Grounded Language Learning Fast and Slow

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Abstract

Recent work has shown that large text-based neural language models, trained with conventional supervised learning objectives, acquire a surprising propensity for few- and one-shot learning. Here, we show that an embodied agent situated in a simulated 3D world, and endowed with a novel dual-coding external memory, can exhibit similar one-shot word learning when trained with conventional reinforcement learning algorithms. After a single introduction to a novel object via continuous visual perception and a language prompt (“This is a dax”), the agent can re-identify the object and manipulate it as instructed (“Put the dax on the bed”). In doing so, it seamlessly integrates short-term, within-episode knowledge of the appropriate referent for the word “dax” with long-term lexical and motor knowledge acquired across episodes (i.e. “bed” and “putting”). We find that, under certain training conditions and with a particular memory writing mechanism, the agent’s one-shot word-object binding generalizes to novel exemplars within the same ShapeNet category, and is effective in settings with unfamiliar numbers of objects. We further show how dual-coding memory can be exploited as a signal for intrinsic motivation, stimulating the agent to seek names for objects that may be useful for later executing instructions. Together, the results demonstrate that deep neural networks can exploit meta-learning, episodic memory and an explicitly multi-modal environment to account for fast-mapping, a fundamental pillar of human cognitive development and a potentially transformative capacity for agents that interact with human users.

1 Introduction

Language models that exhibit one- or few-shot learning are of growing interest in machine learning applications because they can adapt their knowledge to new information, providing a flexible and malleable user interface [Brown et al., 2020; Yin, 2020]. One-shot language learning in the physical world is also of great interest to developmental psychologists; fast-mapping, the ability to bind a new word to an unfamiliar object after a single exposure, is a much studied facet of child learning thought to play a critical role in human language acquisition [Carey and Bartlett, 1978]. An embodied learning system that executed fast-mapping with the same flexibility as the best large-scale text-based language models could lead to similarly improved human-agent interaction between users and game-based agents, virtual-reality avatars or robotic assistants.

We take a step towards this goal by developing an embodied agent situated in a 3D game environment that can learn the names of entirely unfamiliar objects in a single exposure and immediately apply this knowledge to carry out instructions requiring the identification and manipulation of those objects. The agent observes the world via active perception of raw pixels, and learns to respond to linguistic stimuli by executing sequences of motor actions allowing it to move and manipulate objects. It is trained by a combination of conventional reinforcement learning and predictive (semi-supervised) learning. We find that an agent architecture consisting of standard neural network components for
processing vision and language is sufficient to learn to follow language instructions whose meaning is preserved across episodes. However, learning to fast-map novel names to novel objects in a single episode relies on semi-supervised perceptual prediction mechanisms and a novel form of explicit external memory, inspired by the dual-coding theory of knowledge representation [Paivio, 1969], in which retrieval mechanisms can operate independently on visual and/or language representations. With these components, a single agent can exhibit both slow word learning and fast-mapping, and the two learning processes are often complementary. Moreover, the agent exhibits an emergent propensity to integrate both fast-mapped and slowly acquired word meanings in a single episode, successfully executing instructions such as "put the dax in the box" that depend on both slow-learned ("put", "box") and fast-mapped ("dax") word meanings without being trained directly on instructions of that form or prior experience of the particular objects involved.

Via controlled generalization experiments, we find that the agent is reasonably robust to a degree of variation in the number of objects involved in a given fast-mapping task at test time. The agent also exhibits above-chance success when presented with the name for a particular object in the ShapeNet taxonomy [Chang et al., 2015], and then instructed (using that name) to interact with a different exemplar from the same object class, and this propensity can be further enhanced by specific meta-training. Exploring environmental factors that support this robustness, we find that both the number of unique objects observed by the agent during training and the temporal aspect of its perceptual experience of those objects contribute critically to its ability to generalize, particularly its ability to execute fast-mapping with entirely novel objects. Finally, we show that a dual-coding memory schema can provide a more effective basis to derive a signal for intrinsic motivation than a more conventional (unimodal) memory. Equipped with this intrinsic curiosity, an agent can resolve long episodes requiring fast-binding when there are no intermediate environment rewards to stimulate the requisite information discovery.
2 An environment for fast word learning

We conduct experiments in a 3D room built with the Unity game engine. In a typical episode, the room contains a pre-specified number $N$ of everyday 3D rendered objects from a global set $G$ (in this work we consider $3 \leq N \leq 12$, partly because any more objects results in a very crowded environment). In all training and evaluation episodes, the initial positions of the objects and agent are randomized. The objects include everyday household items such as kitchenware (cup, glass), toys (teddy bear, football), homeware (cushion, vase), and so on.

Episodes consist of two phases: a discovery phase, followed by an instruction phase (see Figure 1). In the discovery phase, the agent must explore the room and fixate on each of the objects in turn. When it fixates on an object, the environment returns a string with the name of the object (which is a nonsense word), for example "This is a dax" or "This is a blicket". Once the environment has returned the name of each of the objects (or if a time limit of 30s is reached), the positions of all the objects and the agent are re-randomized and the instruction phase begins. The environment then emits an instruction, for example "Pick up a dax" or "Pick up a blicket". To succeed, the agent must then lift up the specified object and hold it above 0.25m for 3 consecutive timesteps, at which point the episode ends. If the agent first lifts up an incorrect object, the episode also ends (so it is not possible to pick up more than one object in the instruction phase). To provide a signal for the agent to learn from, it receives a scalar reward of 1.0 if it picks up the correct object in the instruction phase. In the default training setting, to encourage the necessary information-seeking behaviour, a smaller shaping reward of 0.1 is provided for visiting each of the objects in the discovery phase. During evaluation, no rewards are available to the agent – they are simply logged to measure its performance.

