Creating Multimodal Interactive Agents with Imitation and Self-Supervised Learning

Interactive Agents Team\(^1\)
\(^1\)DeepMind

A common vision from science fiction is that robots will one day inhabit our physical spaces, sense the world as we do, assist our physical labours, and communicate with us through natural language. Here we study how to design artificial agents that can interact naturally with humans using the simplification of a virtual environment. We show that imitation learning of human-human interactions in a simulated world, in conjunction with self-supervised learning, is sufficient to produce a multimodal interactive agent, which we call MIA, that successfully interacts with non-adversarial humans 75\% of the time. We further identify architectural and algorithmic techniques that improve performance, such as hierarchical action selection. Altogether, our results demonstrate that imitation of multi-modal, real-time human behaviour may provide a straightforward and surprisingly effective means of imbuing agents with a rich behavioural prior from which agents might then be fine-tuned for specific purposes, thus laying a foundation for training capable agents for interactive robots or digital assistants. A video of MIA’s behaviour may be found at https://youtu.be/ZFgRhviF7mY.

1. Introduction

Humans interact with the physical world and one another, and it is through these interactions that much of our cognition was shaped during evolution (Dunbar, 1993). If we hope to build artificial intelligence (AI) capable of human-like thinking, we should therefore consider a holistic setting wherein agents perceive and manipulate their world and understand and produce language, so that they can participate in—and learn from—natural interactions with humans (McClelland et al., 2019; Lake and Murphy, 2021; Winograd, 1972).

In this work we explore how to create artificial agents that interact with humans and their environment. To do so, we use imitation learning approaches (Pomerleau, 1989; Schaal, 1999) that have driven progress in Go (Silver et al., 2016), Starcraft (Vinyals et al., 2019), and perhaps most notably the recent progress in large language models (Brown et al., 2020) and dialogue agents Adiwardana et al. (2020). Imitation learning has proved a surprisingly powerful approach for games and language modelling, but it is unclear the extent to which it may furnish powerful behavioural priors in embodied domains. We study this question in a 3D simulator that is easily operated by human participants. Working to create embodied agents with impressive motor and linguistic capabilities is a difficult problem for several practical reasons, notably: (1) model requirements are more sophisticated, and (2) data sources are not widely available, as they are with text. Our results suggest, however, that by augmenting imitation learning with hierarchical architectures and self-supervised learning it is possible to make agents that are capable, impressive, and surprising using moderately-sized datasets collected directly by researchers.

We build upon our previously introduced methodology (Interactive Agents Team, 2020) in a few crucial ways. First, we significantly increase the scale and complexity of collected data. Second, we simplify the training protocol. Third, we remove all uses of privileged information extracted from our virtual 3D-world simulator. Ultimately, these changes result in an agent artifact that blends perception, language understanding and production, and motor action to competently engage in
extended, and often surprising interactions, and participate in comprehensive, bidirectional language-based communication. The resulting agent, MIA (Multimodal Interactive Agent), is vastly more capable than those presented in the previous work (Interactive Agents Team, 2020). MIA exhibits a diversity of behaviours that were never instructed by researchers, including tidying a room and finding and grouping multiple specified objects. It asks clarifying questions, produces minute long action sequences following coherent goals, and can rapidly learn new objects, nouns, and verbs in mere hours of real-time experience.

Our contributions are as follows:

• We introduce the multi-room Playhouse environment to study natural interactions between humans and agents.
• We produce an agent, MIA, which is capable of engaging in natural interactions with human participants in a 3D simulated world.
• We demonstrate the importance of architectural design and self-supervised losses to performance in situated language agents domains.
• We highlight the importance of human and programmatic evaluation beyond training and validation losses.
• We demonstrate the effects of scale of both data and model size on performance.
• We demonstrate the importance of large-scale data priors for fast learning of new objects and skills as well as their referring nouns and verbs in a practical amount of time (hours).
• We provide a careful comparison to human performance, as evaluated by humans, on tasks involving natural interactions.

2. Language Games in the Playhouse

We explored human and agent interaction in a 3D virtual environment called the Playhouse, based on previous environments built in the Unity game engine (Ward et al., 2020; Interactive Agents Team, 2020). The Playhouse comprises a randomized set of adjoining rooms (such as a living room, pantry, and bathroom) and interactable items (such as toys and household objects). Human and agent embodiment manifests as control of a virtual robot that moves around in space, grasps and manipulates objects, and emits natural language. This setting permits a wide range of behaviours, ranging from simple instruction-following (e.g., "Please pick up the book from the floor and place it on the blue bookshelf.") to creative acting (e.g., “Bring food to the table so that we can eat”).

