Why Build an Assistant in Minecraft?

Arthur Szlam, Jonathan Gray, Kavya Srinet, Yacine Jernite, Armand Joulin, Gabriel Synnaeve, Douwe Kiela, Haonan Yu, Zhuoyuan Chen, Siddharth Goyal, Demi Guo, Danielle Rothermel, C. Lawrence Zitnick, Jason Weston

July 19, 2019

Abstract

In this document we describe a rationale for a research program aimed at building an open "assistant" in the game Minecraft, in order to make progress on the problems of natural language understanding and learning from dialogue.

1 Introduction

In the last decade, we have seen a qualitative jump in the performance of machine learning (ML) methods directed at narrow, well-defined tasks. For example, there has been marked progress in object recognition [57], game-playing [73], and generative models of images [40] and text [39]. Some of these methods have achieved superhuman performance within their domain [73, 64]. In each of these cases, a powerful ML model was trained using large amounts of data on a highly complex task to surpass what was commonly believed possible.

Here we consider the transpose of this situation. Instead of superhuman performance on a single difficult task, we are interested in competency across a large number of simpler tasks, specified (perhaps poorly) by humans. In such a setting, understanding the content of a task can already be a challenge. Beyond this, a large number of tasks means that many will have been seen only a few times, or even never, requiring sample efficiency and flexibility.

There has been measured progress in this setting as well, with the mainstreaming of virtual personal assistants. These are able to accomplish thousands of tasks communicated via natural language, using multi-turn dialogue for clarifications or further specification. The assistants are able to interact with other applications to get data or perform actions. Nevertheless, many difficult problems remain open. Automatic natural language understanding (NLU) is still rigid and limited to constrained scenarios. Methods for using dialogue or other natural language for rich supervision remain primitive. In addition, because they need to be able to reliably and predictably solve many simple tasks, their multi-modal inputs, and the constraints of their maintenance and deployment, assistants are modular systems, as opposed to monolithic ML models. Modular ML systems that can improve themselves from data while keeping well defined interfaces are still not well studied.

Despite the numerous important research directions related to virtual assistants, they themselves are not ideal platforms for the research community. They have a broad scope and need a large amount of world knowledge, and they have complex codebases maintained by hundreds, if not thousands of engineers. Furthermore, their proprietary nature and their commercial importance makes experimentation with them difficult.

In this work we argue for building an open interactive assistant, and through it, the tools and platform for researching grounded NLU. Instead of a "real world" assistant, we propose working in the sandbox construction game of Minecraft¹. The constraints of the Minecraft world (e.g. coarse 3-d voxel grid, simple physics) and the regularities in the head of the distribution of in-game tasks allow numerous hand-holds for NLU research. Furthermore, since we work in a game environment, players may enjoy interacting with the assistants as they are developed, yielding a rich resource for human-in-the-loop research.

The rest of this document describes in more depth the motivations and framing of this program, and should be read as a problem statement and a call-to-arms. Concurrently, we are releasing https://github.com/ facebookresearch/craftassist, which houses data and code for a baseline Minecraft assistant, labeling tools, and infrastructure for connecting players to bots; we hope these will be useful to researchers interested in this

¹Minecraft features: ©Mojang Synergies AB included courtesy of Mojang AB

program or interactive agents more generally. We detail the contents of the framework (https://github.com/facebookresearch/craftassist) in [1].

2 Minecraft

Minecraft² is a popular multiplayer open world voxel-based building and crafting game. Gameplay starts with a procedurally created world containing trees, mountains, fields, and so on, all created from an atomic set of a few hundred possible atomic blocks; and (atomic) animals and other non-player characters (collectively referred to as "mobs"). The blocks are placed on a 3D voxel grid. Each voxel in the grid contains one material, of which most are air (empty); mobs and players have floating point positions. Players can move, place or remove blocks of different types, and attack or be attacked by mobs or other players.

The game has two main modes³: "creative" and "survival". In survival mode the player is resource limited, can be harmed, and is subject to more restrictive physics. The player must gather and combine resources in a process called crafting to build objects. In creative mode the player is not resource limited, cannot be harmed, and is subject to less restrictive physics, e.g., the player can fly through the air. Crafting is not necessary in creative mode since all materials are available to the player. An in-depth guide to Minecraft can be found at https://minecraft.gamepedia.com/Minecraft. Building is a core gameplay component in both modes.

Minecraft allows multiplayer servers, and players can collaborate to build and survive, or compete. It has a huge player base (91M monthly active users in October 2018) [2], and many players are active in creating game mods and shareable content. The multiplayer game has built in text chat for player to player communication. Dialogue between users on multi-user servers is a standard part of the game.

2.1 Task Space

Minecraft players can build things, gather resources, craft (combine resources), attack other players and mobs (nonplayer characters), and chat. Even focusing only on building, the set of things a player could possibly do in the game is enormous; in the most naive sense, it is all possible ways of placing all the possible blocks into as big a world as fits in RAM. Minecraft players are creative, and the diversity of player built objects in Minecraft is astounding; these include landmarks, sculptures, temples, rollercoasters and entire cityscapes. Collaborative building is a common activity in Minecraft.

Nevertheless, the Minecraft task space is constrained, due to restrictions on the environment and player behavior. Physics in Minecraft is particularly simple, and as mentioned above, the world is arranged on a coarse 3D grid. There is a finite (and relatively small) list of atomic game objects (mob types, block types, etc), and a small finite list of crafting formulae. We expect that the distribution of player requests of an assistant will be concentrated on a tiny fraction of what is actually possible in the game. For example, the vast majority of block arrangements are unlikely building requests, and modern ML has shown some success at being able to learn to sample (or retrieve) perceptually pleasing 3d structures [79]. Because an assistant bot could already be helpful by successfully completing common tasks from the head of the distribution even if it fails on tasks from the tail, we believe we can make progress towards a useful assistant without having to be able to succeed at every possible request. If true, this could pave the way to further learning during deployment.

The constraints of the environment allow that *executing* a task is straightforward once it is specified. Movement, construction, crafting, and even scouting and combat can be reasonably scripted. While there might be value in learned representations (of language, the environment, actions, etc.) that come from learning to execute, it is not *necessary* to use ML to solve task execution. On the other hand, because it is possible to script execution, to the extent that it useful to get learned representations, we can easily get supervision to train these.