Given this two-phase episode structure, two distinct learning challenges can be posed to the agent. In a slow-learning regime, the environment can assign the permanent, everyday name (e.g. "cup", "chair") to objects in the environment whenever they are sampled. In this regime, the agent can entirely ignore the discovery phase of episodes, since its long-term knowledge of word-object associations will enable it to pick up the correct target object based on the instruction alone.

By contrast, in the fast-mapping regime, which is the principal focus of this work, the environment assigns a unique nonsense word to each of the objects in the room at random on a per-episode basis. The only way to consistently solve the task is therefore to record the connections between words and objects in the discovery phase, and apply this (episode-specific) knowledge in the instruction phase to determine which object to pick up.

Importantly, specific modifications to the task specification procedure can be made to analyse learning and generalization in the agent. For instance, the number of objects $N$ can be varied, entirely new objects can be introduced from a heldout set $H$ (i.e. $H \cap G = \emptyset$), or a specific intervention can be made between the discovery phase and the instruction phase in the form of a focused modification to the objects (in addition to the default position randomization).

3 Memory architectures for agents with vision and language

The agents that we consider build on a standard architecture for reinforcement learning in multi-modal (vision + language) environments (see e.g. Chaplot et al. [2018], Hermann et al. [2017], Hill et al. [2020]). The visual input (raw pixels) is processed at every timestep by a convolutional network with residual connections (a ResNet). The language input is passed through an embedding lookup layer plus self-attention layer for processing. Finally, a core memory integrates the information from the two input sources over time. A fully-connected plus softmax layer maps the state of this core memory to a distribution over 46 actions, which are discretizations of a 9-DoF continuous agent avatar. A separate layer predicts a value function for computing a baseline for optimization according to the IMPALA algorithm [Espeholt et al. 2018].

We replicated the results of previous studies by verifying that a baseline architecture with LSTM core memory [Hochreiter and Schmidhuber 1997] could learn to follow language instructions when trained in the slow-learning regime. However, the failure of this architecture to learn to perform above-chance in the fast-learning regime motivated investigation of architectures involving explicit external memory modules.
Recent work has shown how, under specific training circumstances, neural networks can acquire an ability for fast learning, a process called meta-learning \cite{Duan2016, Finn2017, Lake2019, Yin2020}. In many cases, particularly when models are required to learn about visual categories from pixel input, an explicit (slot-based) external memory can be important for getting meta-learning to work successfully \cite{Santoro2016, Vinyals2016}. The external memory allows networks to make explicit comparisons between observed category exemplars and novel stimuli, rather than having to compress this knowledge of the past into the transition weights or state of a recurrent network or LSTM \cite{Hung2019, Wayne2018, Graves2016}. To our knowledge, however, explicit external memories have not been applied in contexts like our fast-mapping environment where both vision (pixels) and language (strings) are observed as input data. Given these two observation channels, there are various ways in which observations can be represented and retrieved in external memory. The approaches we consider here differ in the degree to which the information from different modalities and time steps is integrated, stored and retrieved.

**Differentiable Neural Computer (DNC)** \cite{Wayne2018, Graves2016} develop an agent memory based on the Differentiable Neural Computer \cite{Graves2016}. In this model, at each timestep \(t\) a latent vector \(e_t = \psi(h_{t-1}, r_{t-1}, x_t)\), computed from the previous hidden state \(h_{t-1}\) of the agent’s core memory LSTM, the previous memory read-out \(r_{t-1}\), and the current inputs \(x_t\), is written to a slot-based external memory. In our setting, the input \(x_t\) is a simple concatenation \([v_t, l_t]\) of the pooled output of the vision network and the embedding returned by the language network. Before writing to memory, the latent vector \(e_t\) is also passed to the core memory LSTM to produce the current state \(h_t\). The agent reads from memory by producing a query vector \(q(h_t)\) and read strength \(\beta(h_t)\), and computing the cosine similarity between the query and all embeddings currently stored in memory \(e_t (i < t)\). The external memory returns only the \(k\) most similar entries in the memory \([m^j]_{j \leq k}\) (where each \(m^j = e_i\) for some \(i < t\) and \(k\) is a hyperparameter), and corresponding scalar similarities \([s^j]_{j \leq k}\). The returned embeddings are then aggregated into a single vector \(\hat{r}_t\) by normalizing the similarities with a softmax and taking a weighted average of the embeddings:

\[
\hat{s}^j = \frac{\exp(\beta s^j)}{\sum_{j'} \exp(\beta s^{j'})}
\]

\[
\hat{r}_t = \sum_{j \leq k} \hat{s}^j m^j
\]

This reading procedure is performed simultaneously by \(n\) independent read heads, and the results \([\hat{r}_t^1, \ldots, \hat{r}_t^n]\) are concatenated to form the current memory read-out \(r_t\). The vectors \(e_t\) and \(h_t\) are output to the policy and value networks.

**Dual-coding Episodic Memory (DCEM)** We propose an alternative external memory architecture inspired by the Dual-Coding theory of human memory \cite{Paivio1969}, which conjectures that knowledge of the same situation is retained in modality-specific (visual and verbal) codes. To implement this idea, rather than writing latent embeddings based on its core memory state \(h_{t-1}\), the agent writes (separately) the current visual and linguistic observation embeddings, \(v_t\) and \(l_t\), into a key-value external memory with a distinct column corresponding to each modality. Depending on the task, either of these columns can function as the keys of the memory, with the other column as the values. Alternatively, both can operate simultaneously as keys and values. In each case, to read from the memory, a query \(q(v_t, l_t, h_{t-1})\) is computed and compared to the keys of the memory by cosine similarity. The \(k\) values whose keys are most similar to the query, \([m^j]_{j \leq k}\), are returned, again with corresponding scalar similarities, \([s^j]_{j \leq k}\). As above, the returned embeddings are then aggregated into a single memory \(r_t\) this time with a weighting-plus-self-attention mechanism as follows.

