Document-editing Assistants and Model-based Reinforcement Learning as a Path to Conversational AI

Katya Kudashkina1,2,3,4, Patrick M. Pilarski3,4, Richard S. Sutton3,4

1 University of Guelph, 2 Vector Institute for Artificial Intelligence, 3 University of Alberta, 4 Alberta Machine Intelligence Institute

Currently under review. Corresponding author: kudashki@ualberta.ca

Abstract

Intelligent assistants that follow commands or answer simple questions, such as Siri and Google search, are among the most economically important applications of AI. Future conversational AI assistants promise even greater capabilities and a better user experience through a deeper understanding of the domain, the user, or the user’s purposes. But what domain and what methods are best suited to researching and realizing this promise? In this article we argue for the domain of voice document editing and for the methods of model-based reinforcement learning. The primary advantages of voice document editing are that the domain is tightly scoped and that it provides something for the conversation to be about (the document) that is delimited and fully accessible to the intelligent assistant. The advantages of reinforcement learning in general are that its methods are designed to learn from interaction without explicit instruction and that it formalizes the purposes of the assistant. Model-based reinforcement learning is needed in order to genuinely understand the domain of discourse and thereby work efficiently with the user to achieve their goals. Together, voice document editing and model-based reinforcement learning comprise a promising research direction for achieving conversational AI.

Keywords: conversational AI, intelligent assistants, dialogue systems, human-computer interaction, reinforcement learning, model-based reinforcement learning

The ambition of AI research is not solely to create intelligent artifacts that have the same capabilities as people; we also seek to enhance our intelligence and, in particular, to build intelligent artifacts that assist in our intellectual activities. Intelligent assistants are a central component of a long history of using computation to improve human activities, dating at least back to the pioneering work of Douglas Engelbart (1962). Early examples of intelligent assistants include sales assistants (McDermott 1982), scheduling assistants (Fox and Smith 1984), intelligent tutoring systems (Grignetti, Hausmann, and Gould, Anderson, Boyle, and Reiser 1975, 1985), and intelligent assistants for software development and maintenance (Winograd, Kaiser, Feiler, and Popovich 1973, 1988). More recent examples of intelligent assistants are e-commerce assistants (Lu and Smith 2007), meeting assistants (Tür et al. 2010), and systems that offer the intelligent capabilities of modern search engines (Fain and Pedersen, Thompson, Croft, Metzler, and Strohman 2006, 2006, 2010). Building intelligent assistants has been positioned as one of the key areas of development in AI (Waters 1986).

Today, there are already economically important consumer products based on intelligent assistants. Intelligent assistants built on voice interaction, such as Amazon Alexa, Google Personal Assistant, Microsoft Cortana, Apple Siri, Facebook Portal, are among the most important applications of artificial intelligence today. These voice personal assistants help people with many daily tasks, such as shopping, booking appointments, setting timers, and filtering emails. The economic value of these systems is created by generating revenue from selling not only hardware devices, such as smart speakers, but also voice application features, in the form of sales of digital goods as a one-time purchase, subscriptions, or consumables. The revenue from voice personal assistants alone was forecast to grow from $1.6 billion in 2015 to $15.8 billion in 2021 (Tractica 2016). It is hard to think of another area in AI that has more immediate social and economic impact.

Conversational and Purposive Assistants

Today’s voice assistants are fairly limited in their conversational abilities and we look forward to their evolution toward increasing capability. Smart speakers and voice applications are a result of the foundational research that has come to life in today’s consumer products. These systems can complete simple tasks well: send and read text messages; answer basic informational queries; set timers and calendar entries; set reminders, make lists, and do basic math calculations; control Internet-of-Things-enabled devices such as thermostats, lights, alarms, and locks; and tell jokes and stories (Hoy 2018). Although voice assistants have greatly improved in the last few years, when it comes to more complicated routines, such as re-scheduling appointments in a calendar, changing a reservation at a restaurant, or having a conversation, we are still looking forward to a future where assistants are capable of completing these tasks. Are today’s voice systems “conversational”? We say that intelligent assistants are conversational if they are able to recognize and respond to input; to generate their own input; to deal with conversational functions, such as turn taking, feedback, and repair mechanisms; and to give signals that indicate the state...
of the conversation (Cassell 2000). It is our ambition to achieve a conversational AI assistant that demonstrates these properties, communicates in free-form language, and continuously adapts to users’ changing needs, the contexts they encounter, and the dynamics of the surroundings. This conversational AI assistant would understand the domain within which it is assisting and provide appropriate support, as well as a pleasant experience for its users. This kind of assistant has not been developed yet and requires more research. Conversational AI is a primary goal along the path toward creating intelligent assistants in general. Achieving conversational AI would lead to even better intelligent assistants—intelligent assistants that have a genuine, deeper understanding of their domains and users, helping people to achieve their goals.

Key to the effectiveness of an intelligent assistant is that it is able to understand the higher-level goals of a task when assisting its users. Hawkins (1968) defined a goal or a purpose as a future state that is brought about through instrumental control of a choice of actions among alternatives. These higher-level goals or purposes are the reasons for completing a task. These purposes motivate and influence smaller intermediate goals. For example, if a primary goal is flying to San-Francisco, then intermediate goals can be purchasing flight tickets and packing the luggage. We use the word “purpose” to refer to the combination of the high-level context of a task and the user’s goals and use the words “agent” and “assistant” interchangeably. A user interacting with an intelligent assistant has purposes related to the user’s task. An assistant that understands users’ purposes and has its own purposes is a purposive intelligent assistant. Everyone who has worked on intelligent assistants has recognized the importance of agents’ understanding of purposes, yet an assistant that carries this property has not been developed. Building learning systems that genuinely understand purposes has been talked about for decades (Lindgren, Sun, Chen, and Rudnicky, Serban et al. 1968, 2016, 2017b) and is still ahead on the AI research road map in fulfilling the promise of assisting people.

Understanding users’ purposes is key not only for intelligent assistants in general but, in particular, for conversational AI agents. Purpose understanding is important for voice assistants in serving their users and adjusting to the users’ unique preferences. Imagine a user who wants to have a business meeting with a client and interacts with a meeting-booking assistant. In this example, the purpose is a successful business meeting. The user’s initial ask is to book a lunch reservation at a French restaurant for the purpose of the meeting, which triggers an intermediate goal: to make the reservation. A meeting-booking assistant that understands the purpose may suggest an Italian restaurant instead. This is because the assistant has information that the Italian restaurant is quieter and better suited for business meetings, even though the assistant realizes that the suggested restaurant is not a requested French type. The user may accept the intelligent assistant’s suggestion, believing that it might be even better than their initial ask because the suggestion supports the primary purpose, the meeting. The intelligent assistant’s awareness of the purpose is what motivates and drives this scenario. Another example of such a purposive intelligent assistant is a robotic arm or other manipulation device controlled by a human user (e.g., a prosthesis or an industrial robot). Take the case of a human-controlled robotic assistant picking up an object on a chess board or pushing it; both tasks would require different motions or other situation-specific actions from the assistant. If the agent understands the context when assisting with a task, then it would know how to implement a small direct move, like advancing a pawn on the chess board, or an indirect move, like deploying a knight, with minimal delays and micromanagement on the user’s part. The assistant creates a smoother user experience by making better choice of actions when being purposive.

A purposive intelligent assistant improves its capabilities further when it develops goals or purposes of its own. This concept is close to an idea where agent-based adjustable autonomy is not prescribed by the user (see Maheswaran et al., 2003). An example is an iRobot Roomba that cleans a house. Roomba could set a goal of not hurting itself. This intelligent assistant not only seeks and adjusts to the user and their preferences, but also develops and sets its own goals and purposes. It is important that the user should be aware of the intelligent assistant’s goals. This awareness would help the user to adjust their preferences, contributing to a more harmonious interaction. This adjustment between the assistant and the user increases the assistant’s capabilities resulting in a better user experience.

**The Challenge of Conversation**

Efforts to build voice assistants that learn purposes are present not only in modern dialogue systems but go back through four decades of incremental research and development (Carbonell, Winograd, Simmons and Slocum, Power, Bruce, Walker and Grosz, Cohen, Allen, Pollack, Hirschberg, and Webber, Grosz, Woods, Finin, Joshi, and Webber, Carberry, Moore and Paris, Smith and Hipp, Kamm 1971, 1971, 1972, 1974, 1975, 1978, 1978, 1979, 1982–1984, 1986, 1989, 1989, 1994, 1995). Achieving this goal calls for large amounts of computational power, a great deal of engineering effort to overcome architectural challenges, and continual human-machine interaction to produce the data. SHRDLU (Winograd 1971) was an early, well-known dialogue system that responded to instructions and moved objects in a simulated world. Naively, one could believe that SHRDLU demonstrated understanding of purposes; however, today it is known that symbolic manipulation systems would fail in the ambiguous situations humans encounter in real-world settings.

We separate modern dialogue systems into three categories to illustrate their closeness to purposive intelligent assistants. The first category is *entertainment systems* that provide open-domain conversations (see Huang, Zhu, and Gao, 2020). These are chatbots and systems that bring a sense of companionship (e.g., Quarteroni and Manandhar, 2009; Nonaka et al., 2012; Higashinaka et al., 2014; Li et al., 2016a; Smith et al., 2020; Zhou et al., 2020), mostly implemented with sequence-to-sequence models (Sutskever,
The third category is language instruction systems by Goyal, Niekum, and Mooney (2019). Work advancing in this direction is the use of natural language instruction systems that are primarily represented by text-based games (e.g., He et al., 2015; Kaplan, Sauer, and Sosa, 2017; Goyal, Niekum, and Mooney, 2019). These dialogue systems are closer to learning purposes. An example of the work advancing in this direction is the use of natural language instruction systems that are primarily represented by text-based games (e.g., He et al., 2015; Kaplan, Sauer, and Sosa, 2017) or retrieval-based methods, which come a long way yet continue to remain somewhat scripted.