3 Learning and Interaction in Minecraft

We wish to build an intelligent in-game assistant⁴ that can perform whatever players may want it to do (in-game). Simple examples of the assistant's duties could range from building simple or complex structures to entire cityscapes,

²https://minecraft.net/en-us/

³There are 5 modes in total: survival, hardcore, adventure, creative, and spectator.

⁴or playmate, or minion, etc...

breaking down structures, dancing, catching mobs (Minecraft creatures), etc. We intend that the assistant's primary interface should be via natural language using Minecraft chat. Finally, we aim for an agent that is fun, and one that people will want to play and engage with. The purpose of building such an agent is to facilitate the study of the following:

- Synergies of ML components: To explore and evaluate various approaches to building a complex agent. In particular, how the various ML and non-ML components of a system can work together, and how to exploit the synergies of these components. Especially, how to exploit these components to make progress in:
- Grounded natural language understanding: Here, specifying tasks is the challenge, not executing them. How can we build a system to understand what a human wants; and to associate language to a task?
- Self improvement: To make progress in building agents with the ability to improve themselves during deployment and interaction with human players. How to learn new tasks and concepts from dialogue or demonstrations?

The basic philosophy of this program is that we should approach the relevant NLU and self-improvement problems by all means available. In contrast to many agent-in-an-environment settings, where the environment is a challenge used to test learning algorithms, we consider the environment a tool for making the NLU problems more tractable. Thus instead of "what ML methods can learn representations of the environment that allow an agent to act effectively?" we are interested in the problem of "what approaches allow an agent to understand player intent and improve itself via interaction, given the most favorable representations (ML based or otherwise) of the environment we can engineer?". While we are sympathetic to arguments suggesting that we will be unable to effectively attack the NLU problems without fundamental advances in methods for representation learning⁵, we think it is time to try anyway.

Code and other tools to support this program are available at https://github.com/facebookresearch/ craftassist.

3.1 Natural Language Interaction

The assistant should interact with players through natural language. This is not meant to handicap the assistant, and other methods of interaction may also be helpful. However, we believe the flexibility and generality of language will be useful (and perhaps necessary). Natural language allows that players will need no specialized training to play with the assistant. Furthermore, combined with the fact that the agent is just another player in the game, this makes training and evaluation scenarios where a human pretends to be a bot straightforward.

We intend that the player will be able to specify tasks through dialogue (rather than by just issuing commands), so that the agent can ask for missing information, or the player can interrupt the agent's actions to clarify. In addition, we hope dialogue to be useful for providing rich supervision. The player might label attributes about the environment, for example "that house is too big", relations between objects in the environment (or other concepts the bot understands), for example "the window is in the middle of the wall", or rules about such relations or attributes. We expect the player to be able to question the agent's "mental state" to give appropriate feedback, and we expect the bot to ask for confirmation and use active learning strategies.

We consider the natural language understanding (NLU) problem to be the program's central technical challenge. We give some examples in the next section 3.1.1. While a full solution is likely beyond the reach of current techniques, working with an interactive agent in Minecraft allows opportunities for progress. We can rely on agent grounding (a shared knowledge resource between player and agent, in this case the semantics of Minecraft) to aid learning language semantics. Moreover, we expect to spend lots of human effort on making sure common requests are understood by the bot, in order to bootstrap interaction with players. We discuss these in more detail in section 3.1.2

3.1.1 Challenges

The set of things that Minecraft players do for fun (building, crafting, resource gathering) is combinatorially complex. Even focusing on creative mode (where crafting and resource gathering are not relevant dynamics), there is a huge space of things a player could ask an assistant for help with. We give some examples and discuss their complexities:

PLAYER: build a tower 15 blocks tall and then put a giant smiley on top

⁵And we think programs aimed at advancing these are great too!

ASSISTANT: OK [assistant starts building the tower]

To succeed in executing this command, the assistant needs to understand what a "tower" is (and how to build one), understand that "15 blocks high" measures the height of the tower, and what "15" is. It needs to know what a "smiley" is (and how to build it) and understand the relative position "top". In our view, with the assumptions of this program, this is nontrivial but straightforward, for example using techniques as in [100, 101, 53, 52]. However, it is easy to imagine small changes that make it more difficult:

PLAYER: build a tower 15 blocks tall and then put a giant smiley on top ASSISTANT: ok [assistant starts building the tower] PLAYER: wait, stop, make every other block red

Besides needing to know what "every other" means, in this scenario, the assistant has to recognize that the player is referencing a change to the tower and smiley that it is currently building, and that "stop" doesn't mean "stop activity". The assistant also needs to know what "red" is but that is more straightforward. If the assistant does not know what "every other" means, we could imagine a dialogue like

PLAYER: build a tower 15 blocks tall and then put a giant smiley on top

ASSISTANT: Ok [assistant starts building the tower]

PLAYER: wait, stop, make every other block red [assistant recognizes the instruction refers to a change in its current build task,

but doesn't understand the change (and specifically recognizes "every other" as unknown)]

ASSISTANT: What is "every other"?

In our view, this level of flexibility and ability to learn from dialogue and examples is beyond what we can accomplish with our current technology. However, we believe that situating the assistant in an engaging environment that allows simplified perception and task execution opens opportunities to do research at this frontier.

3.1.2 Opportunities

As mentioned in 2.1, the Minecraft task space and environment have many regularities that we can use to simplify task execution. These regularities also create handholds for the NLU problems of specifying tasks and learning from dialogue.

First, they allow us to engineer language primitives or otherwise introduce domain knowledge into data collection and model design. For example, using the knowledge of the basic Minecraft tasks, we can build sets of language/action templates for generating examples commands for these tasks (in addition to crowdsourcing such language). These can be used to build artificial training data and inform the structure of machine learning models that are meant to interpret language. Another example is basic behavioral patterns that elicit data from the user, like asking a player to tag things it sees in the environment, which can be later used as referents. There is a huge space of opportunities for endowing our assistant with a range of language primitives. These allow building useful assistants from which to bootstrap before being able to learn too much from players.