The similarities are first normalized into a distribution

\[
\hat{s}^j = \frac{(1 - s^j)^{-1}}{\sum_{j'} (1 - s^{j'})^{-1}}
\]

and then applied to weight the memories \(\tilde{m}^j = \hat{s}^j m^j\). These \(k\) weighted memory returns are then passed through a (single layer, single attention-head query-key-value) self-attention layer \(A\) and
We compared the different memory architectures with and without semi-supervised reconstruction. As before this is repeated for \( n \) read heads, and the results concatenated to form the current memory read-out \( r_t \). \( r_t \) is then concatenated with \( h_{t-1} \) and new inputs \( x_t \) to compute a latent vector \( e_t = w(h_{t-1}, r_t, x_t) \), which is passed to the core memory LSTM to produce the subsequent state \( h_t \), and finally \( e_t \) and \( h_t \) are output to the policy and value networks.

For the tasks that we consider here, we find that treating the language memory column as keys and the image column as values is most effective. In the more general case where an agent was required to produce as well as respond to language, executing the same process with the key-value roles swapped may be required.

**Gated Transformer XL** We also consider an architecture where the agent’s core memory is a Transformer [Vaswani et al., 2017], including the gating mechanism developed to improve learning outcomes in RL agents by Parisotto et al. [2019]. The only difference from the model as described by [Parisotto et al., 2019] is that we consider a multi-modal environment, where the observations \( x_t \) passed to the core memory are the concatenation of visual and language observation embeddings. We use a 4-layer Transformer with a principal embedding size of 256 (8 parallel heads with query, key and value size of 32 per layer) and a total input window of 1024 timesteps.

Note that there is no reason why the Transformer architecture as described above cannot exploit the principle of dual-coding in a similar way to the DCEM architecture. Information flow in the transformer is based on self-attention mechanisms that combine the current observation with past observations. Since these observations are concatenations of visual and language input, the Transformer can easily execute modality-specific ‘reads’ and ‘writes’ when learning to manage its memory. Given that transformers also include skip-connections between layers, it may also be similarly easy for the network to pass observation-level, modality-specific information directly to the agent’s policy if doing so improves task performance.

### 3.1 Training setup

**Policy learning** The agent’s policy is trained by minimizing the standard V-trace off-policy actor-critic loss [Espeholt et al., 2018]. Gradients flow through the policy layer and the core LSTM to the memory’s query network and the embedding ResNet and self-attention language encoder. We also use a policy entropy loss like in [Mnih et al., 2016] [Espeholt et al., 2018] to encourage random-action exploration. For more details and hyperparameters see Appendix A.

**Observation reconstruction** In order to provide a stronger representation-shaping signal, we make use of a reconstruction loss in addition to the standard V-trace setup. The latent vector \( e_t \) is passed to a ResNet \( g \) that is the transpose of the image encoder, and outputs a reconstruction of the image input \( d_t^{im} = g(e_t) \). The image reconstruction loss is the cross entropy between the input and reconstructed images:

\[
l_{t}^{im} = -x_t^{im} \log d_t^{im} - (1 - x_t^{im}) \log(1 - d_t^{im}).
\]

The language decoder is a simple LSTM, which also takes the latent vector \( e_t \) as input and produces a sequence of output vectors that are projected and softmaxed into classifications over the vocabulary \( d_t^{lang} \). The loss is:

\[
l_t^{lang} = -x_t^{lang} \log d_t^{lang} - (1 - x_t^{lang}) \log(1 - d_t^{lang}).
\]

For more details regarding the flow of information and gradients see Appendix A.

### 4 Experiments

We compared the different memory architectures with and without semi-supervised reconstruction loss on a version of the fast-mapping task involving three objects \( (N = 3) \) sampled from a global set of 30 \( (G = 30) \). As shown in Table 1, only the DCEM and TransformerXL architectures reliably solve the task after \( 1 \times 10^9 \) timesteps of training. On average, the DCEM architecture required fewer training steps than the TransformerXL to obtain optimal performance. Importantly, the TransformerXL and DCEM are the only two architectures that can exploit the principle of dual-coding.
Mean accuracy
Architecture after (1e9) steps
LSTM 0.33
LSTM + Recons 0.55
DNC + LSTM 0.33
DNC + LSTM + Recons 0.48
TransformerXL 0.34
TransformerXL + Recons 0.98
DCEM + LSTM 0.34
DCEM + LSTM + Recons 0.98
Random object selection 0.33

Table 1: Left: Performance of different memory architectures when training on a three-object fast-mapping task with $|G| = 30$. LSTM Long Short-Term Memory [Hochreiter and Schmidhuber, 1997]. DNC Differentiable Neural Computer [Graves et al., 2016]. TransformerXL [Vaswani et al., 2017, Dai et al., 2019], gating mechanism from [Parisotto et al., 2019]. Recons: reconstruction mechanism proposed by [Wayne et al., 2018]. DCEM Dual-Coding Episodic Memory (this work). Right: Learning curves for the four architectures (with reconstruction R), each showing mean ± S.E. over 5 random seeds.

by enabling modality-specific memory query and retrieval mechanisms. The results therefore offer some empirical support for the benefits of the dual-coding principle.

4.1 Generalization

If our long-term objective is to develop agents that can interact with humans (and other agents), and adapt flexibly to human input and teaching, the use of (meta)learning to solve fast-binding tasks from millions of training episodes is only the first step. An equally critical condition is that the knowledge acquired by an agent during this meta-training — particularly its memory-management and binding mechanisms — is sufficiently general to enable sensible inference and behaviour when aspects of the agent’s experience diverge from the setting in which it was trained. To explore the generalization capabilities of our agents, we subjected trained agents to various behavioural probes, and measured their performance across many thousands of episodes without updating their weights. Unless stated otherwise, all experiments in this section involve the DCEM+Recons agent.