Modern dialogue systems have rapidly advanced in the last few years, but remain limited in their ability to learn purposes. The introduction of deep learning techniques through the sequence-to-sequence network by Sutskever, Vinyals, and Le (2014) combined with the massive amount of data and computational power produced amazing results with the recent system GPT-2 (Radford et al. 2019) being a prime example. But is GPT-2 a step toward purposive intelligent assistants? We make a simple distinction and clarify that it is a confined language model that predicts the next word, given all the previous words within some text. GPT-2 is an amazing engineering effort that deserves special recognition. The limitation is that the system’s answering capabilities rely on word-by-word prediction, and not on genuine understanding of a domain or users’ goals. Today’s dialogue systems have come a long way yet continue to remain somewhat scripted, often using a limited number of pre-defined slots and canned responses.

Why is it so difficult to get to the goal that would advance today’s research community’s answers to the challenges of conversational AI and to develop agents that learn purposes? General methods, such as supervised learning, that scale with increased computation, continue to build knowledge into our agents. However, this built-in knowledge is not enough when it comes to conversational AI agents assisting users, especially in complicated domains. One of the biggest problems in conversational AI is the limitlessness of domains, which leads to high expectations of conversational agents. In a general conversation, an intelligent assistant is expected to know everything that a human conversational partner might know and, in some cases, also specialized user-related or world-related information. For example, the agent is expected to know about relevant aspects or patterns in the wider environment and users’ lives, such as what it means to have a schedule. In other words, the agent is expected to know about the world of its user, and a user can potentially ask the agent anything. The research community has an ultimate goal to have intelligent assistants that are able to provide support as effectively as expert human assistants can, but high expectations with respect to an agent’s knowledge about the world and the users are an obstacle on the path to getting there.

We propose that what is really needed is that the domain is tightly scoped and fully accessible to the intelligent assistant, so that the assistant can fully understand it. This leads to the question: Is there a domain in which assistants can have focused conversations with their users and be helpful without knowing everything about the rest of the world but knowing everything about what they have to assist with? We now propose such a domain that allows us to accelerate and advance this field without immediately solving the grand challenge of human-level AI.

**Voice Document Editing**

The challenge of genuine understanding in conversational AI requires us to pick a domain that is small enough for an assistant to fully understand. Document editing is one of the domains that allows an agent to focus a conversation. Imagine an intelligent assistant that helps create and modify a document via a free-form language conversation with a user. This conversation is focused on the document the assistant and the user are authoring. We call this domain voice document editing and propose it as particularly well-suited to develop conversational AI.

The voice document-editing domain fits well into the idea we described earlier: learning purposes enables intelligent assistants to become more helpful and powerful. Document editing assistants could provide better help if they could understand users’ purposes and allow interactions in a free-form language, making the interaction process timely and efficient. They could help create and edit text messages, emails, and other documents on-the-go. Voice document-editing assistants could perform actions such as deleting and inserting words; creating and editing itemized lists; changing the order of words, paragraphs, or sentences; converting one tense to another; or fine-tuning the style. For example, if a user asks an assistant “Please move the second paragraph above”, and then says “Delete the last word in the first sentence”, then the assistant would know that the first sentence the user is referring to is in that particular paragraph that was moved by the assistant’s previous action. Such assistants have been emerging for more than three decades (Ades and Swinheart, Douglas, Lucas, Mikó, and Bennington 1986, 1999, 2004).

We separate today’s dictation systems into two types: the ones that allow voice text modifications in addition to dictation and the ones that do not. Examples of the latter type include systems such as Dragon by Nuance, ListNote, and the Speech Recogniser of iOS (Duffy 2018). Our focus is only on the former type: in these systems, users can write by dictating while walking, cooking, or doing other things, and then edit the document by using pre-defined commands. We refer to them as voice editing-enabled systems. These
are dictation software systems such as SMARTedit (Lau et al. 2001), Apple Dictation (Gruber and Clark 2017), Dictionary.io (Google AI Blog. Digital Inspiration 2020), Google Docs Voice Editor (Douglas, Google 1999, 2020), and Windows Speech Recognition (Microsoft 2020). We now describe how document editing is performed in these systems.

Document editing can be thought of as a manipulation of the manuscript in text blocks. Card, Moran, and Newell (1980) show that, from a cognitive perspective, document editing is structured into a sequence of almost independent unit tasks. The unit tasks are manipulations of selected text blocks, as suggested by a number of patents related to users’ text editing (e.g., Greyson et al., 1997; Takahashi, 2001; Walker, 1998). In particular, a block of text is first identified by a user. Next, the block may be moved around, modified, or formatted in place. A modification operation may include insertion of the new text, or the selected block may be removed completely. Today’s aforementioned voice editing-enabled systems (Lau et al., Gruber and Clark, Google AI Blog. Digital Inspiration, Douglas, Google, Microsoft 1999, 2001, 2017, 2020, 2020) classify document-modification unit tasks into text-editing functions representing the types of text-editing operations people do in their editor of choice.

To demonstrate the suitability of voice document editing for conversational AI, we further look into its advantages. One advantage of a voice document-editing domain is that it excludes the real-world complexities that many other assistive systems have. Consider an intelligent cleaning robot or some other assistive robotic system (e.g., Dario et al., 1996; Salichs et al., 2019). These systems have many real-world complexities, such as the effects of the electronic hardware, materials, sensory systems, surrounding objects, and the variability of sensors. Voice document editing does not have these dependencies and its reduced complexity is favorable for the agent’s learning process and for the researchers’ experimentation.

An important advantage is that the voice document-editing domain serves as a micro world with a finite number of clearly defined concepts for the agent to learn. We refer to this property of the domain as being tightly scoped. The world is represented by a manuscript being dictated and edited by the user. This world is smaller and more manageable than in many other real-life applications of conversational AI, such as open domain conversations for chatbots (e.g., Saleh et al., 2019). It is easier for the agent to learn in this smaller world because the agent only has to learn about the state of the document and its modifications, both of which are fully accessible to the agent. At the same time, the agent does not have to understand the content of the document. For example, it is not necessary for the agent to know about history if a user is writing a historical article, or to know something about medicine if the user is writing a health related article. The agent is not expected to know information about the user that extends beyond the document editing context: what the user had for breakfast, their religion, other aspects of the user’s life, or additional world-related information. The agent, however, knows about the structure of the document and can learn about text blocks, such as paragraphs, sentences, and words. The agent can also know grammatical structure and core organizational components of the document, such as salutations and valedications when composing an email. The voice document-editing domain allows the agent to center what a conversation is about—the document itself and its edits. The finite amount of editing concepts in the fully-accessible document defines fixed bounds for the domain and makes it easier to evaluate the performance. As a result, relative to other real-life applications of conversational AI, the agent has to learn a smaller number of things, which is favorable for the agent and leads to reasonable expectations.

One way to evaluate our choice of voice document-editing domain is to compare it to other domains that may carry similar properties of reduced real-world complexity and being tightly scoped. We compare our domain to voice image editing and task-oriented systems: both are the closest to our definition of the purposive intelligent assistant. We show in which ways voice image editing and task-oriented systems differ from the domain of our choice, consequently making these domains more challenging than voice document editing.

A voice image editing assistant has to be able to recognize the content, which may require the assistant to learn an unlimited number of representations before becoming useful to its users. Consider a conversational image editing system proposed by Manuvinakurike et al. (2018) that is able to recognize voice commands such as “remove the tree”. The ability to execute such commands entails that the system should be able not only to understand the command itself, but also to have a representation of a tree to be able to identify a tree in the image that is being edited. To recognize a tree in an arbitrary image, the agent would have to learn what all possible trees look like. Learning about all possible trees requires the assistant to learn an unlimited number of tree representations, which results in the agent having to acquire infinite multi-domain knowledge. In contrast, in the voice document-editing domain, the agent does not need to understand the content of the document; it only needs to learn how to perform the edits. For example, the user dictated a phrase “There was a tree”. When the user asks to replace the word “tree” with the word “lake”, the voice editing assistant does not need to know what the concept of a “tree” or a “lake” is. It simply needs to transcribe the word from voice to text and to know the replacement operation, because it already knows the location of words in the text. This example illustrates that voice image editing is not tightly scoped compared to voice document editing. While conversational image editing is a suitable domain for incremental dialogue processing, it is more difficult for the agent to become useful to its users in this domain because of the large amount of information it has to learn.

Task-oriented systems also have unlimited concepts for the assistant to learn despite the focus on a particular user goal. Consider a restaurant booking system (e.g., Wen et al., 2017). To be a good assistant, the system has to know something about the user’s schedule, transportation logistics, and many additional concepts. For example, the assistant needs to understand that the reservation cannot be made during
the time when the user is picking up their children. The assistant also needs to know how to select the best location of the restaurant when it comes to transportation logistics. Scheduling and logistics are only a couple of concept examples that the agent is expected to know about in addition to knowing the reservation action. The complexity of the real world leads to a possible unlimited number of concepts that the agent is expected to know. This example demonstrates how task-oriented systems may appear tightly scoped while having unlimited concepts that the assistant has to learn. In contrast, our choice of voice document-editing domain makes learning possible because the agent can learn a limited number of concepts and can still be useful to the user.

Now that we have looked at the advantages of voice document editing, we turn our attention to the current state of such systems. Despite enormous effort in this direction, today’s voice editing assistive systems remain rudimentary. When it comes to text modifications using voice, there are limitations: users can format and edit by using only a few pre-defined commands such as “New line” in order to start a new line or “Go to end of paragraph” when a user wants to move the cursor. If the user says slightly modified versions of commands such as “Let’s go to a new line” or “Move the cursor to the end” instead of the aforementioned pre-defined commands, then the agent may not perform the right action. These constraints limit benefits of editing a document via voice—at the end of the day, a user has to either perform manual text manipulation using a keyboard or carefully remember all the commands to manipulate the manuscript via voice. For example, one of the advanced editors, Google Docs Voice Editor (Google 2020), has over a hundred basic commands that a user would need to memorize or to look up while editing. Communication to the voice editing assistant in a free-form language is yet to be developed.

An assistant that can communicate to the user in a free-form language and be helpful to the user is one of the main challenges in conversational AI. Developing such assistant involves a number of complex elements, that are incredibly challenging in isolation: from natural language understanding, to acoustic prosody, to natural language generation, to response generation, to knowledge acquisition (Eric 2020). Voice document editing combines these elements in one domain and thereby opens up research opportunities that could benefit the advancement of conversational AI. We now propose methods suitable for developing voice document-editing assistants.

