paradigm of Natural Language Processing (NLP) community has changed dramatically. The huge changes brought by PLMs have made various NLP tasks, including chit-chat, more closely linked. Therefore, in this section, we introduce the latest research progress of PLMs, their applications on dialogue systems, and potential directions of dialogue systems in the paradigm of PLMs, which may be a lot of help to the IR community.

6.4.1 The Paradigm of Pre-trained Language Models

Considering its great power, PLMs received great attention from Natural Language Processing (NLP) community and develop rapidly (Zhang and Li, 2021). PLMs are usually stacks of multiple Transformer (Vaswani *et al.*, 2017) layers. At the pre-training stage, PLMs are trained on large-scale textual corpora with unsupervised objectives, e.g., masked language modeling (MLM) (Devlin *et al.*, 2019; Liu *et al.*, 2019b; Lan *et al.*, 2019), casual language modeling (CLM) (Radford *et al.*, 2018a; Radford *et al.*, 2019; Brown *et al.*, 2020), denoising (Lewis *et al.*, 2020; Raffel *et al.*, 2020). By using these unsupervised objectives, PLMs can acquire abundant syntactic (Hewitt and Manning, 2019), linguistic (Jawahar *et al.*, 2019), semantic (Yenicelik *et al.*, 2020) and world knowledge (Petroni *et al.*, 2019), which confirms the effectiveness of pre-train tasks. By simply using the supervised data of downstream tasks to train PLMs, the knowledge contained in the PLMs can easily be adapted to the downstream tasks at the fine-tuning stage. Until now, pre-training and fine-tuning have achieved state-of-the-art performance of almost all NLP tasks, which shows it has become the dominant paradigm of the NLP community. However, even though conventional fine-tuning methods have achieved huge success, the gap between pre-training and fine-tuning in data size and training objectives restrict the capabilities of PLMs, which needs a better way to make full use of PLMs.

Before the age of PLMs, to achieve better performance, a lot of work focused on reformulating the format of one task to another in the NLP community, e.g., reformulating text classification task (Yang *et al.*, 2018) or relation exaction (Zeng *et al.*, 2018) as sequence generating task, summarization task as question answering task (McCann *et al.*, 2018), and parsing task as language modeling task (Charniak *et al.*, 2016). In the Paradigm of PLMs, since effectiveness of pre-training tasks, reformulating the downstream tasks to the format of pre-training tasks, which is named prompt-based learning [1], has excellent potential and gains more and more attention. To make it clearer, we take a simple sentiment classification case: Given a sentence *"This movie is great!"* as input, prompt-based learning first append a prompt to the sentence, which makes the sentence become *"This movie is great! The sentiment of this sentence is [MASK]."* Then, the expected classification outputs are extracted from the MLM head's word predicting probability at the position of [MASK]. Specifically, each label's score is achieved by the predicting probability of its preset corresponding label word (e.g., 'positive', 'negative'). Due to the great power of PLMs, prompt-based learning has incredible progress: Schick and Schütze (2021a) and Schick and Schütze (2021b) reformulate text classification, entailment, and question answering as mask language modeling task, which achieves remarkable performance at the few-shot setting; Brown *et al.* (2020) concatenate examples with labels to the end of input (called in-context learning), which do not need to calculate the gradient of parameters and achieved promising results; Raffel *et al.* (2020) reformulate all NLP tasks to sequence generation tasks and propose a seq2seq PLM (T5) to address all the NLP tasks; to further improve the generalization ability and zero-shot performance of PLMs, Wei *et al.* (2021) and Sanh *et al.* (2021) propose multitask prompted training, which reformulates a large number of downstream tasks' supervised data as the format of pre-trained tasks and then finetune PLMs on these large-scale transformed data.

With the deepening of the research, the capability and generalization ability of PLMs increase rapidly and bring considerable changes in the NLP community. As Figure 6.8 shows, with the rapid development of PLMs (since 2018), the trend of reformulating and unifying in natural language processing tasks accelerated abruptly. Since the link between different NLP tasks becomes close, it is possible to unify chit-chat and others tasks.