4.1.1 Number of objects

In our default fast-mapping task, the agent must explore its environment exhaustively and retain in episodic memory a word-object binding for each of the three objects it encounters. However, for an embodied agent interacting with a human user, there is no reason why the knowledge provided to a trained agent should be limited to just three words and their referents. We therefore probed the robustness of the agent’s exploration policy, and memory writing and reading mechanisms, to fast-mapping episodes with different numbers of objects. In all conditions, the same objects appear in both the discovery and instruction phases of the episode, and the objects are sampled from the same global set $G$ ($|G| = 30$).

As shown in Figures 2(b) and (c) (red curves), with the (default) meta-training setting involving three objects in each episode, performance of the trained agent on episodes involving five objects is approximately 70%, and with eight objects around 50%. This sub-optimal performance suggests that, with this meta-training regime, the agent does tend to overfit, to some degree, to the “three-ness” of its experience. That said, it should also be noted that its accuracy scores in both the five-probe and the eight-probe setting are substantially above that of an agent that has the correct exploration behaviour during the discovery phase, but selects objects at random during the instruction phase ($\frac{1}{3} = 20\%$ and $\frac{1}{5} = 12.5\%$, respectively). Figure 2(b) shows, however, that the overfitting of the agent can be alleviated by increasing the number of objects during meta-training. Importantly, the extent to which the agent can extrapolate to more objects seems to grow itself with the number of objects used during meta-training. An agent meta-trained with five objects and probed with eight objects (green curve,
Figure 2: Accuracy of agents trained on probe trials involving a different number of total objects for agents meta-trained with different numbers of total objects.

Figure 2(c)) achieves higher accuracy (90%) than an agent trained with three objects and probed with five (75%; red curve, 2(b)) – even though chance performance in the former case is substantially lower (i.e. the task is objectively ‘harder’). It is worth noting here that, in terms of fast-mapping with multiple objects, the agent performs notably better than human children: 40-month-old infants can execute fast-mapping for a single-object per trial, but their performance degrades substantially when required to fast-map two words to two objects in a single trial [Wilkinson et al., 2003].

Finally, Figure 2(a) confirms, perhaps unsurprisingly, that the agent has no problem generalizing to episodes with fewer objects than it was trained on.

4.1.2 Novel objects

A truly general binding mechanism should allow agents to quickly learn about any arbitrary new object, not only those of which it has some previous experience. To probe this ability, we instrumented trials with objects sampled from a global test set of novel objects $H: H \cap G = \emptyset, |H| = 10$.

As shown in Figure 3, we found that an agent meta-trained on 20 objects (i.e. $|G| = 20$) was almost perfectly robust to novel objects. As may be expected, this robustness degraded to some degree with decreasing $|G|$, which is symptomatic of the agent specializing (and overfitting) to the particular features and distinctions of the objects in its environment. However, we only observed a substantial reduction in robustness to new objects when $|G|$ was reduced as low as three – i.e. a meta-training experience in which all episodes contain the same three objects (the first three elements of $G$ alphabetically, i.e. a boat, a book and a bottle).

Overall, we found this ability to generalize based on experience of only a small number of different objects surprising. However, it is important to note that an embodied, first-person learner in a world with a high degree of domain randomization receives rich and varied training data, including many different views of objects [Bambach et al., 2018]. Experience of this nature can make substantial differences to an agent’s ability to generalize out of its training domain when compared with less embodied or interactive training regimes [Hill et al., 2019].

4.1.3 Fast category extension

Children aged between three and four can acquire in one shot not only bindings between new words and specific unfamiliar objects, but also bindings between new words and categories. This capacity is demonstrated in studies in which subjects are presented with an unfamiliar tool (or drawing of a tool) and given its name (“this is a dax”) and then required to “point to the dax” among a set of objects (or drawings) containing a different instance of the same type of tool [Behrend et al., 2001, Waxman and Booth, 2000, Vlach and Sandhofer, 2012]. In this way, researchers probe the extension of the child’s concept of dax, identifying the boundaries of the category that forms during the fast-mapping process.

We conducted an analogous experiment by exploiting the category structure in the ShapeNet repository of 3D objects [Chang et al., 2015]. In a test trial, in the discovery phase the agent is presented with exemplars from three novel (held-out) ShapeNet categories (together with nonsense names). In the instruction phase, the agent must then pick up a different and unseen exemplar from one of these
three new categories as instructed. Note that the difficulty in this test is not the unfamiliarity of the test objects per se; as shown in Section 4.1.2, the agent can resolve trials involving identical unfamiliar objects in both the discovery and the instruction phase with over 90% accuracy.

As shown in Figure 4, when trained as described previously, the agent achieves around 55% accuracy on test trials, which is above chance (33%) but still a substantial error rate. However, this performance can be improved by requiring the agent to extend the training object categories as it learns. In this regime, three ShapeNet exemplars from distinct classes are encountered by the agent in the discovery phase of training episodes, and the instruction phase involves different exemplars from the same three classes. When trained in this way, performance on extending novel categories increases to 88%. In this regime (meta) training of the agent has notable similarities to that of matching networks [Vinyals et al., 2016], where the “support set” of the matching network is analogous to the category exemplars that the agent encounters in the discovery phase.
Figure 5: Training and test accuracy on two types of generalization tasks for agents that read different numbers of frames from their memory per query. Left shows generalization to novel objects (Sec 4.1.2) and right shows extension of ShapeNet categories (Sec 4.1.3).