Reinforcement Learning Assistants

Reinforcement learning has been pursued as a natural approach to intelligent assistants (Kozierok and Maes, Pollack et al., Pineau et al. 1993, 2002, 2003). Reinforcement learning starts with an agent that is interactive and goal-seeking. Formally, reinforcement learning is an approach for solving optimal control problems in which a behavior is learned through repeated trial-and-error interactions between a learning system and the world the system operates in. The learned behavior is called a policy, a learning system is an agent, and the world the agent operates in is called an environment. In each interaction with the world, the agent takes an action and receives a reward which can be positive or negative. The agent aims to maximize the expected return, which is the sum of the total rewards in the simplest case (Sutton and Barto 2018). Reinforcement learning has not been previously investigated specifically for voice document editing and it is the approach that we are going to explore in this article.

The first advantage of reinforcement learning is that it provides an opportunity for an intuitive human-computer interaction, in contrast to more common machine learning formulations of supervised and unsupervised learning. In particular, an interactive reinforcement learning agent can directly learn things about its environment with every action and select future actions according to that knowledge. This means that agents are not learning from the input-output pairs that were provided ahead of time, but from direct experience—online learning. Online learning provides a natural opportunity for intuitive interactions, during which intelligent assistants adapt to users. Imagine a voice assistant that recommends fun things to do during travel, similar to the NJFun system (Litman et al., Singh et al. 2000, 2002a) that provided users with information about fun things to do in New Jersey. The assistant can learn about the user’s preferences much faster and provide better recommendations by extracting a reward signal after each suggestion made and adjusting its suggestions accordingly. When this assistant helps a traveler who is interested in music history, it can learn the user’s preferences quickly, based on how satisfied the user was with its previously provided recommendations. The assistant can tailor the recommended places to music history museums, music history festivals, music exhibits, and other similar attractions. This adjustment via online learning between the assistant and the user improves the assistant’s reasoning about its future actions. The importance of online learning and interaction feedback have appeared in many studies (e.g., Long, 1981; Pica, Doughty, and Young, Pica, 1986, 1987; Gass and Varonis, 1994; Bassiri, 2011; Gašić et al., 2011; Gašić et al., 2013a; Ferreira and Lefvre, 2015; Li et al., 2017a; Liu et al., 2017).

The second advantage of reinforcement learning is that users’ feedback can be formulated as a reward signal. Feedback can be used as a goal-directed signal of users’ satisfaction or dissatisfaction with actions the assistant takes, which is one way to evaluate the assistant (see Jiang et al., 2015). In the context of dialogue settings, it is expected that users have a way of communicating their feedback to the assistant, either through voice interaction or physical interaction via a robotic device. Examples of these interactions include: training assistants with animal-like robot clicker techniques (Kaplan et al. 2002); using a combination of reward signals from a human and an environment (Knox and Stone 2012); and using a sparse human-delivered training signal, as in the case of adaptable, intelligent artificial limbs (Pilarski et al. 2011). An intelligent assistant maximizing users’ satisfaction is a reinforcement learning agent maximizing the expected return.

The third advantage of reinforcement learning is that it al-
Reinforcement learning has been applied to conversational AI in various ways since late 1970s. Some of the earliest works were Walker and Grosz, Biermann and Long, Levin, Pieraccini, and Eckert, Singh et al. (1978, 1996, 1997, 2000). In more recent works, Gašić et al. (2011, 2013a) use reinforcement learning in online settings to directly learn from human interactions using rewards provided by users and to optimize the agent’s behavior in reaction to the user. Dhingra et al. (2017) also explore online learning, but in simulated settings. They train their agent entirely from the feedback that mimics the behavior of real users. Such simulated settings are not always available for a learning task and building simulators for dialogue scenarios and tasks is challenging (Cuayahuitl et al., Li et al. 2005, 2016b). To overcome these challenges, Zhou et al. (2017) choose to optimize a policy in offline settings using the raw transcripts of the dialogues, while Liu and Lane (2017a) take an approach of jointly optimizing the dialogue agent and the user simulator. Xu, Wu, and Wu (2018) also apply joint modeling of dialogue act selection but use reinforcement learning only to optimize response generation. A number of others also use reinforcement learning for open-domain dialogue generation (e.g., Ranzato et al., 2015; Li et al., 2016a; Yu et al., 2017; Budzianowski et al., 2017; Xu, Wu, and Wu, 2018; Jaques et al., 2019).

One of the big trends in the last five years has been to use deep reinforcement learning in conversational AI (He et al., Cuayahuitl et al., Shah, Hakkani-Tür, and Heck, Zhao and Eskenazi, Bordes, Bouraeu, and Weston, Budzianowski et al., Shen et al., Liu et al., Su et al., Peng et al., Williams, Asadi, and Zweig, Liu, Peng et al., Tang et al., Weisz et al., Zhang, Zhao, and Yu, Mendez et al., Shin et al., Zhao et al., 2015, 2016, 2016, 2016, 2017, 2017, 2017, 2017, 2017, 2017, 2018, 2018, 2018, 2018, 2018, 2019, 2019, 2019), building on the recent success of deep reinforcement learning on games such as Atari, Go, chess and shogi (Mnih et al., Silver et al., Schrittwieser et al. 2013, 2018, 2019). There is a mix of approaches in this body of work. For example, Liu et al. (2017) use reinforcement learning in combination with supervised learning, and then optimize the agent during the interactions with the users. Shah et al. (2016, 2018) contrast the interpretation of the human feedback as a reward value (Thomaz, Hoffman, and Breazeal, Thomaz, Hoffman, and Breazeal, Knox and Stone, Loftin et al. 2005, 2006, 2012, 2014) and propose an interactive reinforcement learning approach in which the user feedback is treated as a label on the specific action taken by the agent similar to Griffith et al. (2013). Reinforcement learning is studied for policy adaptation between domains in multi-domain settings (e.g., Gašić et al., 2013b; Cuayahuitl et al., 2017; Gašić et al., 2017; Rastogi, Hakkani-Tür, and Heck, 2017; Chen et al., 2018; Liu and Lane, 2017b). Serban et al. (2017a) apply reinforcement learning to select from a number of responses produced by an ensemble of so-called response models. Tang et al. (2018) use reinforcement learning to train multi-level policy that allows agents to accomplish subgoals. Foerster et al. (2016), Sukhbaatar, Szlam, and Fergus (2016), Lazaridou, Pham, and Baroni (2016), Mordatch and Abbeel (2018), and Papangelis et al. (2020) apply reinforcement learning to teaching agents to communicate with each other in multi-agent environments. These works are a small fraction of the large body of research that implements deep reinforcement learning approaches in dia-

Prior Work Applying Reinforcement Learning to Conversational AI

Reinforcement learning has been applied to conversational AI in various ways since late 1970s. Some of the earliest works were Walker and Grosz, Biermann and Long, Levin, Pier-
Model-based Reinforcement Learning

In the dialogue systems that we have discussed so far, the reinforcement learning agent learns policies and value functions, but not a model of the environment that can be used for planning. By models of the environment, or models of the world, we mean any function that the agent can use to predict how the environment will respond to the agent’s actions. We use the term planning to refer to any computational process that takes a model of the environment as input and produces an improved policy for interacting with the modeled environment. The idea of augmenting a reinforcement learning agent with a world model that is used for planning is known as model-based reinforcement learning (Sutton and Barto, Sutton and Pinette, Sutton, Chapman and Kaebbling, Singh, Atkeson and Santamaria, Wiering, Salustowicz, and Schmidhuber, Abbeel et al., Sutton et al., Ha and Schmidhuber, Holland, Talvitie, and Bowling, Schrittwieser et al. 1981, 1985, 1990–1992, 1997, 2001, 2007, 2008, 2018, 2019).

Models and planning are helpful. One advantage of models and planning is that they are useful when the agent faces unfamiliar or novel situations—when the agent may have to consider actions that they have not experienced or seen before. Planning can help the agent evaluate possible actions by rolling out hypothetical scenarios according to the model and then computing their expected future outcomes (Doll, Simon, and Daw, Ha and Schmidhuber 2012, 2018). These outcomes can be computed a few steps ahead and can be thought of as the agent reasoning about the long-term consequences of its actions, similar to how people evaluate the long-term consequences of their decisions. The agent reasoning about the consequences of its actions and acting based on the world model’s predictions is analogous to the way a person reasons and acts based on their understanding of the world. Hypothetical scenarios allow the agent to safely explore the possible consequences of actions. For example, the agent can use hypothetical scenarios to explore actions that in real-life applications could lead to a costly crash or other disaster (Berkenkamp et al. 2017). Another advantage of world models and planning is that they help accelerate the learning of policies (Freeman, Ha, and Metz 2019).

The advantages of world models and planning also arise with intelligent assistants. World models and planning enable intelligent assistants to leverage the interaction information as much as possible, with a minimal amount of prior knowledge and in the absence of external supervision. Thus, models and planning make it possible for the agent to acquire the full benefits of reinforcement learning in conversational AI, which in turn would allow us to create a purposive intelligent assistant that is efficient and useful, can adapt to its users, reason about the consequences of its actions, can control its choice of actions among alternatives, and can learn how the real world works. Planning has been previously explored in dialogue systems outside of reinforcement learning (e.g., Stent, Prasad, and Walker, 2004; Walker et al., 2007; Jiang et al., 2019).