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[1] More related work and other perspectives can be found in the recent survey (Liu *et al.*, 2021; Sun *et al.*, 2021)

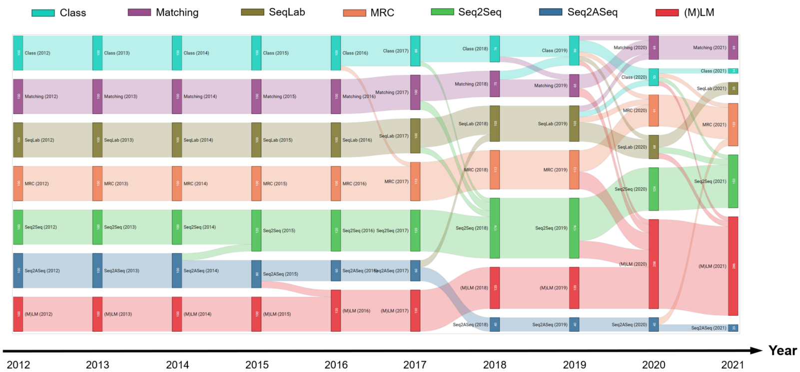

Figure 6.8: Sankey diagram to depict the trend reformulating and unifying in natural language processing tasks (Sun *et al.*, 2021)

6.4.2 PLMs for Dialogue Systems

Since the great potential of PLMs, applying PLMs to dialogue systems gains more and more attention from conversation AI communities. Due to the different characteristics of chit-chat and task-oriented tasks, the difficulty and problems of applying PLMs are also different.

Chit-Chat Due to the distribution difference between dialogue corpora and plain texts, fine-tuning PLMs on dialogue corpus directly is not as effective as other NLP tasks. Therefore, there are a lot of work focusing on constructing dialog-specific PLMs. Due to the high annotation cost of realistic dialogue corpus, researchers usually collect comment chains from social media (Reddit, Twitter, etc) instead. Zhang *et al.* (2020f) release DialoGPT, which is inherited from GPT-2 (Radford *et al.*, 2019) and further trained on dialogue corpus. Adiwardana *et al.* (2020) propose Meena, which uses a seq2seq model and surpass the chit-chat system that has a complex handcrafted framework. Roller *et al.* (2021) release Blender, which also employ a standard seq2seq transformer architecture has three variants with 90M, 2.7B, and 9.4B parameters. Bao *et al.* (2020a) propose PLATO, which is carried out latent recognition task on large-scale dialogue corpus to address one-to-many problems. Bao *et al.* (2020b) introduce curriculum learning and scale-up PLATO to PLATO-

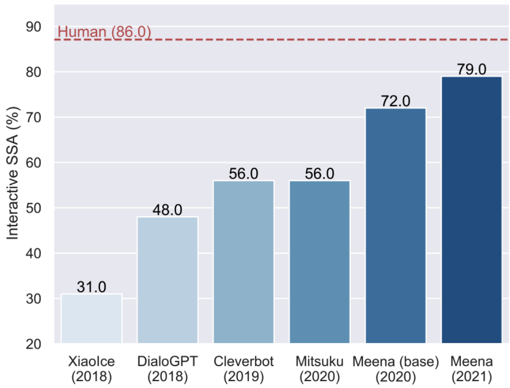

Figure 6.9: Manual evaluation on dialogue systems (Han *et al.*, 2021)

2, which has three model sizes: 1.6B, 314M, and 93M. Bao *et al.* (2021) present the PLATO-XL with up to 11B parameters, which conducts multi-party aware pre-training. Qi *et al.* (2021) extend ProphetNet to chit-chat dialogue tasks and propose two models (ProphetNet-Dialog-En and ProphetNet-Dialog-Zh). Wang *et al.* (2020a) release CDialGPT, which is trained on the 12M Chinese chit-chat conversations. Zhou *et al.* (2021a) build EVA, which is a chit-chat dialogue system and contains a pre-trained dialogue model with 2.8B parameters. As shown in Figure 6.9, with the growth of data size and parameters, the PLMs achieve better performance on chit-chat tasks.

Task-Oriented Dialogue Different from chit-chat, the task-oriented dialogue has explicit goals, which usually needs a modularized pipeline for more interpretability and controllability. Besides, the annotating cost of task-oriented dialogue is higher than chit-chat. Therefore it is more challenging to apply PLMs into task-oriented dialog. Faced with the complexity of the pipeline and the data scarcity problem, Ham *et al.* (2020) and Hosseini-Asl *et al.* (2020) treat the inputs and outputs of all modules as single sequences and then use PLMs to optimize the modules in an end-to-end method (framework is shown in Figure 6.10); Lin *et al.* (2020b) and Peng *et al.* (2020) leverage PLMs to jointly learn DST and dialogue response generation; Yang *et al.* (2021b) fine-tune