Second, the structure of the environment and the head of the task distribution will hopefully allow the assistant to learn language more easily, beyond data generation and model design. This structure can function as a knowledge resource shared between agent and player, and ground concepts the assistant might need to learn. For example, if the user asks the assistant to "build a smiley", the agent can infer that "a smiley" is some kind of block object, as "build" is a common task the bot should already understand. The agent can make connections between "small" and the number of blocks in an object, and "close" and the number of steps it needed to walk. Also, atomic Minecraft objects give a set of reference objects with rich structure that require no learning to apprehend: mob types, block types etc. are given explicitly to the assistant. Furthermore, we might expect to be able to find synergies between learning generative models of block objects and discriminative models of those block objects (and their parts) in addition to the language used to intruct the assistant to build or destroy those objects. In our view, one of the most exciting aspects of building an assistant in Minecraft is this grounding of concepts afforded by the environment and the distribution of tasks.

Third, the basic game is *fun*, and gives us opportunities to understand how to make training (or teaching) an assistant rewarding. We expand on this more in 3.2.1.

PLAYER: Let me show you [player makes a stack of blocks alternating in color; assistant is able to generalize "every other" to new situations]

3.2 Self improvement

One of the oft repeated criticisms of standard statistical ML is that models cannot improve themselves beyond becoming more accurate at the task for which they were designed (and for which the data has been collected and labeled, etc.). They cannot reconfigure themselves for new tasks without a human building a new dataset (or reward function). While this complaint is not very precise, we do believe it is true in spirit, especially for the most successful ML models, such as those used in object recognition, translation, or language modeling. While the features they produce can be useful in many tasks, the model themselves are inflexible.

On the other hand, there are several systems designed explicitly for self improvement, for example [63, 88]. We consider the setting of a Minecraft assistant an ideal setting for studying how to flexibly learn from human interaction. As in [63, 88], instead of trying to "solve" self-improvement by making fundamental advances in ML, we think the setting will allow progress because it allows the correct substrate. That is, we hope we can design frameworks allowing an assistant to improve itself within that framework (but not beyond that); and because of the richness of the Minecraft task space, this allows for non-trivial growth.

3.2.1 Effective (and fun) training

One of the goals of the program is to study how the assistant should interact with people, and what feedback mechanisms should be employed to make training the assistant both efficient and enjoyable. While efficient learning is probably the key technical ML challenge to making the assistant responsive to training, there are many other UI factors that may be as important for making training fun. As part of the project, we want to study how the assistant should respond to feedback so that it is engaging. Moreover, mistakes should be amusing, and the assistant should more generally fail gracefully. These criteria are important in order to incentivize players to both engage with the assistant and to enable it to receive a learning signal to improve itself.

In terms of efficiency (in ML terms, being very sample efficient) and user enjoyment, some major challenges include:

- For the assistant to be immediately responsive to feedback. We suspect this will have a large effect on the players impression of the bot's performance.
- To optimally interact with the user, for example seeking clarification that both gives maximal information and does not bother the player with a succession of annoying questions.
- For the assistant to get the most out of the (rich) feedback that is given [75, 34], i.e. to generalize maximally beyond the individual case being addressed.

So, for example, we can imagine the following dialogue:

```
PLAYER: go over to that tower with the gargoyles [assistant does not know what "gargoyles are", but sees there is only one tower; surmise that that tower must be related to "gargoyles"] [assistant walks to the tower]
ASSISTANT: does this tower have gargoyles?
PLAYER: yes
ASSISTANT: What is a gargoyle?
PLAYER: its the monster on top of the tower [assistant recognizes is it is a part of the tower because of "top" which it already understands]
ASSISTANT: is it this? [assistant moves to the top of the tower]
```

The information the assistant could gain from this dialogue could be learned by seeing lots of objects labeled with "gargoyle", or associating a reward given by a player when it moved to the correct object over lots of plays. But in our view, if the assistant could execute these sorts of language interactions, it could be far more sample efficient. In this case, through the interaction, the agent could learn that a gargoyle is an object made of blocks (and not some other property of a tower, like being tall), find an example of this kind of object and a rough segmentation, and an association between "gargoyle" and the word "monster".

As before, this level of dialogue is still science fiction, and is for illustrating the opportunities of rich feedback. However, one can see that in order to even study these kinds of interactions in a non-toy setting with our current technology, we need an environment where the assistant has a good deal of domain knowledge built in. We also need players who are motivated to teach the assistant. We think it will be useful (and interesting) to design learning behaviors explicitly in addition to trying to learn them.

3.3 Modularity

Many of the recent successes of ML have come from training end-to-end models. Nevertheless, we believe that in this research program, the best path forward is to bootstrap a modular system with both scripted and ML components. We are not *opposed* to end-to-end approaches, and think it may be possible for an ML agent to learn to do everything end-to-end from raw pixel input. However, our view is that this too difficult in the near term, and that the challenges of learning low-level actions and perception are likely to be a distraction from the core NLU and self-improvement problems. In contrast, a modular system allows us to abstract away the lower-level primitives and focus on these problems. Furthermore, using a modular system makes data collection and generation easier. Finally, besides making this research program more accessible, we think modular ML-augmented systems are generally interesting objects of study.

In particular, we do not consider it "cheating" to script useful action, perception, or symbolic manipulation primitives. These might include path-finding and building scripts, and libraries of schematics and shapes; or heuristics for relative directions or sizes of objects. Similarly, we consider it reasonable to use ML components trained for a particular sub-task (perceptual or otherwise). Our frameworks (as in [4]) and models (as in [7, 4, 47]) should be designed to allow for a gradual process of ML-ification where it may be useful.

Abstracting lower-level primitives: The fundamental problem that a Minecraft assistant faces is understanding what the player wants the assistant to do. In contrast, for many requests, execution is more straightforward. In Minecraft, the sequence of (atomic) actions necessary to complete basic tasks (path-planning, building, etc.) can be scripted by directly accessing the game's internal world state. This is clearly not true more generally – in the real world, or even in the settings of other games, the execution of similar basic actions cannot be easily scripted. Furthermore, many of the easily scriptable action primitives in Minecraft (like building) might take hundreds or even thousands of steps to complete, making them non-trivial to learn. Similarly, many perceptual primitives are straightforward to implement, despite being non-trivial to learn. For example, mobs are atomic objects, as are blocks, despite having surface forms (as images) that vary based on viewing angle, occlusions, lighting conditions, etc. In this research program, we consider these and other particulars of the environment as tools for directly engaging the fundamental problem of player intent.