There are a few existing works in conversational AI that already apply model-based reinforcement learning (MBRL) methods. They use a world model to mimic user responses and planning to generate hypothetical experiences that are then used to improve the policy. Lewis et al. (2017) introduced dialogue rollouts, in which planning proceeds by imagining many hypothetical completions of the conversation. They interleaved reinforcement learning updates with supervised updates. This work was followed by Yarats and Lewis (2017) who improved the effectiveness of long-term planning using rollouts. Peng et al. (2018) incorporated planning into dialogue policy learning in their deep Dyna-Q framework, followed by Su et al. (2018) who proposed to control the quality of hypothetical experiences generated by the world model in the planning phase. Wu et al. (2019) extended the deep Dyna-Q framework by integrating a switcher that allows to differentiate between a real or hypothetical experience for policy learning (see also Gao et al., 2019; Zhang et al., 2020). Subsequently, Zhao et al. (2019) built on the work of Peng et al. (2018), using similar world model designs, which is a model-based approach that is similar to the Dyna architecture (Sutton 1990), where learning and planning are combined and the predictions are improved based on the planning (cf. Lison, 2013). All these prior works in conversational AI with MBRL are important developments, yet, do not offer a scalable MBRL agent that is fully capable of assisting the user and combines learning and planning in all aspects. We have begun to explore the combination of learning and planning (Kudashkina et al., 2020). Below we develop the idea of MBRL and identify its major components, which will help to think further about applying MBRL to the voice document editing domain.

There are three primary components of MBRL: an agent state and its construction; an environmental model; and a policy, together with a function that estimates the outcome of the agent’s actions (Figure 1). The first component of the MBRL agent is a representation of where it is at the current time—an agent state. The agent state is an approximation of a minimal environmental state that is the basis of the theory of Markov decision processes. The agent state is a compact summary of all that has come before, which includes all the histories. The agent state changes at every time step based on the actions the agent takes and the observed signals from the environment, which we call observations. The agent state is computed incrementally as a function of the previous agent state, the most recent observation, and the most recent action. This function is called a state update function. The state update function is similar to the recursive state update introduced by Littman and Sutton (2001). The agent state is an essential part of the MBRL architecture and an input that becomes crucial in the intelligent assistant’s decisions.

The second component of MBRL is an environmental model. As discussed, environmental models are fundamental in making long-term predictions and evaluating the consequences of actions based on those predictions. Nortmann et al. (2015) suggest people’s internal models of the world are learned during the interaction with the world and contain the information that is perceived by their brains. Sim-
ilarly, environmental models are learned by the agent during human-computer interaction. Forrester (1971) describes people’s models of the world as the image of the world that humans carry in their head: the concepts and relationship between them that are used to represent a real system. Likewise, environmental models capture the dynamics of the environment and the user-agent interaction within it (Sutton 2019). These dynamics are everything that the agent needs to know about the environment. More precisely, the knowledge of the environment dynamics enables the agent to predict next states and rewards from the previous state and its actions. Thus, environmental models help the agent to make informed action choices by enabling it to compute hypothetical future outcomes of different actions with the modelled environment. Recall that we refer to this computational process as planning. Planning is particularly important because it allows the agent to learn not only from the past actions that resulted in a reward, but also from hypothetical actions for which the agent has not seen a reward. Ng et al. (2004) present a successful application of reinforcement learning that uses a model for autonomous helicopter flight, saving hours of adjustments and flight testing and preventing unnecessary crashes. Their model is learned offline prior the agent training. Ng et al. (2004) start with a human pilot flying the helicopter for several minutes, and then use the data to fit a model of the helicopters dynamics. Similarly, Coates, Abbeel, and Ng (2017) provide an agent with the pre-trained model and the reward function.

The third component of MBRL includes a policy and a function that estimates the outcome of the agent’s actions. These functions are dependent on states or state-action pairs and are called value functions. Policies and value functions are a part of core reinforcement learning methods that do not include environmental models—model-free methods. In simplified terms, value functions compute a numeric value of a given state based on the observed rewards. These values indicate how effective it is for the agent to be in the given state or how effective it is to perform a particular action from that state. Policies and value functions are often approximated by artificial neural networks (Parr et al., 2008, 2008).

The policy and the value function, together with the agent state, the state update function, and the environmental model complete a full MBRL conceptual architecture. This architecture is general and has no domain-specific components. This generality could result in a scalable and potentially lasting impact. The state update function and the environmental model components are critical parts of this architecture and dependent on each other. The agent state serves as an input to and an output of the environmental model, in addition to being an input for the policy and the value function. Discovering and learning models of environment dynamics and state update functions are important steps toward learning users’ purposes during interactions while performing assistive tasks.

There is a diversity of open research areas in MBRL. One area is in the direction of the choice of models (see Chua et al., 2018), such as probabilistic transition models that use Gaussian processes (e.g., Kocjan et al., 2004; Deisenroth, Fox, and Rasmussen, 2013; Kamthe and Deisenroth, 2018), nonlinear neural network models (e.g., Hernandez and Arkun, 1990), generative models (e.g., Buesing et al., 2018), latent state-space models (e.g., Wahlström, Schön, and Deisenroth, 2015; Watter et al., 2015), and policy search methods (e.g., Bagnell and Schneider, 2001; Deisenroth and Rasmussen, 2011; Levine and Abbeel, 2014; Levine et al., 2016). Another area of study is on asymptotic performance of model-based methods to match the asymptotic performance of model-free algorithms (e.g., Chua et al., 2018). The effectiveness of planning methods and data sample efficiency is one more area of active research (e.g., Hafner et al., 2018; Kamthe and Deisenroth, 2018; Kaiser et al., 2019). Silver et al. (2017a) demonstrate the effectiveness of planning methods in applications such as AlphaGo, offering an algorithm based solely on reinforcement learning, without human data, guidance, or domain knowledge beyond game rules. Nevertheless, cases of full model-based reinforcement learning similar to Silver et al. (2017b), in which the environment model is learned from online data and then used for planning, are rare, especially in stochastic domains. Reduction of errors in learned models that resemble the real environment, data efficiency, asymptotic performance, and a choice of planning methods are some of the topics at the forefront of MBRL research.

**Voice Document Editing with MBRL**

We are at the beginning of a wave of real-world applications of AI that use reinforcement learning methods. In particular, voice document-editing assistants are one of the purposive intelligent assistants that can be realized using model-based reinforcement learning. One effort along these lines is what we mentioned before—by Kudashkina et al. (2020). The re-

---

**Figure 1:** A MBRL purposive intelligent assistant with primary components: an agent state and a state update function; an environmental model; and the agent’s policy and value function. Adopted from Sutton and Barto (2018).
alization of voice document-editing assistants can be naturally mapped into MBRL components.

The first component of MBRL, the agent state, encapsulates the representation of the document and the history of the conversation and its edits. The agent’s state is the current document with its structure, such as paragraphs, sentences, words; what was earlier dictated by the user; which actions were taken by the agent; and how satisfied the user was in response to the actions taken. An observation is represented by a combination of the current document’s content and the user’s speech. The observation can be thought of as some information about what is going on in the environment—the document and the user interacting with the assistant. The information contained in the observation is partial because it does not include things such as the user’s emotions or anything else outside of the document. Outside information like users’ emotional reactions can be approximated from additional data such as the time between users’ reactions, their tone of voice, or their facial expressions (e.g., via techniques such as face valuing by Veeriah, Pilarski, and Sutton, 2016, or other cues as suggested by Skantze, 2016).

The second component of MBRL, an environmental model, helps to develop agent’s understanding of what happens to the document if it takes an unseen action. The environmental model captures the dynamics of the user-agent interactions that the agent learns by observing the results of actions taken. Learning environmental models in voice document-editing domain is possible because of the domain being tightly scoped. Learning better models leads to improved planning processes that result in better predictions. Even if the assistant has never heard a command that the user is saying, by using environmental models and planning, the agent would recognize whether the command is a continuation of a dictation or an edit that the user wants to perform. When editing requests are recognized, then the agent can plan which editorial action leads to a better outcome and higher users’ satisfaction.

In the third component of MBRL, the policy in voice document editing is the agent’s behavior in response to user’s requests. This behavior allows the agent to make a choice between continuing to listen to the user when the user wishes to dictate more, and selecting an editing action to manipulate a text block when the user requests an edit. The value function in voice document editing represents a numerical value of user’s satisfaction.

**Remaining Questions**

This article outlined a domain of voice document editing and MBRL methods as particularly well-suited for developing conversational AI. It is appropriate to discuss some questions that may arise when implementing this proposal, yet implementation details are beyond the scope of this article. One such question is that of how ambitious the agent’s learning can be. Recall that there are many complex elements in conversational AI, such as natural language understanding, dialogue management, natural language generation, and response generation. The agent’s learning can focus on only one (or on a few) of the elements, while the remaining elements can be treated as a black box; for example, the user’s speech can be a black box and can be transcribed by existing tools for speech-to-text conversion (e.g., Bijl and Hyde-Thomson, 2001; Rao, 2011). When not treated as a black box, each of the elements has its own challenges; for example, diversity and coherence in natural language generation element (e.g., Yarats and Lewis, 2017; Jang, Lee, and Kim, 2019; Shi et al., 2018; Gu et al., 2019; Wang et al., 2019; Zheng et al., 2019). The agent’s ambitiousness in learning that can vary in its complexity with the choices for and within each element of conversational AI.

The agent’s learning within one element in conversational AI can be thought of as having three levels of complexity. As an example, consider natural language generation. The first level of complexity is when the agent’s responses being entirely pre-defined by a system designer; this means that no language generation occurs. The agent’s learning then focuses only on the selection of actions to satisfy the user, and the agent’s only intelligence is in the learned policy that it follows to select a response. The model of the environment will learn the dynamics of the interactions and still help the agent with this action selection. Despite the absence of language generation, this agent can still be useful to its users. The second level of complexity is when the response generation is treated as a black box and can be supplemented by one of the existing approaches (e.g., Serban et al., 2017a) instead of using pre-defined responses as in the first level. The third level of complexity is when the response generation as an element that is fully learned and this learning becomes a part of the MBRL agent. The response generation is a demonstration of the agent’s ambitiousness in learning within one element of conversational AI.

An ambitious agent is the most desirable; the agent can be fully responsible for learning all the elements of conversational AI, from generating responses to selecting them. An environmental model will be more complex for this sophisticated agent because it will have to learn all about the interaction dynamics between the user and the assistant. These kinds of implementations are often referred to as end-to-end training. Variations of such implementations can include multiple agents with multiple models, where each of the agent-model pairs can be responsible for a particular conversational AI element. Further, there are higher-level models of the world based on extended ways of a temporally abstract behavior, which were introduced as options by Sutton, Singh, and Precup (1999). Higher-level models provide a way of obtaining higher-level planning and reasoning (Sutton 2020).