4.1.4 Role of temporal aspect

In seeking to understand the mechanisms that support the generalization effects reported so far, we found that the parameter $k$ was an important factor, where the top-$k$ memories are returned to the agent policy head per memory read. As the agent explores during the discovery phase of episodes, it writes multiple perspectives of the same object to memory. As shown in Figure 5, both its robustness to entirely novel objects (Section 4.1.2) and its ability to extend categories from novel exemplars (Section 4.1.3), as well as its ability to solve the training task, are enhanced when $k > 1$; i.e. when it determines which object to visit in the instruction phase based on memories written from more than one view of each object.

This observation aligns both with research on human infants [Smith and Yu, 2008] and with recent findings in artificial neural networks [Bambach et al., 2018, Hill et al., 2019], namely that experience of different perspectives of the same object can lead to knowledge and representations that are more amenable to generalization.

4.2 Intrinsic motivation

The default version of the fast mapping task includes a shaping reward designed to encourage the agent to visit all objects in the room in order to learn their names. Without this reward, the credit assignment problem is too challenging for the RL algorithm we employ to solve the basic fast-mapping task. However, we found that the DCEM agent was able to solve the task without shaping rewards by employing a memory-based algorithm for intrinsic motivation (NGU; ?).

NGU computes a similarity score for an embedding from the inverse Euclidean distances to the nearest neighbours present in the episodic memory, as described in Appendix A.3. The similarity score indicates how new or surprising the current embedding is, and the inverse similarity score is used as a reward $r_{\text{NGU}}$ which is added to the extrinsic reward the agent receives, to encourage it to seek out new experiences. By re-setting the episodic memory every episode, policies can be learned that encourage the agent to re-explore its environment every episode.

The crucial question for NGU is which representation to use for the agent’s experience. In the original application, an inverse dynamics loss was used to learn this representation [?]. Here, we instead use the representations computed by the visual and language modules of the agent network, which are optimized based on the observation-reconstruction loss and any episode-final reward. We provide the intrinsic reward to both the DCEM and DNC agents to compare the effects of these two memory architectures.

Unlike the DNC, the external memory in the DCEM agent has distinct keys and values. It is therefore necessary to choose whether to apply the NGU algorithm to the memory’s keys column, its values column, or both. If the algorithm is applied to the language (keys) column, the agent computes novelty or surprisal in the space of language observations $r_{\text{NGU}}^{\text{lang}}$, and if NGU is applied to the visual column, the agent’s notion of surprise $r_{\text{NGU}}^{\text{im}}$ is based on visual observations. In the most general case, both $r_{\text{NGU}}^{\text{lang}}$ and $r_{\text{NGU}}^{\text{im}}$ are computed, and weighted with separate parameters $\lambda_{\text{lang}}, \lambda_{\text{im}}$, so the
Figure 6: Accuracy of agents trained without shaping reward on the 3-object fast-mapping task with $|G| = 30$. Left: language-based intrinsic reward (red curve) enables the agent to solve the task; without intrinsic reward (green curve), or with intrinsic reward based on DNC memory (blue curve), the task is not solved (in the case of DNC, there is only one $\lambda$ as there is only one memory column). Right: different values of the parameter $\lambda_{im}$, showing optimal training with $\lambda_{im} = 0$ and complete failure with $\lambda_{im} = 10^{-3}$. Curves show mean ± S.E. across three seeds in each condition.

Final reward provided to the agent becomes $r = r_{ext} + \lambda_{lang} r_{NGU}^{lang} + \lambda_{im} r_{NGU}^{im}$. The weights $\lambda_{im}$ and $\lambda_{lang}$ are treated as hyperparameters, and will vary from task to task. In the experiments reported here, we found that $\lambda_{lang} = 10^{-3}$ and $\lambda_{im} = 0$ worked best, as shown in Figure 6.

**Effects of $r_{im}$** The right-hand panel of Figure 6 shows the effect of different values of $\lambda_{im}$. To understand these results, it is instructive to examine the temporal density of $r_{NGU}^{lang}$ and $r_{NGU}^{im}$ and the kinds of policies required to maximize those rewards. $r_{im}^{NGU}$ is a dense signal already at the start of training, unlike the language-based one or the extrinsic reward. Therefore the agent will initially learn to maximize $r_{im}^{NGU}$, seeking out varied image input, and experience more task success than when performing random actions (as it would before having received any training). Once the agent has learned to pick up objects, $r_{lang}^{NGU}$ and the extrinsic reward are necessarily much more dense than at the start of training. Since they are aligned with task success, unlike $r_{im}^{NGU}$, any remaining tendency in the policy to explore the image input space will hurt performance at this point. As a future optimization, one could imagine having the agent discover a suitable schedule for $\lambda_{lang}$ and $\lambda_{im}$, to encourage generic exploration early on and more exploitation or targeted exploration at later stages.

### 4.3 Integrating fast and slow learning

When prompted with:

*To do a "farduddle" means to jump up and down really fast. An example of a sentence that uses the word farduddle is:*

The massive text-based language model GPT-3 [Brown et al., 2020] responds with:

*One day when I was playing tag with my little sister, she got really excited and she started doing these crazy farduddles.*

To achieve this feat, GPT-3 must rapidly and coherently integrate the new information conveyed by a user prompt (in this case a description of the meaning of "fardoodle") with the general knowledge of word meanings stored in its weights (either from the prompt, such as "jump" or "up and down", or from the response, such as "sister").

To test this capacity for integrating new information with existing lexical (and perceptual and motor) knowledge in our embodied agent, we combined a fast-mapping task with a more conventional instruction-following task requiring object identification and manipulation. As before, an evaluation
trial consists of discovery and instruction phases. In the discovery phase, the agent must explore to find the names of three unfamiliar objects, but in this case the room also contains a large box and a large bed, both of which are immovable. The positions of all objects and the agent are then re-randomized as before. In the instruction phase, the agent is then instructed to put one of the three movable objects (chosen at random) on either the bed or in the box (again chosen at random). To solve the evaluation trials, the agent must therefore integrate stable, cross-episodic semantic knowledge (of the words "bed", "box" and their referents, and of the motor-behaviour required to pick up, carry and place objects) with fast, episodic knowledge of novel movable objects and their names.