It is not feasible to programmatically define reward functions for the Playhouse because the space of all possible interactions is vast and unpredictable, and because satisfaction criteria can often be ambiguous or subjective. We might instead choose to task humans with assigning reward based on their subjective assessment of an agent’s behaviour, either by absolute score or ranking (Christiano et al., 2017), following an interaction. However, unless these interactions could occur at an enormous scale and fast enough pace, this too is not a feasible approach to training initially randomly behaving agents using purely reinforcement.

Therefore, we follow an approach advocated for by (Interactive Agents Team, 2020) wherein we train agents using imitation to instill them with an intelligent behavioural prior (Galashov et al., 2019). Agents trained in this manner will display some structured and language-driven behaviours. Subsequent reinforcement learning will be more efficient with these agents since humans will be more inclined to continue interactions with AI participants that display rudimentary intelligence. The focus of this report centers on creating agents with intelligent behavioural priors, and we leave further reward-based learning for future work.
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Figure 1 | **Interactions in a simulated “Playhouse” environment.** Humans and agents interact via simulated avatars in the 3-D “Playhouse” environment. The environment contains a randomised set of rooms with domestic objects and children's toys, as well as containers, shelves, furniture, windows, and doors. The diversity of the environment enables interactions involving reasoning about space and object relations, ambiguity of references, containment, construction, support, occlusion, and partial observability. Agents interact with the world by moving around, manipulating objects, and speaking to each other. A Example of two humans interacting in the Playhouse. This episode was selected from a small set that was drawn at random from our dataset. B Depicts a simple interaction wherein the orange solver agent is placing a helicopter into a container while the blue setter agent watches on. C A sampling of the types of objects available in the room. D Two random instantiations of the Playhouse, each with unique configurations of rooms, furniture, and objects.

### 2.1. Collecting Data in the Playhouse

Imitation learning works best when demonstrations are produced by experts and when there are sufficiently many to cover the desired range of behaviours (including, e.g., corrective behaviours (Ross et al., 2011)). For domains such as language, data can be easily obtained by leveraging existing text on the internet (Brown et al., 2020). However, for domains such as robotics (or simulated robotics), data needs to be assembled from scratch. The protocol for organizing the collection of expert demonstration data in the Playhouse is a central contribution of this work.

One approach could be to collect data from humans freely interacting in the Playhouse. However, such data might prove problematic for a host of reasons. First, data may be difficult to model as it might not comprise graded behavioural competencies. Humans come to the environment with an ability to act in simulated worlds, an extensive knowledge base, and nuanced intentions, and hence exhibit already-complex behaviour that takes for granted simpler, but necessary, capacities such as
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Totals

|                                |       |
|--------------------------------|-------|
| Number of train episodes       | 275676|
| Number of test episodes        | 34399 |
| Episode length (minutes)       | 5     |
| Total play time (years)        | 2.94  |
| Number of unique setter...    | 778880|

|                                | Mean  | Std  | 25th | 75th |
|--------------------------------|-------|------|------|------|
| Interaction time per instruction (seconds) | 38.86 | 29.93 | 18.00 | 49.00 |
| Setter utterance length         | 7.88  | 3.37 | 6.00 | 10.00 |
| Solver utterance length         | 2.08  | 2.07 | 1.00 | 2.00  |
| Number of setter instructions per episode | 3.98  | 1.80 | 3.00 | 5.00  |
| Idling proportion               | 0.69  | 0.26 | 0.50 | 0.91  |

Table 1 | Playhouse dataset statistics.

as the ability to identify basic objects. Second, as interactions are guided by the whims of human participants, collected behaviours might naturally collapse to a few characteristic specific modes, and hence might not span the behaviours we ultimately care about. Third, if left unchecked the data might be permeated with undesirable biases. A different approach could be to collect data using templated scripts that human experts must follow. However, this places a burden on researchers to infer the set of scripts whose translations span the desired range of behaviours, which is an impossible feat if one wishes to capture the contextual, ambiguous, and nuanced forces that drive natural human behaviour.