Gathering data: The successes of end-to-end models have been driven by large data; but in this program, there is no (initial) source of data for end-to-end training. The end-to-end task requires human interaction, and with our current technology, agents are not responsive enough to supervision to learn in a way that would be engaging. Again because of the human in the loop, self-play is not straightforward. Simply recording human players playing normally (without an in-game assistant) for behavioral cloning is not ideal, as standard play is different than what we would want the assistant to learn; and having humans play as assistants with other humans does not easily scale. On the other hand, for many action or perception primitives, it easy to collect or generate data specifically for that primitive. These considerations suggest approaches with modular components with clearly defined interfaces, and heterogeneous training based on what data is available (in particular, we are interested in models like [7] that can be trained end-to-end as a whole or separately as components).

Modularity as a more generally useful ML trait: We consider the study of ML-augmented systems as an interesting endeavor in its own right. An open assistant can be used as a laboratory for studying the interactions between ML and non-ML components and how changing one component affects the others. Or how to design and build systems so that their behavior can be easily modified, explained, and engineered, while still having the capability to flexibly learn. While the specific primitives for this program should be designed with the Minecraft assistant in mind, we expect that many of the things we discover about building systems will be useful more generally.

Some researchers might argue that without the fundamental learning algorithms that would allow an agent to build its understanding from the ground up, we cannot scale beyond simple scripts and hand-designed behaviors. We agree that this is a risk, and we certainly agree that scripts and hard-coded perceptual primitives will not be sufficient for real progress⁶. Our view is that the NLU and self-improvement problems have difficulties beyond representation learning that should be confronted as directly as possible, and scripted or separately trained components should be used to the extent they are useful in making progress in these core problems.

⁶However: while there can be important generalization and flexibility benefits from an end-to-end system, so too can there be different generalization and flexibility benefits to having the correct heuristic/symbolic substrate.

4 Literature Review

Existing Research Using Minecraft A number of machine learning research projects have been initiated in Minecraft. Microsoft has built the MALMO project [38] as a platform for AI research. It is often used as a testbed for ML model architectures trained using reinforcement learning methods, e.g. [71, 85, 5, 66, 82]. Some of these use (templated) language to describe mid-level macros [71] or tasks [67]. The work of [55] considers the use of human feedback, but at the action level, not by via language. The Malmo Collaborative AI Challenge⁷ was recently proposed to explore the training of collaborative RL agents, but does not address collaboration with humans, nor the use of language. Most recently [3] collects millions of frames of players doing various tasks in Minecraft, and proposes several (single-player) tasks to evaluate RL and imitation learning methods. [97] considers the use of language in Minecraft to answer templated visual questions. [42] focuses on a dataset and neural model for spatial descriptors ("on top of", "to the left of").

An observational study of how humans would speak to an intelligent game character in Minecraft using a Wizard of Oz approach has been recently conducted [6].

Other Gaming Platforms and Simulated Environments A number of other games are used as platforms for AI research. Many are built to study the development of reinforcement learning based algorithms and do not study language, e.g. Starcraft [80, 86], Atari games [11], Go [74, 84], TORCS [95], Doom [41] and Text adventure games [20, 96]. DeepMind Lab [10] is based on the Quake engine, although it is somewhat removed from the game itself. Some of these systems do not involve a human at all, e.g. one-player Atari Games, while others such as Starcraft and Go do involve an agent interacting with a human, but in an adversarial fashion, rather than as an assistant.

Instead of directly using an existing game platform, another approach has been to implement a simulation for embodied agent research, especially for navigation, QA and situated dialogue. Several such environments have been proposed, such as 3D environments like House3D [94], HoME [16], MINOS [70], Matterport3D [18], AI2-THOR [44], and Habitat [58], as well as more simplistic 2D grid worlds [78, 99, 19]. Within those environments typical tasks to study are language grounding, navigation, embodied QA[21]. The visual content of Minecraft is much less realistic than [94, 16, 70, 18, 44]; but the task space is richer. In [13, 12], the authors explore natural language instruction for block placement, first in 2D and then in 3D. Similar to the setting we consider, visual fidelity is secondary to natural language complexity, and their environment is focused on building instruction, although there the agent is not able to navigate or dialogue with players. One crucial difference between all of these environments and Minecraft is that Minecraft is a engaging game that already has a huge player base, hopefully enabling the study of learning agents that interact with humans via natural language at scale.

To a large extent, all the above platforms have been used mostly to answer questions of the form "how can we design algorithms and architectures that are able to learn via acting in an environment (perhaps integrating multiple modalities)?" In particular end-to-end learning and reinforcement is emphasized, and "cheating" by explicitly using domain knowledge or directly using the underlying mechanics of the simulator is discouraged. The agent is supposed to learn these. In our program, we wish to answer questions of the form "how can we use the simulator as a knowledge resource, shared between player and learning agent, in service of understanding intent from language?". Anything that makes this easier is fair game, including directly using the underlying game objects and domain knowledge about the environment and task space.

Personal Assistants and dialogue Virtual personal assistants have now penetrated the consumer market, with products such as Google Assistant, Siri and Alexa. These systems are grounded in world knowledge; and can be considered "embodied" in an environment consisting of web and device responses. They could be seen as an important platforms for research, especially in terms of dialogue and human interaction. Unfortunately, as they are large proprietary production systems, and as experimentation can negatively affect users and brands, they are not easily used in open (academic) AI research. Currently, such academic research typically involves smaller, less open-ended domains. There is a large body of work on goal-oriented dialogue agents which typically focus on one task at a time, for example restaurant booking [93, 35, 14], airline booking [24, 91], or movie recommendation [50]. Minecraft as a platform is relatively a good setting for goal directed dialogue research, as (1) a Minecraft agent is embodied in an environment with many familiar physical and perceptual primitives, and so offers opportunities for correlating language, perception, and physical actions; and (2) due to its open-ended nature, the setting emphasizes competency at a wide variety

⁷https://www.microsoft.com/en-us/research/academic-program/collaborative-ai-challenge/

of tasks; (3) the game itself is engaging, and (4) amusing enough mistakes are more tolerable.

Semantic Parsing and Program Synthesis Many of the simpler goal-oriented dialogue tasks discussed above can be formulated as slot filling, which can be considered a form of semantic parsing (inferring a machine understandable logical form from a natural language utterance). Semantic parsing has been used for interpreting natural language commands for robots [81, 59] and for virtual assistants [43]. Semantic parsing in turn can be considered a form of the general problem of program synthesis (see [30] for a survey), where the input to the program synthesizer is a natural language description of what the program should do. Recently there have been many works applying ML to semantic parsing [9, 51, 23, 37, 32, 102] and program synthesis from input-output pairs [45, 69, 28, 65, 15, 27] (and non-ML success stories [29]).