We then exposed the DCEM agent to various training regimes to verify whether an agent can exhibit the flexible integration of fast and slow knowledge necessary to solve such trials, and to determine the extent of the training experience necessary to (meta-)learn this capacity. As shown in Figure 7, if the training regime consisted of conventional lifting and putting tasks, together with a fast-mapping lifting task and a fast-mapping putting task, the agent learned to execute the evaluation trials with near-perfect accuracy. Interestingly, performance was only marginally lower (97% vs 96%) if the agent was not trained on the specific objects in the evaluation trials. This shows that the robustness to novel objects observed in Section 4.1.2 is preserved in this more complex setting requiring the agent to move and place objects.

Notably, we also found that substantially-above-chance performance could be achieved on the evaluation trials without needing to train the agent on the evaluation task in any form. If we trained the agent on conventional lifting and putting tasks, and a fast-mapping task involving lifting only, the agent could recombine the knowledge acquired during this training to resolve the evaluation trials as a novel (zero-shot) task with less-than-perfect but substantially-above-chance accuracy. Again, the reduction in performance when the evaluation trial objects were excluded from the agent’s training experience was minimal (71% vs 68%, where chance is 17%). A video of the agent trained in this minimal regime executing evaluation trials is available at [https://tinyurl.com/y5s2jcht](https://tinyurl.com/y5s2jcht).

### 4.4 Verification in DeepMind Lab

The fast-mapping tasks reported so far have all been carried out in a Unity environment. To verify that the observed effects hold beyond this specific environment, we added a new task to the DeepMind Lab suite [Beattie et al., 2016]. At a high level, the design of an episode is very similar to the default fast-mapping task in the Unity environment. The agent must move down a corridor, bumping into...
Train. Test

Architecture | Accuracy (novel objects)
--- | ---
LSTM + Recons | 0.51 0.45
DNC + LSTM + Recons | 0.81 0.70
TransformerXL + Recons | 0.80 0.69
DCEM + LSTM + Recons | 0.98 0.86
Random object selection | 0.5 0.5

Table 2: Left: Architectures compared on DeepMind Lab, scores are mean of the best 3 seeds out of 5 selected on the training set in each condition after $5 \times 10^8$ steps of training. See Table 1 for key to architecture abbreviations. Right: Schematic of episode structure in the DeepMind Lab fast-binding tasks.

(and collecting) three distinct objects. When an agent collects an object it is immediately presented with the (episode-specific) name for that object. After passing three objects, the corridor opens into a room containing two of the three objects found in the corridor. Upon entering the room, the agent is presented with the name corresponding to one of the two objects, and must bump into that object in order to receive a reward of 1. As before, a shaping reward of 0.1 is given as the agent collects each object in the corridor. Compared with the Unity environment, the DeepMind Lab action space is smaller (8 vs. 46 actions), the objects are larger, and the agent has no substantive way to interact with the objects (they disappear the moment the agent collides with them). Note also that the agent must choose between 2 (rather than 3) objects in the instruction phase, so an agent selecting objects at random would achieve 50% accuracy.

To provide some sense of the robustness and generality of the effects observed thus far, we applied the various agent architectures directly to this environment with no environment-specific tuning. As shown in Table 2, without any further tuning of the agent, we observe a similar pattern of results in DeepMind Lab as in the Unity room. As in that case, the TransformerXL and DCEM architectures performed best. Specific seeds in both cases were able to learn the task, but, in the case of DCEM, all seeds successfully mastered the training task. As before, we also observed substantially above-chance ability to apply fast-mapping knowledge zero-shot to unseen objects at test time.

5 Related work

Machine learning Meta-learning, of the sort observed in our agent, has been applied to train matching networks: image classifiers that can assign the correct label to a novel image, given a small support set of (image, label) pairs that includes the correct target label [Vinyals et al., 2016]. In some sense, the challenge faced by matching networks is very similar to the one faced by our agent when extending ShapeNet categories from a single exemplar (Section 4.1.3). Indeed, as with matching networks, we find that meta-training the agent to make such extensions is critical for good performance. Our work shows that such techniques can work in an agent that must learn to explore, exhibit control, and to respond with temporally-extended motor behaviours (object interactions) rather than single class predictions. This setting places greater onus on the memory architecture in particular, as the agent must learn which information to attend to, retain, retrieve and compare over the course of an extended episode of experience. Our work is also inspired by [Snell et al., 2017], who propose a more efficient way to integrate a small support set of experience into a coherent space of image ‘concepts’ for improved fast learning, and [Santoro et al., 2016], who show that the successful meta-training of image classifiers can benefit substantially from external memory architectures such as Memory Networks [Weston et al., 2014] or Differentiable Neural Computers [Graves et al., 2016].

In NLP, meta-learning has been applied to text-based models to train few-shot classifiers for various tasks (see [Yin, 2020] for a recent survey). [Brown et al., 2020] present a diverse array of experiments underlining the extent to which fast-adaptation to unseen prompts can emerge as a by-product of
conventional language-modelling objectives, such as next-word prediction, in transformer-based models with large context windows.

Meta-learning has previously been observed in reinforcement learning agents trained, as our agent, with conventional policy-gradient algorithms [Duan et al., 2016, Wang et al., 2019]. In Model-Agnostic Meta Learning [Finn et al., 2017], models are (meta) trained to be easily tunable (by any gradient algorithm) given a small number of novel data points. When combined with policy-gradient algorithms, this technique yields fast learning on both 2D navigation and 3D locomotion tasks. In cognitive tasks where fast learning is not explicitly required, external memories have proven to help goal-directed agents [Fortunato et al., 2019], and (as we also observed) can be particularly powerful when combined with an observation reconstruction loss [Wayne et al., 2018]. As far as we know, however, no prior applications of memory-based meta-learning have been developed in a multi-modal (vision plus language) environment like the one we consider here.