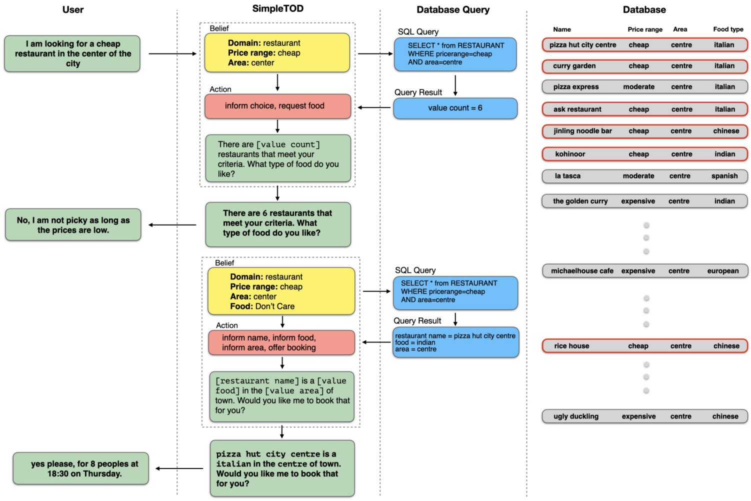

Figure 6.10: Framework of SimpleTOD (Hosseini-Asl *et al.*, 2020)

PLMs on dialogue session level instead of dialogue turn level; Su *et al.* (2021) utilize specific prompts to reformulate the format of sub-tasks of task-oriented dialogue and introduce a multi-task pre-training strategy that uses heterogeneous dialogue corpora; Wu *et al.* (2020b) release TOD-BERT, which is an adaptation of BERT trained on multiple task-oriented datasets with different domains and has a clear advantage on few-shot experiments; Mi *et al.* (2021) propose a self-training approach, which iteratively labels the most confident data from unlabeled dialogue corpus and achieves remarkable performance at few-shot setting; He *et al.* (2021) employ a semi-supervised method to explicitly learn dialogue policy and introduce a consistent regularization term to better use unlabeled data. Overall, it has great potential to use PLMs to unify different sub-tasks of task-oriented dialog.

6.4.3 Towards Unified Dialogue System

As stated in the previous section, with the rapid growth of PLMs, unifying different tasks becomes a trend. Along with this trend, it is a promising direction of constructing a unified dialogue system that uses one model to handle chit-chat, task-oriented dialog, and even work as

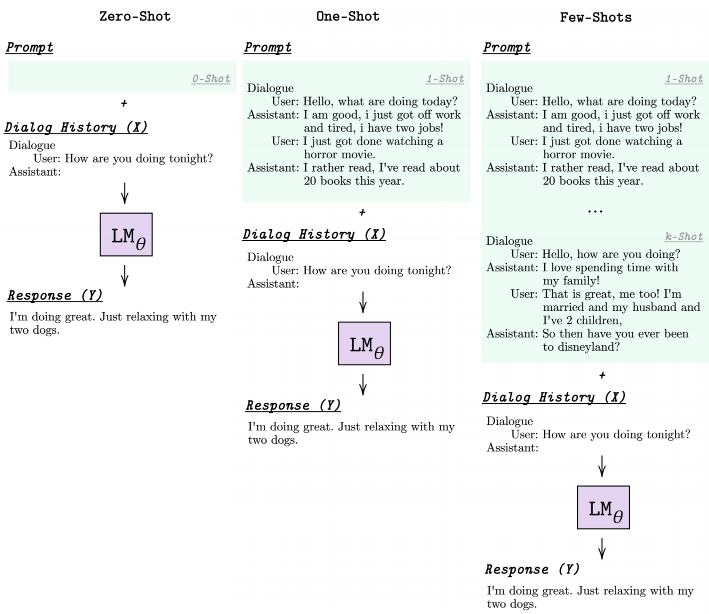

Figure 6.11: Framework of FSB (Madotto *et al.*, 2021)

knowledge bases, which may transfer the huge changes brought by the PLMs to the IR community.