An assistant in Minecraft offers the opportunity for studying program synthesis through interactive dialogue and demonstrations; and in a setting where the agent can learn over time about a player's particular task distribution and language. These have been less studied, although see [36, 31] for dialogue based semantic parsing and [60] for multi-turn program synthesis and [26, 87] for "lifelong" learning to synthesize programs.

Learning to Ground Language outside of Simulators There are numerous works exploring the link between modalities in order to ground language outside of a simulator by considering static resources, e.g. by combining vision and text. Such works typically consider a fixed database of images and associated text, e.g. for image captioning [54], video captioning [98], visual QA [8] or visual dialogue [22, 72].

Learning by Instruction and Interactive Learning We are interested in agents that learn from feedback from the user. Learning from dialogue with varying types of feedback, such as verbal cues (e.g., "Yes, that's right!") was explored for the question answering (QA) setting in [92] and [48], and in a chit-chat setting in [33]. Similar techniques have been applied for teaching machines to describe images via natural language feedback as well [56]. Agents can gather more information by also proactively asking questions rather than just waiting for feedback. This has been studied in (ungrounded) conversational systems [77, 90, 68, 49] and when grounding with images via the CLEVR QA task [62]. Several works have studied how to use language to train a parametric classifier, e.g. [76, 34, 25]. The topic of learning by instruction was also the subject of a NIPS 2018 workshop⁸. While there is some work in learning from dialogue in an embodied setting [17, 83] this is currently relatively unexplored, The program described in this work is related to (and has been inspired by) [89, 87]. In [89] an interactive language learning game is set up between human and machine in order to place blocks appropriately given a final plan. In [87] a more open ended building task is proposed using a grid of voxels. The machine has to learn the language used by humans in a collaborative setting to perform well specified but complex actions in order to draw shapes out of blocks.

We have also been inspired by [63], [61], and [46] and in particular, we share the goal of exploring agents that can learn autonomously from various forms of supervision beyond labels. Perhaps in a naive sense, what we are suggesting is less ambitious than these: instead of learning about the real world as in [63], the goal is to learn how to do tasks in Minecraft (and process the relevant concepts) that are likely to be given to Minecraft assistant. Instead of working towards a method that can learn in an unbounded way, as in [61], we aim "only" for learning within the Minecraft frame, with as advantageous a perceptual and knowledge-representation substrate as we can find. The focus in this work on task specification and learning through language in a known environment recalls the "Frostbite Challenge" in [46]; but we do not consider it important whether our agents have human biases. Nevertheless, it may turn out that succeeding in the Minecraft frame necessitates methods that can learn as desired by [61], and that in order to successfully complete human tasks and learn from human instruction, the agent will need human biases. In any case, we think the setting of an interactive assistant in Minecraft is an ideal frontier to work on these problems.

5 Conclusion

In this work we have argued for building a virtual assistant situated in the game of Minecraft, in order to study learning from interaction, and especially learning from language interaction. We have argued that the regularities of the game

⁸https://nips.cc/Conferences/2018/Schedule?showEvent=10918

environment and task space can and should be used explicitly as tools to make the relevant learning problems more tractable, rather than as diagnostics to measure if a method can learn those regularities.

We hope the broader research community will be interested in in working on this program, and to to that end we open https://craftassist.io with infrastructure for connecting bots to players, and data and code for baseline bots.

References

- [1] Craftassist: A framework for dialogue-enabled interactive agents. https://research.fb.com/ publications/craftassist-a-framework-for-dialogue-enabled-interactive-agents/.
- [2] Minecraft exceeds 90 million monthly active users. https://www.gamesindustry.biz/articles/ 2018-10-02-minecraft-exceeds-90-million-monthly-active-users.
- [3] Minerl. https://web.archive.org/web/20190625193739/http://minerl.io/.
- [4] TorchCraftAI: Core Abstractions. https://torchcraft.github.io/TorchCraftAI/docs/ core-abstractions.html, 2018. Accessed: 2018-11-22.
- [5] Stephan Alaniz. Deep reinforcement learning with model learning and monte carlo tree search in minecraft. *arXiv preprint arXiv:1803.08456*, 2018.
- [6] Fraser Allison, Ewa Luger, and Katja Hofmann. How players speak to an intelligent game character using natural language messages. *Transactions of the Digital Games Research Association*, 4(2), 2018.
- [7] Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Dan Klein. Neural module networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 39–48, 2016.
- [8] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In *Proceedings of the IEEE international conference on computer* vision, pages 2425–2433, 2015.
- [9] Yoav Artzi and Luke Zettlemoyer. Weakly supervised learning of semantic parsers for mapping instructions to actions. *Transactions of the Association for Computational Linguistics*, 1:49–62, 2013.
- [10] Charles Beattie, Joel Z Leibo, Denis Teplyashin, Tom Ward, Marcus Wainwright, Heinrich Küttler, Andrew Lefrancq, Simon Green, Víctor Valdés, Amir Sadik, et al. Deepmind lab. arXiv preprint arXiv:1612.03801, 2016.
- [11] Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279, 2013.
- [12] Yonatan Bisk, Kevin J Shih, Yejin Choi, and Daniel Marcu. Learning interpretable spatial operations in a rich 3d blocks world. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.
- [13] Yonatan Bisk, Deniz Yuret, and Daniel Marcu. Natural language communication with robots. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 751–761, 2016.
- [14] Antoine Bordes, Y-Lan Boureau, and Jason Weston. Learning end-to-end goal-oriented dialog. In *Proceedings* of the International Conference on Learning Representations (ICLR), 2017.
- [15] Matko Bošnjak, Tim Rocktäschel, Jason Naradowsky, and Sebastian Riedel. Programming with a differentiable forth interpreter. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 547–556. JMLR. org, 2017.
- [16] Simon Brodeur, Ethan Perez, Ankesh Anand, Florian Golemo, Luca Celotti, Florian Strub, Jean Rouat, Hugo Larochelle, and Aaron Courville. Home: A household multimodal environment. *arXiv preprint arXiv:1711.11017*, 2017.

