CONTINUOUS LEARNING IN A MODULAR EMBODIED AGENT VIA END-TO-END INTERACTION

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ABSTRACT

In this work we give a case study of an embodied machine-learning (ML) powered agent that improves itself via interactions with crowd-workers. The agent consists of a set of modules, some of which are learned, and others heuristic. While the agent is not “end-to-end” in the ML sense, end-to-end interaction is a vital part of the agent’s learning mechanism. We describe how the design of the agent works together with the design of multiple annotation interfaces to allow crowd-workers to assign credit to module errors from end-to-end interactions, and to label data for individual modules. Over multiple automated human-agent interaction, credit assignment, data annotation, and model re-training and re-deployment, rounds we demonstrate agent improvement.

1 INTRODUCTION

Present day machine learning (ML) research prioritizes end-to-end learning. Not only are end-to-end models able to achieve excellent performance on static tasks, there is a growing literature on how to adapt pre-trained networks to new tasks, and large pre-trained models can have impressive zero-shot performance on unseen tasks. In the setting of embodied agents, this manifests as agents actualized as monolithic ML models, where inputs to the model are the agent’s perceptual sensors, and the model’s outputs directly control agent actions. There are now a number of environments designed for the training of end-to-end embodied agents Beattie et al. (2016); Savva et al. (2019); Guss et al. (2019); Petrenko et al. (2021), and there is hope (and some evidence) that the same sort of transfer and adaptability seen in language and vision models will carry over to the embodied agent setting.

Nevertheless, agents implemented as fully end-to-end ML models are rare in production systems (or in real-world embodied agents, a.k.a. robots). While this in part is a symptom of the rapid improvement and scaling in the literature and the lag in technology transfer, these systems require performance and safety guarantees that are still not easily obtainable from end-to-end ML models; and must be maintainable by human engineers. On the other hand, it is difficult for pipelined agents to learn from experience once deployed. Instead, human engineers design a module, collect and collate data for it, train the appropriate ML model, and then deploy it. Thus the agent’s abilities don’t scale directly with the experience it receives, but rather with the amount of human power that can be brought to bear in building the modules. To somewhat oversimplify, engineers trade off ML scalability (the ability to learn new things through interaction, without engineering investment) for modularity, serviceability, and interpretability.

This work is a case study of automating self-improvement via interactions with people in a pipelined ML-powered agent. The agent consists of a set of modules, some of which are learned, and others heuristic. The agent is not “end-to-end” in the ML sense, but end-to-end interaction is a vital part of the agent’s learning mechanism. Through appropriate UX (user experience) design, crowd workers are able to assign credit to module errors without knowledge of the architecture of the agent. Using this, we automate a loop of human interaction, credit-assignment, module-data-annotation, model-retraining and re-deployment that successfully improves a semantic parsing module over multiple rounds of re-deployment. We thus give evidence it is possible to keep modularity without giving up ML scalability in this setting.

2 SETTING AND METHODS

2.1 THE SETTING

We describe the agent architecture and the world in which it lives.
2.1.1 WORLD

The agent is embodied in a three dimensional voxel world. Each voxel can be occupied by space or an impassable block of material. Movement is possible in any direction, as long as the voxel is unoccupied; and the agent moves via discrete steps of size one voxel. The agent also can turn to look in any direction; and so its pose can be represented by a \((x, y, z, \text{pitch}, \text{yaw})\) tuple. In addition to being able to act by changing its body or head position, the agent can point at rectanguloid regions of space (by visibly flashing them), and can “speak” in text. The agent can also place blocks of various colors, or destroy them.

A human player co-occupies the world with the agent. The human player’s pose is also determined by an \((x, y, z, \text{pitch}, \text{yaw})\) tuple. The human player can also speak in text to the agent, and the agent can see the human player’s pose (including the pitch and yaw, allowing it to decide what the human is looking at). The human can also place blocks and destroy blocks. See the interface in Figure 1.

2.1.2 THE AGENT

We use a Droidlet agent Pratik et al. (2021). The agent’s perceptual input includes the location of the agent’s self pose, the player’s pose, the location and type (i.e. material) of each block in space, and the chat history. It is equipped with heuristic perceptual methods to recognize connected components of blocks and the local ground plane. It also makes use of a BERT-based semantic parsing model further described in Section 2.2 as its natural language understanding (NLU) “perception”.