Another implementation question is how to train voice document-editing assistants: should they learn online or offline? Recall that online learning is learning directly from experience, such as from real human-computer interactions. Offline learning is a traditional approach in supervised learning that relies on pre-constructed datasets. These datasets can be constructed in a number of ways, including real user-computer interactions, and can be used both to build simulators.

One way an offline dataset can be created is by using the Mechanical Turk service, a crowdsourcing web service that
coordinates the supply and demand of tasks (see Paolacci, Chandler, and Ipeirotis, 2010). Using Mechanical Turk, dictation and editing of the resulting documents can be recorded as a dataset, which is then used to create an environment for voice editing simulations. As Dhingra et al. (2017) point out, it is common in the dialogue community to use simulated users for this purpose (e.g., Schatzmann et al., 2007; Cuayáhuítl et al., 2005; Asri, He, and Suleman, 2016).

Another way to obtain offline datasets requires more creative approaches. Consider the work of Feng et al. (2019) in which organizational business documents are used as inputs to generate a conversational offline dataset. In this conversational dataset, the conversation is based on the organization’s workflow. We encourage the reader to think about similar creative ways of obtaining document-editing datasets. For example, with some good engineering, the mechanical manipulations of text blocks in manuscripts can be collected and converted into conversational data with the addition of voice commands.

Our preferred method of training is online learning from real interaction data. Online learning allows the intelligent assistant to adjust to the users during the training process, and it creates an opportunity for the assistant and the user to build the communication resources developed together during their ongoing interaction (see Pilarski et al., 2017). Building communication resources can effectively improve collaboration and interaction between the user and the voice-editing assistant. As Mendez et al. (2019) point out, a widespread adoption by users of such assistants is limited to the assistants’ quality, which often requires the investment of vast amounts of data. Thus, even if we were to have access to systems that allow us to experiment with real online data (e.g., Google, 2020), then the assistant that learns fully online might be of lower quality in the beginning of training than one that was pre-trained with offline datasets. In the past, when a secretary was hired, they were expected to have structural language knowledge. Similarly, it is reasonable to have such expectations of voice editing assistants and pretrain them with some preliminary knowledge learned from offline datasets before these assistants can be offered to users and continue to learn online.

Summary and Implications

In this article, we have proposed that the domain of voice document editing is particularly well-suited for the development of intelligent assistants that can engage in a conversation. To make progress in developing useful assistants for conversational AI, these assistants should be purposive. A natural approach for developing purposive assistants is reinforcement learning, and, in particular, MBRL. This approach is well-suited to assistants that learn and adapt within document editing and general conversational AI settings. Many aspects of using MBRL remain open areas in AI research, in particular, its use within voice document editing. Finding solutions for the voice document-editing domain with MBRL and building these systems can provide us with lessons that move us closer to building other systems that genuinely understand the user and learn their purposes. In this way, a better voice document editing system will also contribute to the development of other assistive systems, moving the research toward the ultimate goal of assistive agents that fully and functionally understand the real world around them.

The realization of voice document-editing assistants not only serves our objectives of creating a purposive assistant and achieving goals of conversational AI, but also results in an application that directly benefits society: from improving productivity to benefiting people with limited typing abilities.

Funding

Support for this work was provided in part by the Arrell Food Institute, the University of Alberta, and the Canadian Institute for Advanced Research AI Catalyst Fund Project #CF-0110.

Acknowledgments

We would like to thank Peter Wittek and Joseph Modayil for their useful discussions and feedback.

References

Abbeel, P.; Coates, A.; Quigley, M.; and Ng, A. Y. 2007. An application of reinforcement learning to aerobatic helicopter flight. In Proceedings of the 21st Conference on Neural Information Processing Systems, pp. 1–8.

Ades, S., and Swinehart, D. C. 1986. Voice annotation and editing in a workstation environment. Technical Report CSL-86-3, XEROX Corporation, Palo Alto Research Center.

Allen, J. F. 1979. A plan-based approach to speech act recognition. Technical Report 131/79, University of Toronto, Department of Computer Science.

Anderson, J. R.; Boyle, C. F.; and Reiser, B. J. 1985. Intelligent tutoring systems. Science 228(4698):456–462.

Asri, L. E.; He, J.; and Suleman, K. 2016. A Sequence-to-Sequence Model for User Simulation in Spoken Dialogue Systems. In Interspeech. ISCA.

Atkeson, C. G., and Santamaria, J. C. 1997. A comparison of direct and model-based reinforcement learning. In Proceedings of International Conference on Robotics and Automation, volume 4, pp. 3557–3564.

Bagnell, J. A., and Schneider, J. G. 2001. Autonomous helicopter control using reinforcement learning policy search methods. In Proceedings 2001 ICRA. IEEE International Conference on Robotics and Automation (Cat. No. 01CH37164), volume 2, pp. 1615–1620. IEEE.

Bapna, A.; Tür, G.; Hakkani-Tür, D.; and Heck, L. 2017. Towards zero-shot frame semantic parsing for domain scaling. ArXiv:1707.02363.

Bassiri, M. A. 2011. Interactional Feedback and the Impact of Attitude and Motivation on Noticing L2 Form. English Language and Literature Studies 1(2):61.

Berkenkamp, F.; Turchetta, M.; Schoellig, A.; and Krause, A. 2017. Safe model-based reinforcement learning with
stability guarantees. In Proceedings of the 31st Conference on Neural Information Processing Systems, pp. 908–918.

Biermann, A. W., and Long, P. M. 1996. The composition of messages in speech-graphics interactive systems. In Proceedings of the 1996 International Conference on Spoken Dialogue, pp. 97–100.

Bijl, D., and Hyde-Thomson, H. 2001. Speech to text conversion. US Patent 6,173,259. Google Patents.

Bordes, A.; Boureau, Y.-L.; and Weston, J. 2017. Learning end-to-end goal-oriented dialog. In Proceedings of the 5th International Conference on Learning Representations.

Bourbakis, N. G., and Kavraki, D. 2001. An intelligent assistant for navigation of visually impaired people. In Proceedings 2nd Annual IEEE International Symposium on Bioinformatics and Bioengineering (BIBE 2001), pp. 230–235. IEEE.

Bruce, B. 1975. Belief systems and language understanding. Trends in Linguistics. Studies and Monographs.

Bruce, B. 1975. Belief systems and language understanding. Trends in Linguistics. Studies and Monographs 19:113–160.

Budzianowski, P.; Ultes, S.; Su, P.-H.; Mrkšić, N.; Wen, T.-T.; Casanueva, I.; Rojas-Barahona, L.; and Gašić, M. 2017. Sub-domain modelling for dialogue management with hierarchical reinforcement learning. ArXiv:1706.06210.

Buesing, L.; Weber, T.; Racaniere, S.; Eslami, S. M. A.; Rezende, D.; Reichert, D. P.; Viola, F.; Besse, F.; Gregor, K.; Hassabis, D.; and Wierstra, D. 2018. Learning and querying fast generative models for reinforcement learning. ArXiv:1802.03006.

Carberry, S. 1989. Plan recognition and its role in understanding dialog. In User Models in Dialog Systems. Springer. pp. 133–162.

Carbonell, J. R. 1971. Mixed-initiative man-computer instructional dialogues. Technical report, Cambridge, Bolt Beranek and Newman.

Card, S. K.; Moran, T. P.; and Newell, A. 1980. Computer text-editing: An information-processing analysis of a routine cognitive skill. Cognitive psychology 12(1):32–74.

Cassell, J. 2000. More than just another pretty face: Embodied conversational interface agents. Communications of the ACM 43(4):70–78.

Chapman, D., and Kaelbling, L. P. 1991. Input Generalization in Delayed Reinforcement Learning: An Algorithm and Performance Comparisons. In Proceedings of the 1991 International Joint Conference on Artificial Intelligence, volume 91, pp. 726–731.

Chen, L.; Chang, C.; Chen, Z.; Tan, B.; Gašić, M.; and Yu, K. 2018. Policy adaptation for deep reinforcement learning-based dialogue management. In IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 6074–6078. IEEE.

Chua, K.; Calandra, R.; McAllister, R.; and Levine, S. 2018. Deep reinforcement learning in a handful of trials using probabilistic dynamics models. In Proceedings of the 31st Conference on Neural Information Processing Systems, pp. 4754–4765.

Coates, A.; Abbeel, P.; and Ng, A. Y. 2017. Autonomous Helicopter Flight Using Reinforcement Learning. Boston, MA: Springer US. pp. 75–85.

Cohen, P. R. 1978. On Knowing What to Say: Planning Speech Acts. Ph.D. Dissertation, University of Toronto, Department of Computer Science.

Croft, W. B.; Metzler, D.; and Strohman, T. 2010. Search engines: Information retrieval in practice, volume 520. Addison-Wesley Reading.

Cuayahuitl, H.; Renals, S.; Lemon, O.; and Shimodaira, H. 2005. Human-computer dialogue simulation using hidden Markov models. In Workshop on Automatic Speech Recognition and Understanding, IEEE, pp. 290–295. IEEE.

Cuayahuitl, H.; Yu, S.; Williamson, A.; and Carse, J. 2016. Deep reinforcement learning for multi-domain dialogue systems. In Workshop on Deep Reinforcement Learning, NIPS.

Cuayahuitl, H.; Yu, S.; Williamson, A.; and Carse, J. 2017. Scaling up deep reinforcement learning for multi-domain dialogue systems. In 2017 International Joint Conference on Neural Networks, pp. 3339–3346. IEEE.

Dario, P.; Guglielmelli, E.; Genovese, V.; and Toro, M. 1996. Robot assistants: Applications and evolution. Robotics and autonomous systems 18(1-2):225–234.

Dean, J. 2019. Looking Back at Google’s Research Efforts in 2018.

Deisenroth, M., and Rasmussen, C. E. 2011. PILCO: A model-based and data-efficient approach to policy search. In Proceedings of the 28th International Conference on machine learning, pp. 465–472. Omnipress.

Deisenroth, M. P.; Fox, D.; and Rasmussen, C. E. 2013. Gaussian processes for data-efficient learning in robotics and control. IEEE transactions on pattern analysis and machine intelligence 37(2):pp. 408–423.