Psychology and cognition A large body of experimental work has investigated fast-mapping since the term was first introduced for infants’ ability to connect new objects to new names [Carey and Bartlett, 1978, Heibeck and Markman, 1987, Markson and Bloom, 1997]. As a mechanism for word-learning, fast-mapping is often contrasted with cross-situational learning, in which statistical evidence for word-object mappings are slowly aggregated over many experiences as a child develops [Frank et al., 2009, Truewell et al., 2013]. In the task we described in Section 4.3 the names for the movable objects must be acquired by fast-mapping, but the names "bed" and "storage box" can be acquired in a cross-situational way. The fact that the DCEM agent is trained with a single (policy-gradient) weight update rule, but learns to execute both fast-mapping and cross-situational learning, is consistent with theoretical proposals that these are not categorically distinct or independent learning processes, and that slow learning mechanisms critically support the emergence of fast-mapping abilities as infants develop [Smith and Yu, 2008, Smith et al., 2014].

The idea that knowledge may be stored in modality-specific codes (specifically visual or image-derived and linguistic or phonological) is central to several theories of cognition. We co-opt the term dual-coding from Paivio [1969], whose theory refers primarily to knowledge representation in semantic memory. A similar separation is central to Baddeley [1992]’s notion of working memory, which corresponds approximately to the episodic, slot-based external memory in our DCEM agent. According to the Context Theory of Classification Learning (CTCL) [Medin and Schaffer, 1978] humans classify a novel object by estimating its similarity to exemplars, which are stored (aligned to, but distinct from, their category labels) in such an episodic memory. The CTCL predicts patterns of human classification errors better than competing models. The provides a degree of additional empirical and theoretical justification for our approach.

One aspect of human learning that the DCEM agent does not account for is the ability to acquire and retain a new concept after a single experience. Knowledge acquisition in our agent is either cross-episodic and semantic (i.e. in the network weights), or fast and episodic (in an external memory emptied after every episode). Episodic knowledge can only indirectly complement semantic knowledge, by influencing the agent’s behaviour, so the agent cannot learn to do something in one shot and retain that knowledge indefinitely. While there is debate about how well infants retain fast-mapped word meanings beyond the immediate experimental context [VLach and Sandhofer, 2012], older learners can quickly learn new concepts (e.g. via definitions) in a way that complements and updates their extant semantic knowledge [Murphy and Medin, 1985, Xu and Tenenbaum, 2007]. Accounting for this fast semantic learning may require new algorithms or learning systems for consolidation of experience, perhaps inspired by mechanisms in the medial temporal lobe thought to support this capacity in humans [McCluggage et al., 1995].

Recent work at the intersection of developmental psychology and machine learning is also relevant to our model in that it shows how the noisy, first-person perspective of a child can support the acquisition of robust visual categories in artificial neural networks [Bambach et al., 2018]. This aligns with our finding that the ability to retrieve multiple viewpoints of an exemplar from episodic memory improves generalization in our agent. Further work training deep networks on data recorded from children’s head cameras shows that unsupervised or semi-supervised learning objectives can substantially improve the quality of the resulting representations [Orhan et al., 2020]. This is congruent with our observation that a reconstruction loss (a form of semi-supervised learning) is critical for obtaining the best performance from our agents.
6 Discussion

Biological learners, including humans, are surrounded by qualitatively distinct physical media such as sound and light, and have evolved specialized mechanisms for processing input from these modalities. For certain tasks relating to language learning, useful information can reside not just in the aggregate content of these input streams, but in the identification of specific knowledge with a particular modality. An episodic memory system that retains knowledge in explicit, modality-specific locations can endow learners with important advantages. Our experiments have highlighted two such benefits. First, mechanisms that allow the agent to query its memory in a modality-specific way (either within or across modalities) can better allow them to rapidly infer and exploit connections between perceptual experience and words, and therefore to realize fast-mapping, a notable aspect of human learning. Second, in cases where it is advantageous to estimate the degree of novelty or "surprise" in the current state of the environment (for instance to derive a signal for intrinsic motivation), a more informative signal may be obtained by separately estimating novelty based on each modality and aggregating the result.

Nevertheless, the advantage of our proposed architecture, the Dual-Coding Episodic Memory, was not definitive on the tasks we considered. A Transformer-based architecture (with no explicit external memory) was also able to solve the tasks, we suspect by exploiting the separation of modality in its knowledge retrieval mechanism in a similar way to the DCEM. Learning in the DCEM was more sample-efficient, but this is perhaps unsurprising given the close alignment between its design and the specific requirements of our tasks. In light of this, and the ubiquity and simplicity of Transformers, is it really worth pursing memory systems with explicit episodic memories? We provide two reasons why the answer may be "yes". First, an explicit episodic buffer can facilitate the non-parametric computation of aggregate statistics across memories, an advantage we observed in our experiments with intrinsic motivation. Second, and perhaps more fundamentally, an episodic memory system may ultimately be essential for fast knowledge consolidation. The potential for memory buffers and offline learning processes such as experience replay to support knowledge consolidation is not a new idea [McClelland et al., 1995] [Mnih et al., 2016] [Lillicrap et al., 2016] [McClelland et al., 2020]. For language learning agents, the need to both rapidly acquire and retain multi-modal knowledge may further motivate explicit external memories. Retaining in memory visual experiences together with aligned (and hopefully pertinent) language (i.e. a dual-coding schema) may facilitate something akin to offline ‘supervised’ language learning. We leave this possibility for future investigations.