The agent also has heuristic, scripted “Tasks” that allow execution of atomic programs like movement to locations in space, re-orienting pose, pointing, or placing blocks. The agent has also limited, scripted dialogue capabilities (also implemented as Tasks) to clarify when needed.

The parameters of these Tasks are provided by a “Controller” module that inputs a partially specified program in the agent’s domain specific language (DSL), either from the output of the NLU module or from the agent’s intrinsic behaviors, and, using the agent’s memory system, fully specifies the program. See Pratik et al. (2021) for more details.

2.2 NLU MODEL DETAILS

The agent uses a neural semantic parser (NSP) to convert commands from players into partially specified programs in the agent’s DSL; these are fully specified into executable Tasks in the agent’s interpreter, see Pratik et al. (2021) for details. The neural semantic parser is the ML module that was improved over the course of our experiments.
The agent’s DSL is similar to the one described in Srinet et al. (2020), using the same top-level commands (Move/Dance, Build/Copy/Destroy/Dig, Stop/Resume), but the children of these have been expanded. For example, a “Copy” top-level command might take a “ReferenceObject” (corresponding to some object in the world) as a child, and the possible queries to specify that ReferenceObject have been expanded from Srinet et al. (2020). The full grammar is included in the supplemental, and some examples are displayed in Figure 2.

The architecture of agent’s semantic parsing model is similar to the one described in Srinet et al. (2020). It is an encoder-decoder seq2seq model where the encoder is finetuned from BERT Devlin et al. (2019) using huggingface, and the decoder is trained from scratch. In order to use a sequence based decoder, we linearize the target logical forms in depth-first order.

![Figure 2: Some examples of commands that can be parsed in the agent’s DSL. Fields of the form $[x, [y, z]]$ where $x$, $y$, and $z$ are numbers are spans of text (e.g. the $y$ through $z$th tokens on the $x$th text input). Fields with keys “filters” correspond to queries to the agent’s database.](image)

**2.3 Learning from Humans**

Human workers are connected with an agent. They interact with it through their web browser, where we render the agent and a representation of the world. Interaction data is gathered through crowd-sourced tasks where the workers are instructed to issue free form commands to the agents, using a category of actions from a suggested list of agent’s capabilities (e.g. ‘build’, ‘destroy’). The workers are given no other instructions about what type of commands to give, other than to be creative and diverse.

After each command, workers are prompted as to whether the task was carried out correctly end-to-end, whether the command was correctly understood, and whether the agent correctly perceived the objects that the workers referred to. If the player marks that the command was not correctly understood, then this the command and the agent’s parse are recorded as an NLU error.

These marked errors are then routed to another set of qualified crowd workers who write the ground truth parses for these commands. These parse annotation tasks are further distributed into small tasks consisting of 1-3 questions that determine the annotation of a particular node in the parse tree. These annotations are then used as training data to improve the NLU model offline. The retrained model is then re-deployed before the next set of human interactions. Figure 3 has a diagram showing the agent learning pipeline. The entire pipeline operates autonomously, from launching interaction jobs, to error annotation, to model retraining, to re-deployment.

**2.3.1 Challenges of Crowd-sourcing Human-Agent Interactions**

Working with humans in the loop involves challenges that go beyond model architectures and learning algorithms. Apart from making tools that are effective for cooperative people, it is necessary to plan for annotators that will sometimes behave erratically, or even adversarially.
Figure 3: A diagram showing the lifelong learning process of the Droidlet agent. The logical form above has been simplified for clarity.