Dhingra, B.; Li, L.; Li, X.; Gao, J.; Chen, Y.-N.; Ahmed, F.; and Deng, L. 2017. Towards end-to-end reinforcement learning of dialogue agents for information access. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, pp. 484–495.

Doll, B. B.; Simon, D. A.; and Daw, N. D. 2012. The ubiquity of model-based reinforcement learning. Current opinion in neurobiology 22(6):1075–1081.

Douglas, H. R. 1999. Method and apparatus for editing documents through voice recognition. US Patent 5,875,429, Google Patents.

Duffy, J. 2018. The Best Dictation Software for 2019. https://zapier.com/blog/best-text-dictation-software [Accessed July 27, 2020].

Engelbart, D. C. 1962. Augmenting human intellect: A conceptual framework. Technical Report AFOSR-3223, Stanford Research Institute.

Eric, M. 2020. NeurIPS 2019 ConvAI Workshop Recap. IEEE Signal Processing Society. https://openai.com/blog/better-language-models [Accessed July 27, 2020].
Fain, D. C., and Pedersen, J. O. 2006. Sponsored search: A brief history. Bulletin of the American Society for Information Science and Technology 32(2):12–13.

Fazeli-Zarandi, M.; Li, S.-W.; Cao, J.; Casale, J.; Henderson, P.; Whitney, D.; and Geramifard, A. 2017. Learning robust dialog policies in noisy environments. In 1st Workshop on Conversational AI, NIPS.

Feng, S.; Fadni, K.; Liao, Q. V.; and Lastras, L. A. 2019. Doc2Dial: A Framework for Dialogue Composition Grounded in Business Documents. In Workshop on Document Intelligence, NeurIPS.

Ferreira, E., and Lefvre, F. 2015. Reinforcement-learning based dialogue system for humanrobot interactions with socially-inspired rewards. Computer Speech & Language 34(1):256–274.

Finin, T. W.; Joshi, A. K.; and Webber, B. L. 1986. Natural language interactions with artificial experts. Proceedings of the IEEE 74(7):921–938.

Finn, C.; Abbeel, P.; and Levine, S. 2017. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pp. 1126–1135. JMLR.org.

Foerster, J.; Assael, I. A.; De Freitas, N.; and Whiteson, S. 2016. Learning to communicate with deep multi-agent reinforcement learning. In Proceedings of the 30th Conference on Advances in Neural Information Processing Systems, pp. 2137–2145.

Forrester, J. W. 1971. Counterintuitive behavior of social systems. Theory and decision 2(2):pp. 109–140.

Fox, M. S., and Smith, S. F. 1984. Isisa knowledge-based system for factory scheduling. Expert systems 1(1):25–49.

Freeman, D.; Ha, D.; and Metz, L. 2019. Learning to Predict Without Looking Ahead: World Models Without Forward Prediction. In Proceedings of the 33rd Conference on Advances in Neural Information Processing Systems, pp. 5380–5391.

Gao, J.; Galley, M.; Li, L.; et al. 2019. Neural Approaches to Conversational AI. In Foundations and Trends® in Information Retrieval, volume 13, pp. 127–298. Now Publishers, Inc.

Gašić, M.; Jurčiček, F.; Thomson, B.; Yu, K.; and Young, S. 2011. On-line policy optimisation of spoken dialogue systems via live interaction with human subjects. In IEEE Workshop on Automatic Speech Recognition & Understanding, pp. 312–317. IEEE.

Gašić, M.; Breslin, C.; Henderson, M.; Kim, D.; Szummer, M.; Thomson, B.; Tsiakoulis, P.; and Young, S. 2013a. Online policy optimisation of bayesian spoken dialogue systems via human interaction. In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 8367–8371. IEEE.

Gašić, M.; Breslin, C.; Henderson, M.; Kim, D.; Szummer, M.; Thomson, B.; Tsiakoulis, P.; and Young, S. 2013b. POMDP-based dialogue manager adaptation to extended domains. In Proceedings of the SIGDIAL 2013 Conference, pp. 214–222. Metz, France: Association for Computational Linguistics.

Gašić, M.; Mrkšić, N.; Rojas-Barahona, L. M.; Su, P.-H.; Ultes, S.; Vandyke, D.; Wen, T.-H.; and Young, S. 2017. Dialogue manager domain adaptation using gaussian process reinforcement learning. Computer Speech & Language 45:552–569.

Gass, S. M., and Varonis, E. M. 1994. Input, interaction, and second language production. Studies in Second Language Acquisition 16(3):283–302.

Google AI Blog. Digital Inspiration. 2020. Dictation.io. http://dictation.io [Accessed July 27, 2020].

Google. 2020. Type with your voice: Edit your document. https://support.google.com/docs/answer/4492226 [Accessed February 22, 2020].

Goyal, P.; Niekum, S.; and Mooney, R. J. 2019. Using natural language for reward shaping in reinforcement learning. In Kraus, S., ed., Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, pp. 2385–2391. Macao, China: International Joint Conferences on Artificial Intelligence Organization.

Greysen, A. M.; Hokit, J. D.; Kaptanoglu, M.; Wagner, A. M.; and Capps, S. P. 1997. Method and apparatus for the manipulation of text on a computer display screen. US Patent 5,666,552. Google Patents.

Griffith, S.; Subramanian, K.; Scholz, J.; Isbell, C. L.; and Thomaz, A. L. 2013. Policy shaping: Integrating human feedback with reinforcement learning. In Proceedings of the 27th Conference on Advances in Neural Information Processing Systems, pp. 2625–2633.

Grignetti, M. C.; Hausmann, C.; and Gould, L. 1975. An intelligent on-line assistant and tutor: NLS-SCHOLAR. In Proceedings of the May 19-22, 1975, National Computer Conference and Exhibition, pp. 775–781. ACM.

Grosz, B. 1983. Team: A transportable natural language interface system. In Proceedings of the 1st Conference on Applied Natural Language Processing, pp. 38–45. Santa Monica, California: Association for Computational Linguistics.

Gruber, T. R., and Clark, G. C. 2017. Dictation that allows editing. US Patent App. 15/268,215. Google Patents.

Gu, X.; Cho, K.; Ha, J.-W.; and Kim, S. 2019. DialogWAE: Multimodal response generation with conditional wasserstein auto-encoder. In International Conference on Learning Representations.

Gupta, A.; Zhang, P.; Lalwani, G.; and Diab, M. 2019. CASA-NLU: Context-Aware Self-Attentive Natural Language Understanding for Task-oriented Chatbots. In Proceedings of EMNLP-IJCNLP 2019.

Ha, D., and Schmidhuber, J. 2018. World models. In Proceedings of the Thirty-second Conference on Neural Information Processing Systems. Montréal, Canada: Curran Associates, Inc.

Hafner, D.; Lillicrap, T.; Fischer, I.; Villegas, R.; Ha, D.; Lee, H.; and Davidson, J. 2018. Learning latent dynamics for planning from pixels. In Proceedings of the 36th Interna-
Li, J.; Monroe, W.; Ritter, A.; Galley, M.; Gao, J.; and Jurafsky, D. 2016a. Deep reinforcement learning for dialogue generation. ArXiv:1606.01541.

Li, X.; Lipton, Z. C.; Dhingra, B.; Li, L.; Gao, J.; and Chen, Y.-N. 2016b. A user simulator for task-completion dialogues. ArXiv:1612.05688.

Li, J.; Miller, A. H.; Chopra, S.; Ranzato, M.; and Weston, J. 2017a. Dialogue learning with human-in-the-loop. In Proceedings of the 5th International Conference on Learning Representations. Toulon, France: OpenReview.net.

Li, J.; Miller, A. H.; Chopra, S.; Ranzato, M.; and Weston, J. 2017b. Learning through dialogue interactions by asking questions. In Proceedings of the 5th International Conference on Learning Representations. Toulon, France: OpenReview.net.

Li, X.; Chen, Y.-N.; Li, L.; Gao, J.; and Celikyilmaz, A. 2017c. End-to-end task-completion neural dialogue systems. In Proceedings of the 8th International Joint Conference on Natural Language Processing, pp. 733–743. Taipei, Taiwan: AFNLP.

Li, M.; Weston, J.; and Roller, S. 2019. ACUTE-EV AL: Improved Dialogue Evaluation with Optimized Questions and Multi-turn Comparisons. In 3rd Workshop on Conversational AI, NeurIPS.

Lindgren, N. 1968. Purposive systems: The edge of knowledge. IEEE spectrum 5(4):89–100.

Lipton, Z.; Li, X.; Gao, J.; Li, L.; Ahmed, F.; and Deng, L. 2018. BBQ-networks: Efficient exploration in deep reinforcement learning for task-oriented dialogue systems. In Thirty-Second AAAI Conference on Artificial Intelligence, pp. 5237–5244.

Lison, P. 2013. Model-based bayesian reinforcement learning for dialogue management. ArXiv:1304.1819.

ListNote. 2020. ListNote Speech-to-Text Notes. https://zapier.com/blog/best-text-dictation-software/#listnote.

Litman, D.; Singh, S.; Kearns, M.; and Walker, M. 2000. NJFun: a reinforcement learning spoken dialogue system. In ANLP-NAACL 2000 Workshop: Conversational Systems, pp. 17–20.

Littman, M. L., and Sutton, R. S. 2001. Predictive representations of state. In Proceedings of the 14th Conference on Advances in Neural Information Processing Systems, pp. 1555–1561. MIT Press.

Liu, B., and Lane, I. 2017a. Iterative policy learning in end-to-end trainable task-oriented neural dialog models. In Automatic Speech Recognition and Understanding Workshop, IEEE, pp. 482–489. IEEE.

Liu, B., and Lane, I. 2017b. Multi-domain adversarial learning for slot filling in spoken language understanding. In 1st Workshop on Conversational AI, NIPS.

Liu, B.; Tür, G.; Hakkani-Tür, D.; Shah, P.; and Heck, L. 2017. End-to-end optimization of task-oriented dialogue model with deep reinforcement learning. ArXiv:1711.10712.
Moore, J. D., and Paris, C. L. 1989. Planning text for advisory dialogues. In Proceedings of the 27th Annual Meeting on Association for Computational Linguistics, pp. 203–211. Association for Computational Linguistics.