- [17] Rehj Cantrell, Paul Schermerhorn, and Matthias Scheutz. Learning actions from human-robot dialogues. In RO-MAN, 2011 IEEE, pages 125–130. IEEE, 2011.
- [18] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Nießner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3d: Learning from rgb-d data in indoor environments. arXiv preprint arXiv:1709.06158, 2017.
- [19] Maxime Chevalier-Boisvert, Dzmitry Bahdanau, Salem Lahlou, Lucas Willems, Chitwan Saharia, Thien Huu Nguyen, and Yoshua Bengio. Babyai: First steps towards grounded language learning with a human in the loop. arXiv preprint arXiv:1810.08272, 2018.
- [20] Marc-Alexandre Côté, Ákos Kádár, Xingdi Yuan, Ben Kybartas, Tavian Barnes, Emery Fine, James Moore, Matthew Hausknecht, Layla El Asri, Mahmoud Adada, et al. Textworld: A learning environment for text-based games. arXiv preprint arXiv:1806.11532, 2018.
- [21] Abhishek Das, Samyak Datta, Georgia Gkioxari, Stefan Lee, Devi Parikh, and Dhruv Batra. Embodied question answering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, volume 5, page 14, 2018.
- [22] Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José MF Moura, Devi Parikh, and Dhruv Batra. Visual dialog. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, volume 2, 2017.
- [23] Li Dong and Mirella Lapata. Language to logical form with neural attention. arXiv preprint arXiv:1601.01280, 2016.
- [24] Layla El Asri, Hannes Schulz, Shikhar Sharma, Jeremie Zumer, Justin Harris, Emery Fine, Rahul Mehrotra, and Kaheer Suleman. Frames: a corpus for adding memory to goal-oriented dialogue systems. In *Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue*, pages 207–219, Saarbrücken, Germany, August 2017. Association for Computational Linguistics.
- [25] Mohamed Elhoseiny, Babak Saleh, and Ahmed Elgammal. Write a classifier: Zero-shot learning using purely textual descriptions. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2584– 2591, 2013.
- [26] Alexander L Gaunt, Marc Brockschmidt, Nate Kushman, and Daniel Tarlow. Lifelong perceptual programming by example. 2016.
- [27] Alexander L Gaunt, Marc Brockschmidt, Nate Kushman, and Daniel Tarlow. Differentiable programs with neural libraries. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 1213–1222. JMLR. org, 2017.
- [28] Alexander L Gaunt, Marc Brockschmidt, Rishabh Singh, Nate Kushman, Pushmeet Kohli, Jonathan Taylor, and Daniel Tarlow. Terpret: A probabilistic programming language for program induction. *arXiv preprint arXiv:1608.04428*, 2016.
- [29] Sumit Gulwani, William R Harris, and Rishabh Singh. Spreadsheet data manipulation using examples. Communications of the ACM, 55(8):97–105, 2012.
- [30] Sumit Gulwani, Oleksandr Polozov, Rishabh Singh, et al. Program synthesis. *Foundations and Trends*® *in Programming Languages*, 4(1-2):1–119, 2017.
- [31] Daya Guo, Duyu Tang, Nan Duan, Ming Zhou, and Jian Yin. Dialog-to-action: conversational question answering over a large-scale knowledge base. In Advances in Neural Information Processing Systems, pages 2942–2951, 2018.
- [32] Kelvin Guu, Panupong Pasupat, Evan Zheran Liu, and Percy Liang. From language to programs: Bridging reinforcement learning and maximum marginal likelihood. *arXiv preprint arXiv:1704.07926*, 2017.

- [33] Braden Hancock, Antoine Bordes, Pierre-Emmanuel Mazare, and Jason Weston. Learning from dialogue after deployment: Feed yourself, chatbot! arXiv preprint arXiv:1901.05415, 2019.
- [34] Braden Hancock, Paroma Varma, Stephanie Wang, Martin Bringmann, Percy Liang, and Christopher Ré. Training classifiers with natural language explanations. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1884–1895. Association for Computational Linguistics, 2018.
- [35] Matthew Henderson, Blaise Thomson, and Jason D Williams. The second dialog state tracking challenge. In *Proceedings of the 15th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL)*, pages 263–272, 2014.
- [36] Mohit Iyyer, Wen-tau Yih, and Ming-Wei Chang. Search-based neural structured learning for sequential question answering. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics* (*Volume 1: Long Papers*), pages 1821–1831, 2017.
- [37] Robin Jia and Percy Liang. Data recombination for neural semantic parsing. *arXiv preprint arXiv:1606.03622*, 2016.
- [38] Matthew Johnson, Katja Hofmann, Tim Hutton, and David Bignell. The malmo platform for artificial intelligence experimentation. In *IJCAI*, pages 4246–4247, 2016.
- [39] Rafal Jozefowicz, Oriol Vinyals, Mike Schuster, Noam Shazeer, and Yonghui Wu. Exploring the limits of language modeling. *arXiv preprint arXiv:1602.02410*, 2016.
- [40] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. *arXiv preprint arXiv:1710.10196*, 2017.
- [41] Michał Kempka, Marek Wydmuch, Grzegorz Runc, Jakub Toczek, and Wojciech Jaśkowski. Vizdoom: A doom-based ai research platform for visual reinforcement learning. In *Computational Intelligence and Games* (CIG), 2016 IEEE Conference on, pages 1–8. IEEE, 2016.
- [42] Nikita Kitaev and Dan Klein. Where is misty? interpreting spatial descriptors by modeling regions in space. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 157–166, 2017.
- [43] Thomas Kollar, Danielle Berry, Lauren Stuart, Karolina Owczarzak, Tagyoung Chung, Lambert Mathias, Michael Kayser, Bradford Snow, and Spyros Matsoukas. The alexa meaning representation language. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers), volume 3, pages 177–184, 2018.
- [44] Eric Kolve, Roozbeh Mottaghi, Daniel Gordon, Yuke Zhu, Abhinav Gupta, and Ali Farhadi. Ai2-thor: An interactive 3d environment for visual ai. *arXiv preprint arXiv:1712.05474*, 2017.
- [45] Brenden M Lake, Ruslan Salakhutdinov, and Joshua B Tenenbaum. Human-level concept learning through probabilistic program induction. *Science*, 350(6266):1332–1338, 2015.
- [46] Brenden M Lake, Tomer D Ullman, Joshua B Tenenbaum, and Samuel J Gershman. Building machines that learn and think like people. *Behavioral and brain sciences*, 40, 2017.
- [47] Dennis Lee, Haoran Tang, Jeffrey O Zhang, Huazhe Xu, Trevor Darrell, and Pieter Abbeel. Modular architecture for starcraft ii with deep reinforcement learning. In *Fourteenth Artificial Intelligence and Interactive Digital Entertainment Conference*, 2018.
- [48] J. Li, A. H. Miller, S. Chopra, M. Ranzato, and J. Weston. Dialogue learning with human-in-the-loop. *arXiv* preprint arXiv:1611.09823, 2016.
- [49] J. Li, A. H. Miller, S. Chopra, M. Ranzato, and J. Weston. Learning through dialogue interactions. arXiv preprint arXiv:1612.04936, 2016.