A major issue (common to many crowd-worker deployments) has been - dealing with workers who, covertly or overtly, try to cheat their way through the task. Cheating in this case could mean not doing the task at all, trying to game our qualification criteria, or simply doing the bare minimum to pass but not engaging with the task. The combination of the following methods has allowed for very high quality data collection:

- Workers must first qualify for our interaction task by answering a simple set of questions to prove they are not a bot and are capable of reading the instructions.
- We disable the submission button until a basic list of criteria have been met, and we don’t advertise what those criteria are beyond the task instructions.
- By offering performance incentives, we make it more profitable to not cheat than to cheat.
- We blacklist workers who repeatedly perform poorly.
- We ask workers to reflect on their own performance, which facilitates perspective-taking and improved performance on repeated iterations of the task. Dow et al. (2012)

Even workers who are not acting adversarially can present challenges to development. They may not understand the instructions if not presented clearly, their knowledge of the English language may vary, and they may not have a strong aptitude with technology to navigate the interface. These constraints necessitate a focus on usability and user testing throughout the life cycle of the project.

While the human factor presents varied challenges to the development of the agent interface, it has also created a continuous feedback cycle that facilitates overall agent improvement. We have many users of the system issuing thousands of commands, some of which cause the agent to crash or behave in unexpected ways. We would not discover these edge cases very quickly on our own.

### 2.3.2 Error Routing

There could be several types of issue that cause the agent to fail to execute a command. One example is that the user asks the agent to do something that is not expressible in its DSL ("let’s play chess") or that is in its DSL, but part
of the command refers to something the agent does not know (“build a camel”, where the agent does not know what a “camel” is). The agent can also fail because its visual perception module did not recognize an object, because it did not correctly retrieve the right information from memory, and the focus of this paper: because the NLU model failed to accurately parse the command.

Differentiating between these types of failure is essential for being able to route the correct data to the correct annotator. In normal operation, only commands that are marked as containing an NLU error are sent to be annotated to so that ground truth for those commands is added to the data set.

This process of differentiating between types of errors is executed using a decision tree that is presented to the worker one question at a time. In the Appendix there are examples of this decision tree in Figure 13, which represents the correct error marking flow after an NLU error, and Figure 14, which represents the error marking flow after a non-NLU task error.

3 RELATED WORK

There is a large literature on human in the loop machine learning, see Wu et al. (2021) for a survey.

Our setting is an embodied agent with a language interface. There is existing work showing improvement after multiple rounds of re-deployment with dialogue agents, for example Hancock et al. (2019); Shuster et al. (2021); Kiela et al. (2021).

Some prior work building towards sophisticated interactive tools for “machine teaching” Simard et al. (2017), where ML naïve users are able to guide model training towards high accuracy and coverage, has been considered in the literature and many such tools exist as deployed services, for example Ratner et al. (2017) (commercialized at https://snorkel.ai/) or https://scale.com/. These are superior to the re-deployment loop described in this work in the sense that the model re-training occurs “in-session”, and the machine teacher can immediately see the results of their annotations and adjust accordingly. Furthermore, these also have tools for automatically generating labeled data from rules or automating data augmentation. However, the work described in this case study is complementary to these, in that it focuses on automating the end-to-end data-collection and retraining of ML models that are important internal components of an embodied agent. We give evidence that fully modular ML systems will be able to self-improve even if gradients cannot pass from one part of the system to another. In future work, we hope to combine our system with responsive in-session learning as described in these services.

Our work is inspired by Wang et al. (2017), where multiple rounds of users build up a semantic parser for a voxel world editor. In Shah et al. (2021) the authors propose a competition to train embodied agents in a voxel world through language descriptions. Our work is also related to Suhr et al. (2019), where the authors build an interactive environment where (embodied) players and agents (playing as the role of a language issuing “leader” with full observability or faster moving “follower” with partial observability) collaborate via natural language to collect cards by moving to their spatial locations. A followup Kojima et al. (2021) is especially relevant; in that work they show how multiple rounds of learning can continue to improve the language generation capabilities of a “leader” model. In addition to the embodied agents and players, our work shares with Kojima et al. (2021) multiple rounds of data collection and the use of player feedback after “execution” to label examples. However, the key difference is that in Kojima et al. (2021) the agent is a single ML model, whereas in this work, we aim to show that credit can be assigned to different components in a modular system, the data for the component can be annotated, and the component re-trained without any engineer intervention.