Moore, A. 2015. Artificial Intelligence: 10 Things To Know. Association for Computational Linguistics. Proceedings of the 27th Annual Meeting of the Association for Computational Linguistics. Moore, J. D., and Paris, C. L. 1989. Planning text for advisory dialogues. In Proceedings of the 16th Conference on Advances in Neural Information Processing Systems. MIT Press. pp. 799–806.

Ng, A. Y.; Kim, H. J.; Jordan, M. I.; and Sastry, S. 2004. Autonomous helicopter flight via reinforcement learning. In Thrun, S.; Saul, L. K.; and Schölkopf, B., eds., Proceedings of the 16th Conference on Advances in Neural Information Processing Systems. MIT Press. pp. 363–372.

Nonaka, Y.; Sakai, Y.; Yasuda, K.; and Nakano, Y. 2012. Towards assessing the communication responsiveness of people with dementia. In International Conference on Intelligent Virtual Agents, pp. 496–498. Springer.

Papangelis, A.; Namazifar, M.; Khatri, C.; Engberg, S.; Matthews, J. T.; Dunbar-Jacob, J.; McCarthy, C. E.; et al. 2002. Pearl: A mobile robotic assistant for the elderly. In Workshop on automation as eldercare, AAAI, pp. 85–91.

Paolacci, G.; Chandler, J.; and Ipeirotis, P. G. 2010. Running Experiments on Amazon Mechanical Turk. Judgment and Decision making 5(5):411–419.

Papangelis, A.; Namazifar, M.; Khatri, C.; Wang, Y.-C.; Molino, P.; and Tür, G. 2020. Plato Dialogue System: A Flexible Conversational AI Research Platform. ArXiv:2001.06463.

Parr, R.; Li, L.; Taylor, G.; Painter-Wakefield, C.; and Littman, M. L. 2008. An analysis of linear models, linear value-function approximation, and feature selection for reinforcement learning. In Proceedings of the 25th international conference on Machine learning, pp. 752–759.

Peng, B.; Li, X.; Li, L.; Gao, J.; Celikyilmaz, A.; Lee, S.; and Wong, K.-F. 2017. Composite task-completion dialogue policy learning via hierarchical deep reinforcement learning. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, pp. 2231–2240. Copenhagen, Denmark: Association for Computational Linguistics.

Peng, B.; Li, X.; Gao, J.; Liu, J.; and Wong, K.-F. 2018. Deep Dyna-Q: Integrating Planning for Task-Completion Dialogue Policy Learning. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Association for Computational Linguistics.

Pica, T.; Doughty, C. J.; and Young, R. 1986. Making input comprehensible: Do interactional modifications help? TTL-International Journal of Applied Linguistics 72(1):1–25.

Pica, T. 1987. Second-language acquisition, social interaction, and the classroom. Applied linguistics 8(1):3–21.

Pilarski, P. M., and Sutton, R. S. 2012. Between instruction and reward: human-prompted switching. Technical Report FS-12-07, AAAI 2012 Fall Symposium on Robots Learning Interactively from Human Teachers (RLIHT), Arlington, VA.

Pilarski, P. M.; Dawson, M. R.; Degris, T.; Fahimi, F.; Carey, J. P.; and Sutton, R. S. 2011. Online human training of a myoelectric prosthesis controller via actor-critic reinforcement learning. In Proceedings of the IEEE International Conference on Rehabilitation Robotics, pp. 134–140. Zurich, Switzerland: IEEE.

Pilarski, P. M.; Sutton, R. S.; Mathewson, K. W.; Sherstan, C.; Parker, A. S.; and Edwards, A. L. 2017. Communicative Capital for Prosthetic Agents. ArXiv:1711.03676.

Pilarski, P. M.; Sutton, R. S.; and Mathewson, K. W. 2015. Prosthetic devices as goal-seeking agents. In Second Workshop on Present and Future of Non-Invasive Peripheral-Nervous-System Machine Interfaces: Progress in Restoring the Human Functions, PNS-MI.

Pineau, J.; Montemerlo, M.; Pollack, M.; Roy, N.; and Thrun, S. 2003. Towards robotic assistants in nursing homes: Challenges and results. Robotics and autonomous systems 42(3-4):271–281.

Pollack, M. E.; Brown, L.; Colbry, D.; Orosz, C.; Peintner, B.; Ramakrishnan, S.; Engberg, S.; Matthews, J. T.; Dunbar-Jacob, J.; McCarthy, C. E.; et al. 2002. Pearl: A mobile robotic assistant for the elderly. In Workshop on automation as eldercare, AAAI, pp. 85–91.

Pollack, M. E.; Hirschberg, J.; and Webber, B. 1982. User participation in the reasoning processes of expert systems. In Proceedings First National Conference on Artificial Intelligence (AAAI-82), pp. 358–361. University of Pennsylvania.

Power, R. 1974. A computer model of conversation. Ph.D. Dissertation, The University of Edinburg.

Quarteroni, S., and Manandhar, S. 2009. Designing an interactive open-domain question answering system. Natural Language Engineering 15(1):73–95.

Radford, A.; Wu, J.; Child, R.; Luan, D.; Amodei, D.; and Sutskever, I. 2019. Language models are unsupervised multitask learners. OpenAI Blog, https://openai.com/blog/better-language-models. [Accessed July 23, 2020].

Ranzato, M.; Chopra, S.; Auli, M.; and Zaremba, W. 2015. Sequence level training with recurrent neural networks. ArXiv:1511.06732.

Rao, A. P. 2011. Predictive speech-to-text input. US Patent 7,904,298. Google Patents.

Rastogi, A.; Hakkani-Tür, D.; and Heck, L. 2017. Scalable multi-domain dialogue state tracking. In IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), pp. 561–568. IEEE.
Rumelhart, D. E.; Smolensky, P.; McClelland, J. L.; and Hinton, G. 1986. Sequential thought processes in PDP models. Parallel Distributed Processing: Explorations in the Microstructures of Cognition 2:pp. 7–57. MIT Press.

Saleh, A.; Jaques, N.; Ghandeharioun, A.; Shen, J. H.; and Picard, R. 2019. Hierarchical reinforcement learning for open-domain dialog. In 3rd Workshop on Conversational AI, NeurIPS.

Salichs, M. A.; Ge, S. S.; Barakova, E.; Cabibihan, J.-J.; Wagner, A. R.; Gonzalez, A. C.; and He, H., eds. 2019. Preface–Social Robotics: 11th International Conference, ICSR. Springer.

Schatzmann, J.; Thomson, B.; Weilhammer, K.; Ye, H.; and Young, S. 2007. Agenda-based user simulation for bootstrapping a POMDP dialogue system. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Companion Volume, Short Papers, pp. 149–152. Association for Computational Linguistics.

Schrittwieser, J.; Antonoglou, I.; Hubert, T.; Simonyan, K.; Sifre, L.; Schmitt, S.; Guez, A.; Lockhart, E.; Hassabis, D.; Graepel, T.; Lillicrap, T.; and Silver, D. 2019. Mastering Atari, Go, chess and shogi by planning with a learned model. In Proceedings of the Thirty-third Conference on Neural Information Processing Systems. Vancouver, Canada: Curran Associates, Inc.

Selfridge, O. G. 1993. The Gardens of Learning: A Vision for AI. AI Magazine 14(2):36–48.

Serban, I. V.; Sankar, C.; Germain, M.; Zhang, S.; Lin, Z.; Subramanian, S.; Kim, T.; Pieper, M.; Chandar, S.; Ke, N. R.; et al. 2017a. A deep reinforcement learning chatbot. ArXiv:1709.02349.

Serban, I. V.; Sordoni, A.; Lowe, R.; Charlin, L.; Pineau, J.; Courville, A.; and Bengio, Y. 2017b. A hierarchical latent variable encoder-decoder model for generating dialogues. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, pp. 3295–3301. AAAI.

Shah, P.; Hakkani-Tür, D.; Tür, G.; Rastogi, A.; Babna, A.; Nayak, N.; and Heck, L. 2018. Building a conversational agent overnight with dialogue self-play. ArXiv:1801.04871.

Shah, P.; Hakkani-Tür, D.; and Heck, L. 2016. Interactive reinforcement learning for task-oriented dialogue management. In Workshop on Deep Learning for Action and Interaction, NIPS.

Shen, Y.; Huang, P.-S.; Gao, J.; and Chen, W. 2017. ReasonNet: Learning to Stop Reading in Machine Comprehension. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1047–1055.

Shi, Z.; Chen, X.; Qiu, X.; and Huang, X. 2018. Toward Diverse Text Generation with Inverse Reinforcement Learning. Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence.

Shin, J.; Xu, P.; Madotto, A.; and Fung, P. 2019. Happybot: Generating empathetic dialogue responses by improving user experience look-ahead. ArXiv:1906.08487.
Proceedings of the 28th Conference on Advances in Neural Information Processing Systems, pp. 3104–3112.

Sutton, R. S., and Barto, A. G. 1981. An adaptive network that constructs and uses and internal model of its world. *Cognition and Brain Theory* 4(3):217–246.

Sutton, R. S., and Barto, A. G. 2018. *Reinforcement learning: An introduction*. MIT press.

Sutton, R. S., and Pinette, B. 1985. The learning of world models by connectionist networks. In *Proceedings of the seventh annual conference of the cognitive science society*, pp. 54–64.

Sutton, R. S.; Szepesvári, C.; Geramifard, A.; and Bowling, M. P. 2008. Dyna-style planning with linear function approximation and prioritized sweeping. In *Proceedings of the 24th Conference on Uncertainty in Artificial Intelligence*, pp. 528–536.

Sutton, R. S.; Singh, S.; and Precup, D. 1999. Between MDPs and semi-MDPs: Learning, planning, and representing knowledge at multiple temporal scales. *Artificial Intelligence* 112:118–211.

Sutton, R. S. 1990. Integrated architectures for learning, planning, and reacting based on approximating dynamic programming. In *Proceedings of the Seventh International Conference on Machine Learning*, pp. 216–224. Morgan Kaufmann.