Our approach occupies a middle ground between these two possibilities. We centered Playhouse interactions on language games, which are a collection of both prompted interaction-types and free-form instructions (Lynch and Sermanet, 2020) from which human players can base their behaviour (Interactive Agents Team, 2020). All language games had the same basic structure: a setter would receive a prompt from which they could design an interaction, which they propose to a solver agent. For example, the setter might receive a prompt to “Ask the other player a question about the existence of an object”, and after some exploration to discover possibilities, the setter could translate this into the task: “Please tell me whether there is a blue duck in a room that does not also have any furniture”. The combination of (1) a small set of prompts, (2) the random, combinatoric structure of the Playhouse, and (3) the natural linguistic and intentional variation that humans exhibit ensured that interactions were unique, and together spanned the set of competencies we hoped agents to learn. To ensure we sufficiently captured the richness of natural human behaviour, we also included free-form instructions, which gave setters more leeway in guiding interactions, within certain constraints (namely, interactions should resemble, in the participants’ best judgement, those from the templates, and should be closely monitored for any arising ethical concerns). A notable example of creative free-form instructions is: “Now take any object that you like and hit the tennis ball off the stool so that it rolls near the clock, or somewhere near it.”

3. Multimodal Interactive Agent Training & Design

An abundance of expert human behavioural data and a lack of programmatic reward functions motivate a straightforward training regime centered on basic representation learning techniques, which has seen much success in recent large-scale models such as GPT-3 (Brown et al., 2020). Below we describe the essential ingredients: supervised learning of actions (Pomerleau, 1989; Osa et al.,
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and an additional cross-modal self-supervised learning objective that significantly improves performance beyond supervised learning alone. Since trained agents are difficult to evaluate given the free-form nature of the Playhouse environment, we also describe a protocol for assessing learned behaviour relative to human baselines.

3.1. Training

3.1.1. Behavioural Cloning

Training comprises a straightforward imitation learning technique, behavioural cloning (BC), which frames behaviour copying as a sequence learning problem. Our data comprise temporal sequences of human behaviour, called trajectories, which include observation sequences \( o_{1:T} \equiv (o_0, o_1, o_2, \ldots, o_T) \) and action sequences \( a_{1:T} \equiv (a_0, a_1, a_2, \ldots, a_T) \). Given a dataset of solver-only trajectories we implement the following loss function, which we derive from the forward Kullbach-Leibler divergence between the expert and agent policies in Interactive Agents Team (2020):

\[
\mathcal{L}^{bc}(\theta) = -\frac{1}{B} \sum_{n=1}^{B} \sum_{t=0}^{K} \ln \pi_{\theta}(a_{n,t} | o_{n,\leq t}),
\]

where \( B \) is the minibatch size, \( K \) is the backpropagation-through-time window size.

3.1.2. Modality Matching using Contrastive Self-Supervised Learning

Techniques that improve generalization will benefit agents in the Playhouse because evaluation environments are bound to be unique from the agent’s training data. This is due to the combinatorics and programmatic randomness of the Playhouse (variations in house layouts, object existence, and object placement can produce an inexhaustible source of newness), and because of the dependence of the agent’s observations on its actions (deviations in observations or actions from that which are exactly specified by the data will drive the agent to never-before-seen states).

We found one contrastive self-supervised representation learning technique, which involves cross-modality matching (Alayrac et al., 2020), particularly useful in this regard. It is implemented as an auxiliary training loss wherein the agent must predict whether vision and language embeddings match (i.e., they are produced from a trajectory from the dataset as normal), or they do not match (i.e., visual embeddings are produced from the input image of one trajectory in the dataset, and language embeddings are produced from the language input from a different trajectory). The agent processes these visual and language embeddings using its perceptual encoder (see section 3.2), the output of which is fed to an MLP discriminator that produces a binary predictor of whether the embeddings match or not. Practically, we implement this at the level of the minibatch: the batch of data used for the behavioural cloning loss comprise the “matches”, and a shuffling of vision and language embeddings from the minibatch comprise the mis-matches:

\[
\mathcal{L}^{cr}(\theta) = -\frac{1}{B} \sum_{n=1}^{B} \sum_{t=0}^{T} \left[ \ln D_{\theta}(o_{n,t}^V, o_{n,t}^L) + \ln (1 - D_{\theta}(o_{n,t}^V, o_{SHIFT(n),t}^L)) \right],
\]

where \( B \) is the batch size and \( SHIFT(n) \) is the \( n \)-th index after a modular shift of the integers: \( 1 \rightarrow 2, 2 \rightarrow 3, \ldots, B \rightarrow 1 \), and superscripts denote the modality (\( V \) for vision, \( L \) for language). Although language emissions are sparse in each trajectory, we implement language input observations as “sticky”; e.g., upon the setter emitting a language utterance, the solver will repeatedly receive this same utterance as input until the setter emits a new utterance. This implies that there will always be vision and language pairs that can be matched (or not) at each timestep, except for the
first timesteps in an episode that occur prior to the setter speaking. For simplicity, we use \( D_\theta() \) to denote the processing of observations up through the agent’s perceptual encoder, and into a separate discriminator MLP, which is only engaged during learning. While the addition of this loss requires an extra forward pass through the perceptual encoder, we observe that the computational overhead results in less than a 1% deduction in training speed.