Unifying Chit-Chat and Task-Oriented Dialogue With the help of powerful PLMs, it is more and more possible to unify chit-chat and task-oriented dialog. Zhao *et al.* (2021) propose a unified dialogue system (UniDS), which unifies chit-chat and task-oriented in a schema. Specifically, based on the end-to-end PLM framework for task oriented dialog, they see chit-chat as a type of dialogue policy and fine-tune the PLMs on the mixed data of chit-chat and task-oriented dialog. Because of the capability to switch between two types of dialogues, UniDS is more robust than previous approaches. With large-scale pre-training and 11B parameters, PLATO-XL (Bao *et al.*, 2021) achieve SOTA results on both chit-chat and task-oriented dialogue datasets, which is strong enough to be the foundation model of conversational AI. Madotto *et al.* (2021) create an chatbot named the Few-Shot Bot (FSB), which can be adapted to handle different dialogue tasks without training,

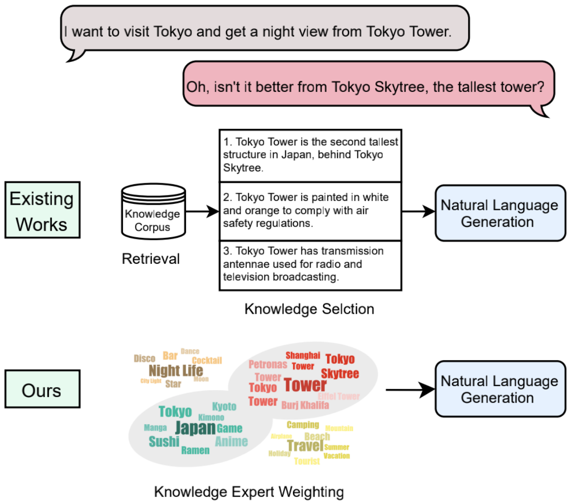

Figure 6.12: Illustration of KnowExpert (Xu *et al.*, 2021)

whose framework is shown in Figure 6.11. To be more specific, based on in-context learning (Brown *et al.*, 2020), they concatenate examples at the start and propose a strategy to select appropriate task-specific prompt to transform the format of the dialogue context. The most significant advantage of FSB is that it is based on general PLMs other than dialog-specific PLMs, which avoids the annotation cost of dialogue corpus. With the exploration of unifying chit-chat and task-oriented dialog, it is more and more possible that construct a unified dialogue system.

Language Model as Knowledge Bases To explore whether PLMs can work as knowledge bases, Petroni *et al.* (2019) propose a benchmark named LAMA and use 'fill-in-blank' problems to probe the world knowledge from PLMs, which shows PLMs has learned abundant world knowledge during pre-training.

To test the ability of the PLMs as a knowledge base, Roberts *et al.* (2020), Lewis *et al.* (2021), and Wang *et al.* (2021) explore closed-book QA tasks, where models need to answer the question without the help of an external knowledge base. In the dialogue tasks, there is also some pioneering work to explore using PLMs as knowledge bases to generate responses. Tuan *et al.* (2020) fine-tune a language model as a knowledge generation model; Xu *et al.* (2021) inject knowledge into lightweight adaptors named KnowExpert and leverage these knowledge to generate informative response so as to avoid suffering the slow speed of the retrieval process, whose framework is shown in Figure 6.12; Zhou *et al.* (2021b) utilize PLMs to generate relevant knowledge explicitly at first and then generate a response, which is named 'think before talk'. As response generative approaches are more and more critical in dialogue systems, with tremendous progress made by utilizing PLMs as knowledge bases, it is also a promising direction that uses generative approaches to get relevant knowledge passages.

In conclusion, because of the great potentials of PLMs, constructing a unified dialogue system, which is beyond chit-chat, becomes more and more hopeful.

6.5 Discussions

We can conclude that chit-chat links tasks in two aspects. From the perspective of system combination, the chit-chat module is a vital supporting component of the task-oriented system, which can improve user experience in completing tasks. From the side of techniques, it is also possible to build a unified framework that can support both chit-chat conversations and tasks in the era of large-scale pre-trained language models. It can be imaged that, interleaving chit-chat and task-oriented dialogues will be more prevalent in the near future. Through combining the merits of chit-chat and traditional task-specific conversations, conversational AI systems will be competent to various types of tasks in a more natural and intelligent way. However, there are some obstacles to overcome. The first challenge is the lacking of enough training examples that have both task-specific and chit-chat annotations. Another problem is the generalization of task-specific knowledge, such as knowledge graphs, domain-specific document texts.