There are several works showing how humans can interactively teach robotic agents, for example Saxena et al. (2014); Paxton et al. (2017); Mandlekar et al. (2018); Cabi et al. (2019); Mandlekar et al. (2020). In Saxena et al. (2014), the authors demonstrate large-scale crowd-sourcing of data for perceptual and knowledge-base components of a robotics system. In Mandlekar et al. (2018; 2020) crowd-workers are connected with robotic manipulators to demonstrate movements or parts of movements. COSTAR Paxton et al. (2017) is a modular system for teaching robots to carry out tasks using behavior trees. Our work is similar to COSTAR in that it is built on a modular system with perception decoupled from action generation; but in this work we focus on the infrastructure for crowd-sourcing annotations, rather than mechanisms for live human teaching.

Finally, our work builds on the ideas of Carlson et al. (2010); Mitchell et al. (2018). Our hope is to demonstrate progress towards embodied incarnations of these.
### Table 1: The number of commands for which each row description applies. "All Commands" refers to all commands from the data presented here. "De-duplicated, Valid Commands" refers to the subset of ‘All Commands’ that are unique and ask the agent to perform a task within its capabilities. "Marked Agent Errors" refers to the number of times a worker indicated, after issuing a command and observing the resulting agent behavior, that the agent failed to perform the task. "Marked NLU Errors" refers to the subset of ‘Marked Agent Errors’ for which workers indicated the agent did not understand the command, based on a report of the NSP output. "Marked NLU Errors Successfully Annotated" refers to the subset of ‘Marked NLU Errors’ for which a ground truth logical form was successfully added to the data set through the annotation process. The remainder were outstanding at the time of model retraining and redeployment but remain accessible for later use. "Marked ‘True’ NLU Errors" refers to the subset of ‘Marked NLU Errors Successfully Annotated’ for which the ground truth annotation varied from the NSP inference. The ratio of the two previous values forms the worker error marking precision. "All Known NLU Errors” refers to the subset of ‘De-duplicated, Valid Commands’ for which a) a ground truth logical form exists in the data set and b) the ground truth annotation varied from the NSP inference. The ratio of ‘Marked ‘True’ NLU Errors’ to ‘All Known NLU Errors’ forms the estimate of worker error marking recall.

| Pipeline Stage                              | Number of Commands |
|---------------------------------------------|--------------------|
| All Commands                                | 22,685             |
| De-duplicated, Valid Commands               | 18,163             |
| Marked Agent Errors                         | 7,461              |
| Marked NLU Errors                           | 2,559              |
| Marked NLU Errors Successfully Annotated    | 2,403              |
| Marked "True" NLU Errors                    | 2,138              |
| All Known NLU Errors                        | 4,944              |

4 **Results**

4.1 **NLU Error Collection**

In Table 1 the results of the NLU error generation funnel are reported. In total, over the course of the experiments, we collected 18,163 de-duplicated commands.

In early runs, we found that training only on new data where the NLU model failed led to feedback effects. We updated our protocol to re-train using all de-duplicated commands at each iteration (including the ones the model correctly parsed). We leave methods for balancing the cost of labeling against distributional stability for future work.

Even though we annotated all of the commands on later re-deployments, we calculated the accuracies of workers in routing errors - in ongoing and future work we expect to have several ML models active in the agent. Workers are relatively precise: 89% of the time they mark a command as resulting in an NLU error, it turns out to be a true error. However, we estimate only 43% of NLU errors are marked. This is an estimate because it can only be calculated for commands for which there has ever been an annotation. Future work on interaction task design will attempt to address this discrepancy.

4.2 **NLU Model Improvements**

We have run 10 iterations of the full interaction → routing → annotation → retrain pipeline. The first 5 iterations were run 16 weeks ago over a period of 3 weeks. In these, we did not re-deploy the NLU model after an iteration. For the next 5 iterations taken over the last two weeks, we redeployed the re-trained model at each iteration.

In order to measure the improvements of the NLU model, for each new tranche of data from the iterations, we randomly split into a train, valid and test set. We then build a sequence of training data sets $R_n$ which are the union of the first $n$ training sets, $V_n$ which are the union of the first $n$ validation sets, and $T_n$, the union of the first $n$ test sets. Here $R_0$ is taken from Srinet et al. (2020); this is used to train the initial deployed model.