Figure 2 | Multimodal Interactive Agent (MIA) Design. A series of ResNet blocks downsample the incoming image, while language tokens index an learnable embedding table. Together these embeddings comprise the input to a multi-modal Transformer, whose output is aggregated and provided as input to an LSTM memory. The output of the LSTM conditions both the hierarchical movement policy and language policy, implemented as an LSTM (which unrolls 8x per input, producing 8 sets of consecutive movement actions) and a Transformer, respectively. MIA is trained using behavioural cloning on each of its actions (no-op, move, look, rotate, push and pull, grab, and text) in addition to an auxiliary contrastive loss. Please see the main text for full details.

3.2. Perception

MIA receives input from visual (96 × 72 RGB pixels) and symbolic (text-based language tokens) modalities. For vision we employ conventional ResNet blocks (He et al., 2016) (with strides 1, 1, 2, 2 per block and a consistent kernel shape of (3, 3), altogether comprising 20 total convolution layers), which produce a 24×18×512 output representation from the input image. For language processing, we produce embeddings from a tokenized version of language input by indexing a learnable embedding table with a vocabulary of 4000 subwords. The 432 (24 × 18) vectors from the visual spatial array, the language embeddings, and two dedicated output embeddings (akin to the “CLS”embeddings in the BERT model (Devlin et al., 2018)) are gathered to form the input to a multi-modal transformer (MMT) (Vaswani et al., 2017), consisting of 4 layers, 8 heads, and 512 embedding size. The output of the MMT is the concatenation of the two output embeddings and a feature-wise mean pooling of all other output embeddings (that is, all the embeddings that produce queries, which include the two dedicated output embeddings and the language embeddings. The visual embeddings are only cross-attended to, and hence only produce keys and values). This is then provided as input to a two-layer, 1024-unit LSTM “memory”, whose output is fed to each policy head.
3.3. Hierarchical Control

3.3.1. High-Level Control

In the non-hierarchical setting, MIA receives observations and produces a set of movement actions 15 times per second. In the hierarchical setting, new observations arrive only every 8 steps (i.e., 3.75 times per second), and thus, MIA is tasked with producing 8 consecutive sets of movement actions in a row before receiving a new observation. Hierarchical control is implemented with an LSTM that receives input from the “memory” LSTM, and unrolls for 8 steps, providing inputs to each of the movement policies (see section 3.3.2) on each of these 8 “internal” steps. Language actions are emitted from the high-level controller. They're sampled one token at-a-time, up to a maximum of 25 per high-level step, using the same vocabulary as for language-input tokenization. For the language policy we use a transformer with teacher forcing (4 layers, 8 heads, and 256 embedding size). The language policy, like the movement policies (see section 3.3.2) also models "no-ops", which are binary decisions to predict a non-action (during training) or produce a non-action (during acting).

3.3.2. Low-Level Control

MIA's movement action space largely resembles that used by humans: Look actions are modelled as a mouse movement to a bin in visual space \((-1, 1)\) for \(x\)– and \(y\)– coordinates, using 51 bins for each), implemented as two MLPs. Move actions are similarly modelled as a decision in a binned, two-dimensional translational-force space \((-1, 1)\) for \(up\) – \(down\) and \(left\) – \(right\) translations, using 101 bins for each), implemented as a MLPs. Object rotations (i.e., angular movements applied to objects when they are being grasped) are modelled along the three cardinal axes, implemented as a recursive discrete decision procedure whereby the agent first chooses from among 3 coarse bins between \((-1, 1)\), and then chooses from 3 finer bins within the previously chosen coarse bin, and so on, until a choice is made at a granularity of 0.1. This is implemented using an LSTM. Push and pull actions are similarly modeled. Grab actions are modelled as a binary action (e.g., mouse click), implemented as an MLP. We also found a form of autoregressivity to be useful: within each policy, look actions in the \(x\)– dimension condition look actions in the \(y\)– dimension. Rotations in the \(x\)– and \(y\)– dimensions condition rotation in the \(z\)– dimension. Between policies, move actions condition look actions, and move and look actions condition rotation actions, and move, look, and rotation actions condition push and pull actions. There is no autoregressivity across time.