7

Conclusions

7.1 Current Progress

In witness of the resurgent and rapid ascend of chit-chat systems, many works based on deep learning have been presented in the last few years. In this paper, we survey these recently released papers from varied aspects, and the main progress can be summarized as:

- Current chit-chat systems mainly leverage three different types of solutions, e.g., retrieval-based methods, generation-based models, and ensemble models.
- The most challenging problems that we are encountering in building chit-chat systems are long-range context modeling, one-to-diversity, human factors learning and fusion, knowledge and grounding, and the combination of pre-trained language models. Recent studies have made substantial progress on these problems.
- We sketch the landscape of conversational AI in the age of deep learning from the perspective of chit-chat.
- We discussed the connections between chit-chat dialogue systems and conventional task-oriented conversation systems, as well as

newly emerging IR tasks.

7.2 On-Going Struggles and Possible Future Trends

Through analyzing existing researches of chit-chat dialogue systems, we sort out the ongoing struggles and possible future trends as below.

The Intrinsic Challenges of Chit-Chat. Although tremendous progress has been made in recent years in utilizing deep neural models to construct chit-chat systems, some intrinsic challenges of chit-chat are still not completely solved so far, even for state-of-the-art models. Among which, the most salient two problems are:

- As stated by Huang *et al.*, 2020b, consistency is crucial for chatbots to gain long-term confidence and trust. With recent strong neural methods, there are still some deficiencies to respond consistently given the dialogue context and present consistent behaviors, which requires modeling long-range context information, long-term dialogue history, user profile, personas of the chatbots.
- One-to-diversity is a nagging problem of chit-chat conversation. As discussed in Section 4.3, researchers have tried a bunch of methods from different aspects (i.e., data manipulation, generation frameworks, training objectives, and leveraging extra resources) to mitigate the one-to-diversity problem. Owing to the lack of one-to-diversity data and the variability of chit-chat, one-to-diversity is still an open question.
- Another challenge for chit-chat systems is how to achieve a better understanding of the dialogues such as context, semantics, structure, discourse. With a better understanding of the dialogues, the performance of dialogue systems will be enhanced.
- Besides, evaluation of the chit-chat system is still an open challenge since chit-chat conversations are intricate and difficult to formulate. It is non-trivial to devote more efforts to design better evaluation methods, especially for generation-based systems.

More Sophisticated Requirements in Applications. With the fast evolution of conversational AI systems and the closer links between chit-chat dialogues and goal-oriented tasks, chatbots have to meet more sophisticated requirements in applications, which will pose new challenges for IR and NLP researchers.

- As demonstrated in Chapter 6, the line between chit-chat and goal-oriented tasks has become increasingly blurred. Chit-chat systems will be expected to detect user needs and complete these goals in real-time. In turn, goal-oriented tasks also need more pertinent skills of chit-chat to achieve the pre-set goals.
- Commonsense knowledge learning and utilizing of chit-chat systems are still in the preliminary stage. Further efforts are needed to build commonsense-aware chit-chat systems.
- With the development of mobile internet and applications, chit-chat systems require processing multi-modal information and dealing with heterogeneous data.
- Besides, with the wider application of conversational AI systems, it is non-trivial to pay more attention to the ethical issues and possible bias in human-machine conversations.

New Paradigm Based on Pre-Trained Language Models. Starting from BERT, pre-trained language models have changed the phase of NLP and IR fields. Various pre-trained models have been introduced in chit-chat systems, either as the backbone of generation model or providing context-aware vector representation for context-response matching in retrieval-based systems, and achieved impressive improvements. Recent researches further reveal that pre-trained language models are still underexplored, and thus tapping the potential of pre-trained language models for chit-chat systems is a valuable direction.

- One of the merits of large-size PLMs is their generalization ability, which can transfer self-trained knowledge to enhance chit-chat conversation modeling. Introducing PLMs can easily achieve domain adaptation and topic shifts.

- Another promising attribute of PLMs is their few-shot/zero-shot capabilities. For instance, GPT-3 does not even need to fine-tune model parameters to complete various tasks, which only needs to give a prompt or a few demonstration cases. Following this line, various prompt-based methods have been proposed very recently for different classification tasks. It is predictable that prompt-based methods for chit-chat conversations will occur in the near future to better leverage the few-shot/zero-shot capabilities of PLMs.

- We also have to say that PLMs suffer from model efficiency and data efficiency to improve generalization ability and prevent over-fitting on small datasets. Thus, how to speed up PLMs and improve data efficiency beyond all doubt are crucial for chit-chat systems.

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