For each tranche of data $n$, we compare three models. The first is the baseline, trained on $R_0$. The next is the continually-learned model, trained on $R_n$ (trained the same way as the model that was used for obtaining $R_{n+1}$ for 100 epochs. Finally, we take the continually learned model trained on $R_n$, and then finetune it for 10 epochs on $R_0$; we call this the “re-biased” model.
Figure 4: On the left: model accuracies (exact match of parse) on $T_{10}$ (union of all collected test data). On the right: accuracies of all models on $T_0$ (base test data collected in Srinet et al. (2020)). The $x$ axis is the number of training examples. Red is continually learned, Blue is re-biased, and Gray is baseline. The continually learned model does worse over time on the base-test dataset (which was collected with a different procedure), but improves on the full data. Re-biased improves on the full data (but less than non-re-biased) without losing on the base data. See Section 4.2 for details.

We repeated the model training 5 times for each tranche with different random seeds. Our main results are Figure 4. The colored lines represent mean values of model accuracy across all 5 experiments and the shaded error bands represent the standard error.

In the left of Figure 4, we show the accuracy of the model trained on $R_n$ (all the data up to the $n$th interaction job) vs. the original baseline, all tested on the final test data $T_{10}$ (the union of the test sets from each tranche). The $x$ axis is the total number of training examples used for that model, arranged in the sequence the were obtained, and the $y$ axis is accuracy, where accuracy is taken to be an exact match of the annotated parse. We can see a steady improvement on the final test set in the continually learned models over the baseline. The re-biased model also improves, although not quite as much.

In right of Figure 4, we show the results of training on $R_n$ and testing on $T_0$ (the initial test data, from Srinet et al. (2020)). The continually-learned semantic parsing models perform worse on $T_0$ even though they are trained with a larger amount of data; but this is not surprising, as the collection procedure for the base data $R_0$ was different than $R_i$ for $i > 0$, and so the distribution is different. Specifically, most of the commands in $R_0$ were collected by asking crowd-workers what they might ask an agent to do; whereas in this work, the crowdworkers are actually connected to the agent, and interact with it, giving multiple commands in each session. The re-biased model manages to keep its performance almost at the level of the baseline (while improving on the new data).

4.3 **Annotator Experience Improvements**

The NLU model improvement rate is a function of the quantity and diversity of the NLU system errors, and is constrained to the first order by the resources available to fund interactions with the agent. Therefore, the goal of our UI/UX (user interface and user experience) research is to efficiently generate and correctly mark as many high quality errors as possible in each interaction, and a focus on interface usability is critical to this end. We have been guided by standard usability heuristics, the most impactful of which are listed here below.

- **Aligning With Design Standards** - Utilizing UI components and affordances that match user expectations, as well as reducing overall visual clutter helps reduce cognitive load of using the interface.
- **Forced Choices** - Providing clear, blocking choices for important UI tasks rather than relying on the user to recognize a branch in workflow and select the appropriate option.
- **Visual Feedback** - Implementing clear and easy to understand visual indicators of agent status as well as the quality of the interaction (number and diversity of commands) helps the workers understand our expectations better.
- **Performance Incentives** - Shifting to paying workers a lower base rate with incentives for good performance both: lowers the cost of data collection on a per-error basis and results in higher worker pay.
Figure 5: The charts above show the number of commands workers issued per interaction task (left two charts) and the stoplight performance score described in Section 4.3.3 (right two charts) before (first and third charts) and after (second and fourth charts) issuing performance incentives. The red line indicates the authors’ target for each metric. There are fewer data in the third chart, because a recording bug in UI/UX Experiment 3 caused half of these data to be lost.

While there is not an obvious baseline of usability for a specific interface, Figure 6 shows the cost efficiency improvements for each iteration as the project progressed, providing a strong validation of effort spent improving task usability. Over the course of the four UI/UX experiments listed, the cost of collecting a single NLU error fell by 71%. Below is more detail on the nature of each of the four UI/UX experiments. The experiments are cumulative, meaning each experiment includes the changes made in the previous.