3.4. Evaluation

We monitored MIA's performance in three ways: (1) via the total loss and its sub-components (see Figure 2A), (2) via scripted probe tasks that serve as a heuristic evaluation of rolled-out behaviours during training (Figure 2C), and (3) via live human-agent interactions (Figure 2B). In some domains, like language, log probabilities correlate well with model “performance”. However, in our setting this proved to not be true; e.g., drastically overfit models can perform better, and architecture changes that improve log probabilities can result in worse performance. Therefore, scripted probe tasks and live human-agent interactions are central to agent iteration, despite being more computationally demanding, slow, and subjective.

3.4.1. Scripted Probe Tasks

We constructed a suite of probe tasks to evaluate performance on several dimensions, including counting, identifying colors, lifting items, and more refined object positioning. For each task, agents were presented with a templated instruction (e.g., “place a duck on top of the table”), which was then
evaluated using a scripted reward model. Crucially, these reward models were used for evaluation only; agents never received rewards from the environment for the purposes of optimization.

### 3.4.2. Human Evaluation

Since we aim to build agents that can carry our natural interactions with humans, the ultimate metric we care about is human evaluation of agent interactions. So, upon training agents we asked human participants to interact with agents in a setting that closely mimicked data collection. Humans played the role of the setter, while agents performed the role of the solver. Importantly, humans were not adversarial: they did not search for agent failures, nor did they try to coax the agent into undesirable modes of behaviour. Rather, they carried out interactions similar to those as when they interacted with humans during data collection. After an interaction, human setters provided feedback as to whether the interaction was successful, which we then report as the agent success rate.

### 4. Performance, Ablations, & Modifications

MIA achieves over 70% success rate in human-rated online interactions, representing 75% of that achieved by humans in similar positions. As indicated in figure 3, according to our probe tasks MIA is most successful at “going” and “lifting”, and less successful at more demanding motor tasks (such as positioning objects relative to each other) and language production tasks demanding complex cognition (such as counting). The results from our probe tasks also reveal weaknesses in scripting probe tasks for evaluation. For example, performance is low on tasks that ask the agent to mention the colors of items in the room, though this is not necessarily because the agent is poor at identifying colors. Rather, limitations in anticipating possible valid natural language responses (“blue”, “light blue”, “cyan”, “sky blue”, etc.) prevent us from accurately assessing the model’s abilities. Similar logic applies to motor tasks (e.g., how high should an agent lift an object to be “successful”? What if the object is a table?). Indeed, post-hoc correction of our reward metric for “counting” can reveal a pre- and post-fluctuation of up to 30% on the evaluated score (data not shown). It is precisely these researcher-centric deficiencies, if permeated into a reward model for reinforcement learning, that would result in less robust and less natural agent behaviours.

Figure 3 also indicates that we are in the over-fitted regime of training. The total loss shows mild overfitting—and the movement behavioural cloning loss perhaps none at all—but the language behavioural cloning and contrastive representation losses clearly indicate that agents could profit from more data. These results also highlight an aspect of integrated-agent training that is unique from more constrained domains like language modeling: the dynamics of each loss are different, making it difficult to apply techniques, such as model scaling, in a straightforward manner. While modeling motor actions could profit from larger models, this might be counteracted by more severe overfitting when modeling language. Nevertheless, a relatively simple way to improve performance (which we motivated further in section 5) is to collect and train on more data.

We performed a series of ablations and agent design modifications to better understand the role of various components in MIA. In particular, the ablations assessed the impact of removing visual inputs, language inputs, the auxiliary contrastive representation loss, and the hierarchical movement policy. We also determined the importance of visual resolution in the multi-modal transformer by modifying the structure of visual processing to downsample the image to $6 \times 5 \times 512$ (i.e., producing 30-pixel feature maps as opposed to 432-pixel feature maps in the baseline).

As with many ablations, there is a confounding factor: removing agent components alters the agent’s computational capacity (i.e., the number of total parameters), which can impact performance (see section 5). Unfortunately, there is no clear way to compensate for these parameter differences.
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**Figure 3 | Performance, ablations and modifications.** A Loss curves. The top row shows the loss of MIA on training and validation datasets during training. After training on 5G timesteps the behavioural cloning loss on movement actions is fairly flat while the behavioural cloning loss on language actions and the contrastive representation learning loss have started to overfit. B Human evaluation. The bottom left plot compares the success rate of humans and MIA, with various ablations applied, when playing the role of a solver in a Playhouse language game, as judged by human setters. The episodes are divided according to the prompt given to the human setter, as either “Instruction following”, e.g. “Ask the other player to put something on top of something else”, or “Question answering”, e.g. “Ask the other player a question about the color of something”. C Scripted probe tasks. The bottom right plot compares the success rate of humans and agents on six automated testing tasks. These supply a pre-scripted setter question or instruction (e.g. Position = “Put the X near the Y”), where the response can be unambiguously scored as successful or unsuccessful by the environment engine.