Sutton, R. S. 2019. Toward a New Approach to Model-based Reinforcement Learning. Technical report, University of Alberta.

Sutton, R. S. 2020. Experience and Intelligence: Toward a Scalable AI-Agent Architecture. Vector Institute for Artificial Intelligence, Visitor Talk.

Takahashi, F. 2001. *Document editing system and method*. US Patent 6,202,073. Google Patents.

Tang, D.; Li, X.; Gao, J.; Wang, C.; Li, L.; and Jebara, T. 2018. Subgoal discovery for hierarchical dialogue policy learning. *ArXiv:1804.07855*.

Thomaz, A. L.; Hoffman, G.; and Breazeal, C. 2005. Real-time interactive reinforcement learning for robots. In *Workshop on human comprehensible machine learning*, AAAI.

Thomaz, A. L.; Hoffman, G.; and Breazeal, C. 2006. Reinforcement Learning with Human Teachers: Understanding How People Want to Teach Robots. In *The 15th IEEE International Symposium on Robot and Human Interactive Communication*, RO-MAN 2006, pp. 352–357. IEEE.

Thompson, C. 2006. Google’s China Problem. *The Power of Information*. School of Journalism, Stony Brook University.

Todorov, E.; Erez, T.; and Tassa, Y. 2012. Mujoco: A physics engine for model-based control. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 5026–5033. IEEE.

Tractica. 2016. *The Virtual Digital Assistant Market Will Reach $15.8 Billion Worldwide by 2021*. A market intelligence firm. https://www.tractica.com/newsroom/press-releases/the-virtual-digital-assistant-market-will-reach-15-8-billion-worldwide-by-2021/ [Accessed July 23, 2020].

Tür, G.; Stolcke, A.; Voss, L.; Peters, S.; Hakkani-Tür, D.; Dowding, J.; Favre, B.; Fernández, R.; Frampton, M.; Frandsen, M.; et al. 2010. The CALO Meeting Assistant System. *IEEE Transactions on Audio, Speech, and Language Processing* 18(6):1601–1611.

Tür, G.; Hakkani-Tür, D.; and Schapire, R. E. 2005. Combining active and semi-supervised learning for spoken language understanding. *Speech Communication* 45(2):171–186.

Veeriah, V.; Pilarski, P. M.; and Sutton, R. S. 2016. Face valuing: Training user interfaces with facial expressions and reinforcement learning. In *Workshop on Interactive Machine Learning, IJCAI*.

Wahlström, N.; Schön, T. B.; and Deisenroth, M. P. 2015. From pixels to torques: Policy learning with deep dynamical models. *ArXiv:1502.02251*.

Walker, D. E., and Grosz, B. J. 1978. *Understanding spoken language*. Elsevier Science Inc.

Walker, M. A.; Stent, A.; Mairesse, F.; and Prasad, R. 2007. Individual and domain adaptation in sentence planning for dialogue. *Journal of Artificial Intelligence Research* 30:413–456.

Walker, R. C. 1998. *Text processor*. US Patent 5,802,533. Google Patents.

Walker, M. A. 2000. An application of reinforcement learning to dialogue strategy selection in a spoken dialogue system for email. *Journal of Artificial Intelligence Research* 12:pp. 387–416.

Wang, Z.; Schaul, T.; Hessel, M.; Van Hasselt, H.; Lanctot, M.; and de Freitas, N. 2016. Dueling network architectures for deep reinforcement learning. In *Proceedings of the 33rd International Conference on Machine Learning*, volume 48. New York, USA: JMLR: W&CP.
Wang, Y.; Si, P.; Lei, Z.; Xun, G.; and Yang, Y. 2019. HSCJN: A Holistic Semantic Constraint Joint Network for Diverse Response Generation. In 3rd Workshop on Conversational AI, NeurIPS.

Waters, R. C. 1986. KBEmacs: Where’s the AI? AI Magazine 7(1):47–47.

Watter, M.; Springenberg, J.; Boedecker, J.; and Riedmiller, M. 2015. Embed to control: A locally linear latent dynamics model for control from raw images. In Proceedings of the 28th International Conference on Neural Information Processing Systems, pp. 2746–2754. Cambridge, USA: MIT Press.

Weisz, G.; Budzianowski, P.; Su, P.-H.; and Gašić, M. 2018. Sample efficient deep reinforcement learning for dialogue systems with large action spaces. IEEE/ACM Transactions on Audio, Speech, and Language Processing 26(11):2083–2097.

Wen, T.-H.; Vandyke, D.; Mrkšić, N.; Gašić, M.; Rojas Barahona, L. M.; Su, P.-H.; Ultes, S.; and Young, S. 2017. A Network-based End-to-End Trainable Task-oriented Dialogue System. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pp. 437–449. Valencia, Spain: Association for Computational Linguistics.

Wiering, M.; Salustowicz, R.; and Schmidhuber, J. 2001. Model-based reinforcement learning for evolving soccer strategies. In Computational intelligence in games, pp. 99–132. Springer.

Williams, J. D.; Asadi, K.; and Zweig, G. 2017. Hybrid code networks: practical and efficient end-to-end dialog control with supervised and reinforcement learning. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics.

Winograd, T. 1971. Procedures as a representation for data in a computer program for understanding natural language. Technical report, MIT.

Winograd, T. 1973. Breaking the complexity barrier again. In ACM SIGIR Forum, volume 9, pp. 13–30. ACM. Reprinted in David R. Barstow, Howard E. Shrobe, and Erik Sandewall (Eds.), Interactive Programming Environments, McGraw-Hill Book Co., New York, 1984.

Woodrow, H. 1946. The ability to learn. Psychological Review 53(3):147–158.

Woods, W. 1984. Natural language communication with machines: An ongoing goal. Artificial intelligence applications for business pp. 195–209.

Wu, Y.; Li, X.; Liu, J.; Gao, J.; and Yang, Y. 2019. Switch-based active deep Dyna-Q: Efficient adaptive planning for task-completion dialogue policy learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pp. 7289–7296.

Xu, C.; Wu, W.; and Wu, Y. 2018. Towards explainable and controllable open domain dialogue generation with dialogue acts. ArXiv:1807.07255.

Yarats, D., and Lewis, M. 2017. Hierarchical Text Generation and Planning for Strategic Dialogue. In Proceedings of the 35th International Conference on Machine Learning, Stockholm, Sweden: PMRL 80.

Young, S.; Gašić, M.; Thomson, B.; and Williams, J. D. 2013. POMDP-based statistical spoken dialog systems: A review. In Proceedings of the IEEE, volume 101, pp. 1160–1179. IEEE.

Yu, L.; Zhang, W.; Wang, J.; and Yu, Y. 2017. Seqgan: Sequence generative adversarial nets with policy gradient. In Thirty-First AAAI Conference on Artificial Intelligence. AAAI.

Zhang, Z.; Takano, R.; Huang, M.; and Zhu, X. 2020. Recent Advances and Challenges in Task-oriented Dialog System. Science China Information Sciences. Under Review.

Zhang, J.; Zhao, T.; and Yu, Z. 2018. Multimodal hierarchical reinforcement learning policy for task-oriented visual dialog. ArXiv:1805.03257.

Zhao, T., and Eskenazi, M. 2016. Towards end-to-end learning for dialog state tracking and management using deep reinforcement learning. In Proceedings of the SIGDIAL 2016 Conference, 1–10. Los Angeles: Association for Computational Linguistics.

Zhao, Y.; Wang, Z.; Yin, K.; Zhang, R.; Huang, Z.; and Wang, P. Dynamic Reward-based Dueling Deep Dyna-Q: Robust Policy Learning in Noisy Environments. In Thirty-Fourth AAAI Conference on Artificial Intelligence.

Zheng, Y.; Chen, G.; Huang, M.; Liu, S.; and Zhu, X. 2019. Personalized dialogue generation with diversified traits. In 3rd Workshop on Conversational AI, NeurIPS.

Zhou, M.; Arnold, J.; and Yu, Z. 2019. Building task-oriented visual dialog systems through alternative optimization between dialog policy and language generation. In Proceedings of EMNLP-IJCNLP 2019.

Zhou, L.; Small, K.; Rokhlenko, O.; and Elkan, C. 2017. End-to-end offline goal-oriented dialog policy learning via policy gradient. In Workshop on Conversational AI, NIPS.

Zhou, L.; Gao, J.; Li, D.; and Shum, H.-Y. 2020. The Design and Implementation of XiaoIce, an Empathetic Social Chatbot. Computational Linguistics 46(1):53–93.
Katya Kudashkina is pursuing her PhD at the Vector Institute for Artificial Intelligence and the University of Guelph, working closely with RLAI Lab at University of Alberta. In the past, she has founded two AI startups: UDIO AgTech, and Cultura. Prior to that she spent over six years at the Canada Pension Plan Investment Board and at IBM. She studied Engineering in Russia, and then moved to Canada where she completed a degree in Computer Science and then received her MBA at the University of Toronto.

Dr. Patrick M. Pilarski is a Canada Research Chair in Machine Intelligence for Rehabilitation at the University of Alberta, an Associate Professor in the Department of Medicine, and a Fellow of the Alberta Machine Intelligence Institute. As part of his research, Dr. Pilarski explores new machine learning techniques for sensorimotor control and prediction, including reinforcement learning methods for human-machine interaction, communication, and user-specific device optimization. Dr. Pilarski is the author or co-author of more than 80 peer-reviewed articles, a Senior Member of the IEEE, and has been supported by provincial, national, and international research grants.

Richard S. Sutton is a distinguished research scientist at DeepMind in Edmonton and a professor in the Department of Computing Science at the University of Alberta. Prior to joining DeepMind in 2017 and the University of Alberta in 2003, he worked in industry at AT&T and GTE Labs, and in academia at the University of Massachusetts. He received a PhD in computer science from the University of Massachusetts in 1984 and a BA in psychology from Stanford University in 1978. He is co-author of the textbook Reinforcement Learning: An Introduction from MIT Press. He is also a fellow of the Royal Society of Canada, the Association for the Advancement of Artificial Intelligence, the Alberta Machine Intelligence Institute, and CIFAR.