- [50] Raymond Li, Samira Ebrahimi Kahou, Hannes Schulz, Vincent Michalski, Laurent Charlin, and Chris Pal. Towards deep conversational recommendations. In *Advances in Neural Information Processing Systems*, pages 9748–9758, 2018.
- [51] Chen Liang, Jonathan Berant, Quoc Le, Kenneth D Forbus, and Ni Lao. Neural symbolic machines: Learning semantic parsers on freebase with weak supervision. *arXiv preprint arXiv:1611.00020*, 2016.
- [52] Percy Liang. Learning executable semantic parsers for natural language understanding. *Commun. ACM*, 59(9):68–76, August 2016.
- [53] Percy Liang, Michael Jordan, and Dan Klein. Learning dependency-based compositional semantics. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 590–599. Association for Computational Linguistics, 2011.
- [54] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014.
- [55] Zhiyu Lin, Brent Harrison, Aaron Keech, and Mark O Riedl. Explore, exploit or listen: Combining human feedback and policy model to speed up deep reinforcement learning in 3d worlds. *arXiv preprint arXiv:1709.03969*, 2017.
- [56] Huan Ling and Sanja Fidler. Teaching machines to describe images via natural language feedback. *arXiv* preprint arXiv:1706.00130, 2017.
- [57] Dhruv Mahajan, Ross Girshick, Vignesh Ramanathan, Kaiming He, Manohar Paluri, Yixuan Li, Ashwin Bharambe, and Laurens van der Maaten. Exploring the limits of weakly supervised pretraining. arXiv preprint arXiv:1805.00932, 2018.
- [58] Manolis Savva*, Abhishek Kadian*, Oleksandr Maksymets*, Yili Zhao, Erik Wijmans, Bhavana Jain, Julian Straub, Jia Liu, Vladlen Koltun, Jitendra Malik, Devi Parikh, and Dhruv Batra. Habitat: A Platform for Embodied AI Research. arXiv preprint arXiv:1904.01201, 2019.
- [59] Cynthia Matuszek, Evan Herbst, Luke Zettlemoyer, and Dieter Fox. Learning to parse natural language commands to a robot control system. In *Experimental Robotics*, pages 403–415. Springer, 2013.
- [60] Mikaël Mayer, Gustavo Soares, Maxim Grechkin, Vu Le, Mark Marron, Oleksandr Polozov, Rishabh Singh, Benjamin Zorn, and Sumit Gulwani. User interaction models for disambiguation in programming by example. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, pages 291–301. ACM, 2015.
- [61] Tomas Mikolov, Armand Joulin, and Marco Baroni. A roadmap towards machine intelligence. In *International Conference on Intelligent Text Processing and Computational Linguistics*, pages 29–61. Springer, 2016.
- [62] Ishan Misra, Ross Girshick, Rob Fergus, Martial Hebert, Abhinav Gupta, and Laurens van der Maaten. Learning by asking questions.
- [63] T. Mitchell, W. Cohen, E. Hruschka, P. Talukdar, J. Betteridge, A. Carlson, B. Dalvi, M. Gardner, B. Kisiel, J. Krishnamurthy, N. Lao, K. Mazaitis, T. Mohamed, N. Nakashole, E. Platanios, A. Ritter, M. Samadi, B. Settles, R. Wang, D. Wijaya, A. Gupta, X. Chen, A. Saparov, M. Greaves, and J. Welling. Never-ending learning. In *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI-15)*, 2015.
- [64] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602, 2013.
- [65] Arvind Neelakantan, Quoc V Le, Martin Abadi, Andrew McCallum, and Dario Amodei. Learning a natural language interface with neural programmer. *arXiv preprint arXiv:1611.08945*, 2016.
- [66] Junhyuk Oh, Valliappa Chockalingam, Satinder Singh, and Honglak Lee. Control of memory, active perception, and action in minecraft. *arXiv preprint arXiv:1605.09128*, 2016.