However, as our data will show in section 5, since the differences in parameter counts for these ablations are minimal, performance loss due to decreased capacity should be minimal compared to the effects of the ablations themselves. The parameter counts for the various agents are: baseline 57M, no language input 56M, no vision 52M, no auxiliary contrastive representation loss 56M, no hierarchical movement policy 66M, and modified visual processing to further downsample the input image 57M.

As the results show, there are clear performance degradations for each ablation and modification. Downsampling the input image less (i.e., using more pixels as input to the MMT) is best, though intriguingly, using a Vision Transformer-style technique (Dosovitskiy et al., 2020) that extracts image patches from the full resolution input image does not perform as well as using ResNet blocks (data not shown), which corroborates recent similar findings (Wu et al., 2021).

While we provide evidence that the hierarchical movement policy significantly improves agent performance, the reason for its impact is unclear. We hypothesize that a few effects could be important: First, by forcing the agent to act every 8 steps, we cause adjacent observations to be more visually
distinct, which could aid learning (consider the converse scenario if the agent were forced to act with a higher frequency: adjacent observations would be nearly identical but have potentially different target policies, which creates complications for learning). Second, our implementation offers a form of data augmentation, as we can randomly vary the initial observation to be any of the first 8 observations at the beginning of a given data trajectory. Third, the agent may genuinely, and implicitly learn useful hierarchical policies wherein its lower-level controller captures repeatable action sequences that merely need to be triggered by the higher-level controller.

Notably, when MIA is trained on the same Playroom data as in Interactive Agents Team (2020), it outperforms the reported behavioural-cloning agent, which is augmented with privileged information, by 20% on average across the single-room scripted probe tasks.

5. Data and Parameter Scaling

![Figure 4](image.png)

Figure 4 | **Data and model scaling.** Total loss, scripted probe performance, and human evaluation for data and model scaling. All agents were trained to 5G steps, coinciding with convergence on scripted probe tasks, except for the early stopping condition which ends training at the point of lowest validation loss. Error bars represent standard error across 3 seeds. The baseline model with 56M parameters was trained on differently-sized datasets (A, B, C. top row), or differently sized models were trained on the full dataset (A, B, C. bottom row). Validation losses decrease as dataset sizes increase, although this trend is not true for increasing model size (A). Nevertheless, for scripted probe tasks (B) and human evaluation (C) there are clear improvements when increasing both dataset size and model size. Performance on both scripted probe tasks (data not shown) and human evaluation (C) is worse at the early stopping point, without exception.

Contemporary machine learning research has uncovered remarkable empirical effects regarding scale (Kaplan et al., 2020, e.g.); in particular, model performance scales using a power-law trend with dataset size, model size (in terms of number of parameters), and compute. These effects have traditionally been observed in the language domain, which is characterized by massive dataset sizes, standardized architectures, and refined training protocols. In this work, however, we are in a decidedly different regime. We assume we have collected an abundance of data, but the results in figure 4, particularly the losses, indicate that we could still be in a “low data” regime where overfitting is
more pronounced and scaling effects are more difficult to see (Kaplan et al., 2020). Moreover, the cognitively rich tasks force us to iterate our model architecture as we explore the effects of our choices on, for example, memory formation and retrieval, language production, motor control, and visual object identification, making model inductive biases a perpetually confounding factor in our research. This architectural flux, combined with a complicated training protocol involving a handful of losses to optimize, lead to natural questions of whether scaling effects can also be observed in the Playhouse.

In figure 4 we present some mixed evidence after training four differently-sized models (5M, 16M, 56M (baseline), and 121M) on five differently-sized datasets (\(\frac{1}{10}, \frac{1}{5}, \frac{1}{4}, \frac{1}{2}\), and the full dataset size). In terms of the total training loss, larger models achieve lower values for each dataset size, and predictably, training losses are lower in the smaller data regimes (implying an easier ability to memorize particular examples as dataset sizes decrease). The effects of scaling on the validation loss are more difficult to interpret: the total loss shows little difference between model sizes, though it displays a clear trend with dataset size when keeping model size constant. When analyzing individual losses we see a clear effect for some, such as the hierarchical movement BC loss. The language and contrastive representation losses, on the other hand, show clear and quick overfitting for each model (as in figure 2).