4.3.1 EXPERIMENT 1 - CLARITY AND VERBOSITY

The goal of the first experiment was to reduce visual clutter, verbosity, and text complexity. Hirth et al. (2020) finds that “Incomprehensible Instructions” are the single most frustrating aspect of task design when present. Experiment 1 reduced the number of instruction words by almost half, and paginated the remaining so workers were never reading more than a few sentences at a time. The instructions are attached in Appendix B, Figure 10. After the initial read during the task, instructions are hidden but available through a drop-down mechanism to further reduce clutter on screen. The information from the instructions most relevant to producing good interaction data is copied outside the instructions window immediately next to the interaction interface for easy reference.

4.3.2 EXPERIMENT 2 - VISUAL FEEDBACK AND FORCED CHOICES

The purpose of the second experiment was to ensure that the worker is not confused about the agent status or what to do next. After each command, the agent must receive and interpret it, then potentially plan and carry out an action or set of actions, as well as respond to the user if appropriate. Experiment 2 introduced messages to report the agent status periodically.

The second change in this experiment was to make the error marking decision tree described in Section 2.3.2 and shown in Figures 13 and 14 in the Appendix. If error marking is a passive call-to-action, workers may not mark effectively because they may not remember to mark erroneous commands or may be eager to move on with the task. By forcing the worker to decide one way or the other before continuing, a much higher percentage of agent errors are captured.

4.3.3 EXPERIMENT 3 - ALIGN WITH DESIGN STANDARDS

Human-Computer Interaction research has shown that familiarity with an interface reduces cognitive load, and therefore increases task accuracy and reduces task completion time. For a review of this concept see Hollender et al. (2010). Experiment 3 replaced the chat interface with a UI that closely resembles that one would find on a cell phone or the help window of a website, with the purposes of better aligning with workers’ existing mental model of a chat interface.

This experiment also introduced a new component to the interface - a stoplight that serves as an feedback indicator of the overall task performance to the worker. If the light is red the worker knows that their performance is unsatisfactory, and so forth. The metric used to determine the stoplight color is a weighted average of the log of: the number of commands issued, the diversity of commands in-session (average word edit distance between each session command), and the average creativity of the commands (word edit distance compared to all previously issued commands). The weights and thresholds driving the stoplight indicator were empirically tuned to align with the results a worker should obtain by engaging in good faith with the task.
| Experiment Name                               | Number of tasks Completed | Data Generation Efficiency Ratio |
|----------------------------------------------|---------------------------|---------------------------------|
| Baseline                                     | 17                        | 1.0                             |
| Exp1 - Instruction Clarity and Verbosity     | 106                       | 1.1                             |
| Exp2 - Visual Feedback and Forced Choices     | 197                       | 2.5                             |
| Exp3 - Design Standards Alignment            | 191                       | 3.1                             |
| Exp4 - Performance Incentives                | 150                       | 3.5                             |

Figure 6: Table showing the efficiency of data collection (NLU errors collected per $) as UI/UX improvements were made, reported as a ratio between the efficiency of that experiment and the baseline value before any UI/UX improvements were made. Data generation efficiency is computed as an average over all tasks completed in that experiment. UI/UX experiments are cumulative, not independent (each includes the changes of the previous).

4.3.4 EXPERIMENT 4 - PERFORMANCE INCENTIVES

The final experiment in this series was meant to operationalize the stoplight introduced in the previous section by offering performance incentives based on the “stoplight score”, or the score out of 10 that determines the stoplight color. In this experiment, workers receive a lower base pay in addition to a bonus payment after completion based on their score. Workers can see their expected bonus reported in real time after they issue each command.

This change had several notable effects. Firstly, nearly all of the workers achieved a score in the “green” performance band, compared to the previous experiment where approximately 2/3 did, shown in Figure 5. Second, while the cost per interaction task went up, and therefore worker compensation per time went up, data generation efficiency measured in NLU errors per dollar actually rose. Furthermore, workers responded to the change positively, providing qualitative feedback that in addition to increasing their compensation, the change also improved the enjoyability and clarity of the task. This is evidence that further task gamification and/or incentives alignment may be fruitful and mutually beneficial direction for future research.

5 DISCUSSION

In this work have given an example of an ML powered pipelined agent that uses end-to-end interaction as a crucial part of its learning mechanism; and demonstrated that it can improve over multiple rounds of re-deployment. This is made possible in part through UX allowing naive crowdworkers with no knowledge of the system architecture to route errors and complete complex annotations in an assembly-line style.