- [67] Junhyuk Oh, Satinder Singh, Honglak Lee, and Pushmeet Kohli. Zero-shot task generalization with multi-task deep reinforcement learning. arXiv preprint arXiv:1706.05064, 2017.
- [68] Sudha Rao and Hal Daumé III. Learning to ask good questions: Ranking clarification questions using neural expected value of perfect information. *arXiv preprint arXiv:1805.04655*, 2018.
- [69] Scott Reed and Nando De Freitas. Neural programmer-interpreters. arXiv preprint arXiv:1511.06279, 2015.
- [70] Manolis Savva, Angel X Chang, Alexey Dosovitskiy, Thomas Funkhouser, and Vladlen Koltun. Minos: Multimodal indoor simulator for navigation in complex environments. arXiv preprint arXiv:1712.03931, 2017.
- [71] Tianmin Shu, Caiming Xiong, and Richard Socher. Hierarchical and interpretable skill acquisition in multi-task reinforcement learning. *arXiv preprint arXiv:1712.07294*, 2017.
- [72] Kurt Shuster, Samuel Humeau, Antoine Bordes, and Jason Weston. Engaging image chat: Modeling personality in grounded dialogue. arXiv preprint arXiv:1811.00945, 2018.
- [73] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587):484, 2016.
- [74] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587):484, 2016.
- [75] Shashank Srivastava, Igor Labutov, and Tom Mitchell. Joint concept learning and semantic parsing from natural language explanations. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1527–1536. Association for Computational Linguistics, 2017.
- [76] Shashank Srivastava, Igor Labutov, and Tom Mitchell. Zero-shot learning of classifiers from natural language quantification. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics* (*Volume 1: Long Papers*), pages 306–316, 2018.
- [77] Florian Strub, Harm De Vries, Jeremie Mary, Bilal Piot, Aaron Courville, and Olivier Pietquin. End-to-end optimization of goal-driven and visually grounded dialogue systems. *arXiv preprint arXiv:1703.05423*, 2017.
- [78] Sainbayar Sukhbaatar, Arthur Szlam, Gabriel Synnaeve, Soumith Chintala, and Rob Fergus. Mazebase: A sandbox for learning from games. *arXiv preprint arXiv:1511.07401*, 2015.
- [79] Minhyuk Sung, Hao Su, Vladimir G Kim, Siddhartha Chaudhuri, and Leonidas Guibas. Complementme: weakly-supervised component suggestions for 3d modeling. ACM Transactions on Graphics (TOG), 36(6):226, 2017.
- [80] Gabriel Synnaeve, Nantas Nardelli, Alex Auvolat, Soumith Chintala, Timothée Lacroix, Zeming Lin, Florian Richoux, and Nicolas Usunier. Torchcraft: a library for machine learning research on real-time strategy games. arXiv preprint arXiv:1611.00625, 2016.
- [81] Stefanie Tellex, Thomas Kollar, Steven Dickerson, Matthew R Walter, Ashis Gopal Banerjee, Seth Teller, and Nicholas Roy. Understanding natural language commands for robotic navigation and mobile manipulation. In *Twenty-Fifth AAAI Conference on Artificial Intelligence*, 2011.
- [82] Chen Tessler, Shahar Givony, Tom Zahavy, Daniel J Mankowitz, and Shie Mannor. A deep hierarchical approach to lifelong learning in minecraft. In *AAAI*, volume 3, page 6, 2017.
- [83] Jesse Thomason, Jivko Sinapov, and Raymond Mooney. Guiding interaction behaviors for multi-modal grounded language learning. In *Proceedings of the First Workshop on Language Grounding for Robotics*, pages 20–24, 2017.
- [84] Yuandong Tian, Qucheng Gong, Wenling Shang, Yuxin Wu, and C Lawrence Zitnick. Elf: An extensive, lightweight and flexible research platform for real-time strategy games. In *Advances in Neural Information Processing Systems*, pages 2659–2669, 2017.

- [85] Hiroto Udagawa, Tarun Narasimhan, and Shim-Young Lee. Fighting zombies in minecraft with deep reinforcement learning. Technical report, Technical report, Stanford University, 2016.
- [86] Oriol Vinyals, Timo Ewalds, Sergey Bartunov, Petko Georgiev, Alexander Sasha Vezhnevets, Michelle Yeo, Alireza Makhzani, Heinrich Küttler, John Agapiou, Julian Schrittwieser, et al. Starcraft ii: A new challenge for reinforcement learning. arXiv preprint arXiv:1708.04782, 2017.
- [87] Sida I Wang, Samuel Ginn, Percy Liang, and Christoper D Manning. Naturalizing a programming language via interactive learning. *arXiv preprint arXiv:1704.06956*, 2017.
- [88] Sida I. Wang, Samuel Ginn, Percy Liang, and Christopher D. Manning. Naturalizing a programming language via interactive learning. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 929–938. Association for Computational Linguistics, 2017.
- [89] Sida I Wang, Percy Liang, and Christopher D Manning. Learning language games through interaction. *arXiv* preprint arXiv:1606.02447, 2016.
- [90] Yansen Wang, Chenyi Liu, Minlie Huang, and Liqiang Nie. Learning to ask questions in open-domain conversational systems with typed decoders. *arXiv preprint arXiv:1805.04843*, 2018.
- [91] Wei Wei, Quoc Le, Andrew Dai, and Jia Li. Airdialogue: An environment for goal-oriented dialogue research. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3844– 3854, 2018.
- [92] J. E. Weston. Dialog-based language learning. In Advances in Neural Information Processing Systems (NIPS), pages 829–837, 2016.
- [93] Jason Williams, Antoine Raux, Deepak Ramachandran, and Alan Black. The dialog state tracking challenge. In *Proceedings of the SIGDIAL 2013 Conference*, pages 404–413, 2013.
- [94] Yi Wu, Yuxin Wu, Georgia Gkioxari, and Yuandong Tian. Building generalizable agents with a realistic and rich 3d environment. *arXiv preprint arXiv:1801.02209*, 2018.
- [95] Bernhard Wymann, Eric Espié, Christophe Guionneau, Christos Dimitrakakis, Rémi Coulom, and Andrew Sumner. Torcs, the open racing car simulator. *Software available at http://torcs. sourceforge. net*, 4:6, 2000.
- [96] Zhilin Yang, Saizheng Zhang, Jack Urbanek, Will Feng, Alexander H Miller, Arthur Szlam, Douwe Kiela, and Jason Weston. Mastering the dungeon: Grounded language learning by mechanical turker descent. arXiv preprint arXiv:1711.07950, 2017.
- [97] Kexin Yi, Jiajun Wu, Chuang Gan, Antonio Torralba, Pushmeet Kohli, and Josh Tenenbaum. Neural-symbolic vqa: Disentangling reasoning from vision and language understanding. In Advances in Neural Information Processing Systems, pages 1039–1050, 2018.
- [98] Haonan Yu, Jiang Wang, Zhiheng Huang, Yi Yang, and Wei Xu. Video paragraph captioning using hierarchical recurrent neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4584–4593, 2016.
- [99] Haonan Yu, Haichao Zhang, and Wei Xu. Interactive grounded language acquisition and generalization in a 2d world. In *International Conference on Learning Representations*, 2018.
- [100] John M. Zelle and Raymond J. Mooney. Learning to parse database queries using inductive logic programming. In *Proceedings of the Thirteenth National Conference on Artificial Intelligence - Volume 2*, AAAI'96, pages 1050–1055. AAAI Press, 1996.
- [101] Luke S. Zettlemoyer and Michael Collins. Learning to map sentences to logical form: Structured classification with probabilistic categorial grammars. In *UAI*, pages 658–666. AUAI Press, 2005.
- [102] Victor Zhong, Caiming Xiong, and Richard Socher. Seq2sql: Generating structured queries from natural language using reinforcement learning. arXiv preprint arXiv:1709.00103, 2017.