To get a clearer picture we also measured the performance metric that we ultimately care about: human-evaluated behavioural competency during online interactions. The results here are consistent (low standard error across seeds) and clear: increasing model size and dataset size clearly benefit performance.

Altogether, these results lead us to believe that we may be in the low-data regime for the Playhouse, suggesting that performance gains are to be had by collecting more data (and then subsequently scaling model size). The results also highlight the problems with analyzing the effects scaling in these more complicated settings where a handful of losses, jointly optimized, each exhibit different learning dynamics and interact with each other in unknown ways: the values we observe for the losses may obfuscate the effects of scale on ultimately more important behavioural metrics.

6. Behavioural Transfer

![Figure 5](image-url)

**Figure 5 | Behavioural Transfer.** We quantified the agent performance when learning a new noun (a drum) or verb (to clear) as a function of quantity of human demonstrations, measured in hours. With both a new noun and new verb agent performance quickly improves with mere hours of demonstration experience.

We investigated how much data is needed to learn how to interact with a new, previously unseen object (new noun). Starting with a pre-trained MIA, we began new training on varying amounts of data from humans interacting with a novel object (a drum), in addition to the data from the original
dataset. The amount of data is quantified in hours of new data measured as real time experience (note: this measures the time required to collect this data in human hours, not the amount of time the agent experiences it during the course of supervised training). After training, we evaluated the ability of the agents to perform simple tasks with the new object (answering about its color and lifting it). We observe that using less than 12 hours of human interaction is enough to reach the final performance on subsequent language and motor tasks involving drums. (figure 5 B).

To study how much data is needed to learn a new command (the verb “to clear”), we again start with a pre-trained MIA and co-train it on novel episodes where humans are instructed to remove all objects from a surface (e.g., table or shelf). The original pre-trained agent is incapable of performing this behavior, which is to be expected as this command is not present in the original data. However, after training on novel episodes containing examples of this behavior, we observe that with around 1 hour of human demonstrations the agent reaches near optimal performance at this task.

Altogether these results suggest that while agents do not generalize zero-shot to new nouns or verbs, they have a sufficiently rich behavioural prior such that subsequent training on small amounts of experience allow rapid adaptation to new objects and actions.

7. Discussion & Conclusion

In this work we've built upon the paradigm introduced in Interactive Agents Team (2020) to construct an agent, MIA, that emphasises a holistic integration of embodied control, perception, and language understanding and production (McClelland et al., 2019; Lake and Murphy, 2021). The goal was to elicit behaviours that are naturalistic and appropriately exploratory (Turing, 1950; Winograd, 1972), and hence, are capable of subsequent efficient tuning using reinforcement.

Imitation of human behaviour was central to our training approach. Unlike other domains, like language (Devlin et al., 2018; Radford et al., 2019; Brown et al., 2020), human behavioural data in 3D simulated worlds often needs to be collected and curated from scratch. Some previous work has collected human (child) multimodal behavioural data (Roy et al., 2006; Yoshida and Smith, 2008; Sullivan et al., 2020), but has not used it to train artificial agents. Social learning, imitation, and mimicry is prevalent in the the animal kingdom (Laland, 2004; Byrne, 2009). In humans, infants naturally imitate both the language and actions they encounter (Chomsky, 1959; Heyes and Galef Jr, 1996). However, in AI, imitating multi-modal, embodied behavioural data is especially challenging because latent in all trajectories of human experience are intentions and goals. It is not clear whether we currently possess the algorithms and models that can interpret implicit causal factors of human behaviour (Ortega et al., 2021), and hence, can engage in consistent and coherent naturalistic interactions. Nevertheless, as in previous work we observe that some techniques, such as dataset and model scaling, reliably improve performance as measured by human evaluators. In addition, a number of architectural improvements proved crucial: self-supervised learning that gauged whether cross-modality representations “matched” or not, and hierarchical control of motor actions both substantially improved agent performance.