In future work, we would like to extend the approaches discussed in this work to agents with learnable perceptual systems and learnable Task executors; or even learnable memory and Controller modules. More generally, we think these approaches will valuable in the even context of works like Dalmia et al. (2019); Veniat et al. (2020) that build modular ML systems that allow automatic credit assignment, as hybrids that empower humans to teach the system at the level of its modules while automatically assigning credit when such humans are unavailable could be more powerful than either end-to-end or pipelined systems.

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A Agent’s Domain Specific Language (DSL)

This section describes the details of logical form of each action pictorially. We support three dialogue types: HUMAN_GIVE_COMMAND, GET_MEMORY and PUT_MEMORY. We support the following actions in our dataset: Build, Dance, Get, Spawn, Resume, Fill, Destroy, Move, Undo, Stop, Dig and FreeBuild.

In figure 7, we represent an event in the agent’s grammar and DSL:

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![Figure 7](image)

Figure 7: The agent’s DSL showing the structure of an event.

In figure 8, we show a full pictorial representation of actions in the agent’s DSL:

Filters add a lot of expressiveness to the agent’s grammar, we show a representation of filters in figure 9

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![Figure 8](image)

Figure 8: The representation of an action in agent’s DSL.
Figure 9: The representation of filters in agent’s DSL.
B DATA GENERATION INTERFACE - HUMAN INTELLIGENCE TASK (HIT)

This appendix describes the interface used by crowd-sourced workers to interact with the Droidlet agent and generate data by issuing commands.

Figure 10 is the instructions popup, which is the first thing that the worker sees when starting the HIT. The instructions are paginated to reduce each section to a digestible amount of content.
Figure 11 shows the view of the HIT page that workers see at the beginning of the task. There is a prompt in the chat to start the clock (each interaction is a minimum of five minutes), and there is a prompt superimposed over the voxel world window indicating that users need to click once in that window in order for the voxel world to render. The "stoplight" performance score is a 0 out of 10 at the start of the HIT, and no feedback is available yet. The instructions, which were shown in a popup previously, are available for review in the dropdown at the top of the page. However, the agent capabilities are always available for easy reference just to the left of the interaction window.

Figure 12 shows two of the status messages that workers see after submitting a command. These status messages are available so that the worker is not confused about what is happening at any given time, and can more reliably identify if there is a bug or the agent has frozen. The four status messages that are shown after every command are, in order: "sending command", "command received", "assistant thinking", and "assistant is doing the task". The first is cleared when the agent acknowledges having received the command. The second is cleared after 500ms. The third is cleared after the NSP has parsed the command. The fourth and final status is cleared after the agent has completed the task, if it knows how. After the fourth status message is cleared the next UI screen that appears is the error routing screen, which the user must progress through before being allowed to issue another command.

Figure 13 and Figure 14 show the error marking flows after the agent processes a command containing an NLU error and a non-NLU task error, respectively. Correct error marking is critical in order to appropriately route the appropriate data to the appropriate annotator. After completing this decision tree presented one question at a time, the worker is returned back to the original interaction window shown in Figure 1.
Figure 12: Status update messages given to workers as the agent is processing instructions and performing the task. The worker retains the ability to issue a "stop" command while the agent is working.
Figure 13: Error routing flow for a command that contains an NLU error.
Figure 14: Error routing flow for a command that does not contain an NLU error but which the agent does not complete correctly (in this case a perception error).
C Model Training Details

For the standard model retraining job, we train the models for 100 epochs (on average till lack of improvement on $V_n$). The batch size is set to 24 in order to fit into a single 16G GPU chip.

For Transformer decoder learning rate, we are choosing between 0.0000005, 0.000001 and 0.000005 while for the encoder learning rate we are choosing between 0.0 and 0.000001. This gives us a total number of 6 different combinations of hyperparameters for each model training job; we validate on $V_n$. All other parameters are the default from hug.

For model re-biasing, we train the models on the original training dataset for 10 epochs (this is roughly till lack of improvement on $V_0$, the initial validation set from Srinet et al. (2020)).