Our setting is a natural one in which to study “language grounding” (Harnad, 1990), wherein sensorimotor embodiment combines with language production and understanding to produce models that more closely approach human-like symbolic behaviour (Santoro et al., 2021). Work in robotics and in 3D simulated environments has pursued similar ideas, such as natural language conditioning of tasks (Lynch and Sermanet, 2020; Hill et al., 2019; Anderson et al., 2017; Das et al., 2018). However, to our knowledge our work is unique in combining language conditioning with unconstrained language production, in an embodied setting demanding complex navigation and manipulation for upwards of 5 minutes, with a human in-the-loop.
An exciting direction that remains unexplored is to also train setter agents using the data produced by humans whose role it is to set tasks and questions. “Self-play”-like settings have proved powerful in developing agents in games, where agent roles are symmetric, and reward signals provide positive and negative feedback signals per experience (Silver et al., 2016; Vinyals et al., 2019). It is less clear, however, how one could leverage agent setter-agent solver dynamics in the Playhouse environment where roles are asymmetric and rewards do not exist, beyond using the extra data for generic representation learning.

One challenge for future work pertains to the diversity and flexibility of language comprehended or produced by our agents, as it is far more constrained (both semantically and syntactically) than in the case of non-embodied systems trained on web-scale text data (Brown et al., 2020). Nevertheless, a useful intelligent robot would not need to be an unconstrained source of knowledge, provided that it can communicate efficiently and effectively about its physical environment.

In addition, the control and perception challenges faced by our agents are substantially simpler than they would be in a physical robot. While our data is generated by participants sitting at computers, making research comparatively rapid, analogous data for a physically-embodied interactive agent might require teleoperation of specialized and expensive hardware (Jang et al., 2021). On the other hand, unlike many current robotic systems, our agent must integrate learning perception and control with memory and language. Generic models for perception and control skill learning are rapidly improving, and we hope that such techniques might soon combine with the approach described here to yield a system capable of all of these things. Another key challenge when transitioning from simulation to reality is the collection of adequate data.

A final pressing challenge for future work is how to appropriately evaluate interactive agents like MIA. None of our current mechanisms—training loss, scripted probe tasks, and online human-agent evaluation—are ideal for research. Training losses and scripted probe tasks are only heuristic measures of performance; they generally correlate with better agents, but these metrics do not necessarily move monotonically with human judgement. This is particularly troublesome since we explicitly optimize the training loss, and not human judgement, and ideally the measure that we optimize should be precisely the measure that we ultimately care about. On the other hand, real-time human-agent evaluation is expensive, requiring many human hours. It is also high-variance and inconsistent, as live human interactions will necessarily be different every time, and humans may shift their content over time. Nevertheless, models trained to mimic human judgements may ultimately help us tackle open-ended evaluation for multi-modal and real-time environments.
8. Authors & Contributions

Josh Abramson contributed to agent development, imitation learning, data and tasks, running and analysis of experiments, engineering infrastructure, writing, and as a technical lead.

Arun Ahuja contributed to agent development, imitation learning, data and tasks, running and analysis of experiments, engineering infrastructure, writing, and as a technical lead.

Arthur Brussee contributed to environment development.

Federico Carnevale contributed to agent development, imitation learning, running and analysis of experiments, writing, and as a sub-effort lead for agent development.

Mary Cassin contributed to environment development.

Felix Fischer contributed to engineering infrastructure.

Petko Georgiev contributed to agent development, engineering infrastructure, evaluation development, environment development, running and analysis of experiments and as a technical lead.

Alex Goldin contributed to project management.

Mansi Gupta contributed to engineering infrastructure.

Tim Harley contributed to engineering infrastructure.

Felix Hill contributed to environment development.

Peter C Humphreys contributed to agent development and writing.

Alden Hung contributed to agent development, imitation learning and as a sub-effort lead for agent development.

Jessica Landon contributed to data and tasks, engineering infrastructure, evaluation development and as a sub-effort lead for data and evaluation.

Timothy Lillicrap contributed to agent development, imitation learning, data and tasks, environment development, evaluation development, writing, and as an effort lead.

Hamza Merzic contributed to technical infrastructure.

Alistair Muldal contributed to data and tasks, evaluation development and as a sub-effort lead for data and evaluation.

Adam Santoro contributed to agent development, imitation learning, running and analysis of experiments and writing.

Guy Scully contributed to project management.

Tamara von Glehn contributed to agent development, engineering infrastructure, imitation learning and running and analysis of experiments.

Greg Wayne contributed to agent development, imitation learning, data and tasks, environment development, evaluation development, writing, and as an effort lead.

Nathaniel Wong contributed to environment development.

Chen Yan contributed to agent development, data and tasks, engineering infrastructure, imitation learning, running and analysis of experiments and writing.

Rui Zhu contributed to agent development, engineering infrastructure, environment development and writing.

Corresponding Authors:
Greg Wayne (gregwayne@deepmind.com) & Timothy Lillicrap (countzero@deepmind.com)

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