We also highlight several other implications of this work regarding the proximate challenge of developing linguistic agents that can adapt flexibly to human input. First, we found that semi-supervised learning to support richer observation representations was critical for success regardless of the memory architecture that was used. This observation coincides with other recent demonstrations of the efficacy of such techniques for representation learning [Doersch et al., 2015] [Gidaris et al., 2018] [Gregor et al., 2019]. Second, we have shown that, much like GPT-3 and other large text-based models, goal-directed and embodied neural network agents that acquire visual and motor skills in interaction with their environment can also apply meta-learning to integrate ‘fast’ and ‘slow’ lexical knowledge. Many substantial challenges remain for this research programme, however. These include widening the agent’s scope to unconstrained user language (as with GPT-3), and the capacity to respond via language or motor behaviour and to combine both types of response in optimal ways.
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A Agent architecture details

A.1 Architecture diagrams

Figure 8: Agent architecture. See figure 9 for details of the dual coding episodic memory component. Dashed lines correspond to connections across timesteps.

Figure 9: DCEM architecture. This corresponds to the ‘memory’ component in the agent architecture. NB: the similarity computation and selection of nearest neighbours is replicated for each read head, but not depicted here to avoid clutter. Dashed lines correspond to connections across timesteps.
A.2 Hyperparameters

| Parameter                                      | Value |
|------------------------------------------------|-------|
| image width                                    | 96    |
| image height                                   | 72    |
| ResNet kernel size                             | $3 \times 3$ |
| convolutional layers per ResNet block          | 2     |
| ResNet blocks                                  | 2, 2, 2 |
| ResNet strides between blocks                  | 2, 2, 2 |
| ResNet number of channels                      | 16, 32, 32 |
| post-ResNet layer output size (visual embedding)| 256   |
| language encoder embedding size                | 32    |
| language encoder self-attention key / query size | 16    |
| language encoder self-attention value size     | 16    |
| language encoder output size (instruction embedding) | 32    |
| language decoder hidden size                   | 32    |
| number of memory read heads                    | 3     |
| memory aggregation self-attention key / query size | 256   |
| memory aggregation self-attention value size   | 256   |
| latent representation size                     | 256   |
| core LSTM hidden size                          | 512   |
| policy latent size                             | 256   |
| value latent size                              | 256   |
| policy cost                                    | 0.1   |
| entropy cost                                   | $10^{-3}$ |
| reconstruction cost                            | 1.0   |
| return cost                                    | 0.5   |
| discount factor                                | 0.95  |
| unroll length                                  | 128   |
| batch size                                     | 64    |
| Adam learning rate                             | $10^{-4}$ |
| Adam $\beta_1$                                 | 0     |
| Adam $\beta_2$                                 | 0.95  |
| Adam $\epsilon$                                | $5 \times 10^{-8}$ |

Table 3: Agent hyperparameters. The return cost (not discussed in the main text) is used to weight the baseline estimate term in the V-trace loss.

A.3 Intrinsic motivation algorithm

The intrinsic reward is based on the similarity (Euclidean distance) between the new embedding $\mathbf{e}$ and the nearest neighbors already present in memory $\{\mathbf{e}_i\}$. The average distance $\bar{\rho}$ used below is a lifetime average of all $\rho_i$ that is updated with every computation.

$$
\rho_i = \frac{|\mathbf{e} - \mathbf{e}_i|^2}{\bar{\rho} + c} \\
\epsilon = \max(\rho_i - \rho_{\min}, 0) + \epsilon \\
s = \left(\sum_i k_i\right)^{1/2} + c \\
r_{\text{NGU}} = \begin{cases} 
\frac{1}{s} & \text{if } s < s_{\max} \\
0 & \text{otherwise}
\end{cases}
$$

The computation introduces the constants $c$, $\epsilon$, $\rho_{\min}$, and $s_{\max}$, and the number of neighbours $|\{\mathbf{e}_i\}|$ used for the similarity estimate. Table [4] lists the values we used.
B Environment details

B.1 Unity action space

The following discrete actions (and strengths) are available to the agent in all experiments except for those in DM-Lab. The scalar strengths are translated into force and torque (for rotations) by the environment engine.

| Movement without grip | Fine grained movements without grip | Movement with grip |
|-----------------------|------------------------------------|--------------------|
| NOOP,                 | MOVE_RIGHT(0.05),                  | GRAB,              |
| MOVE_FORWARD(1),      | MOVE_RIGHT(-0.05),                 | GRAB + MOVE_FORWARD(1), |
| MOVE_FORWARD(-1),     | LOOK_DOWN(0.03),                   | GRAB + MOVE_FORWARD(-1), |
| MOVE_RIGHT(1),        | LOOK_DOWN(-0.03),                  | GRAB + MOVE_RIGHT(1), |
| MOVE_RIGHT(-1),       | LOOK_RIGHT(0.2),                   | GRAB + MOVE_RIGHT(-1), |
| LOOK_RIGHT(1),        | LOOK_RIGHT(-0.2),                  | GRAB + LOOK_RIGHT(1), |
| LOOK_RIGHT(-1),       | LOOK_RIGHT(0.05),                  | GRAB + LOOK_RIGHT(-1), |
| LOOK_DOWN(1),         | LOOK_RIGHT(-0.05),                 | GRAB + LOOK_DOWN(1), |
| LOOK_DOWN(-1),        |                                    | GRAB + LOOK_DOWN(-1), |

| Fine grained movements with grip | Object manipulation | Fine grained object manipulation |
|----------------------------------|---------------------|---------------------------------|
| GRAB + MOVE_RIGHT(0.05),         | GRAB + SPIN_RIGHT(1),| GRAB + PULL(0.5),               |
| GRAB + MOVE_RIGHT(-0.05),        | GRAB + SPIN_RIGHT(-1),| GRAB + PULL(-0.5),              |
| GRAB + LOOK_DOWN(0.03),          | GRAB + SPIN_UP(1),   | PULL(0.5),                      |
| GRAB + LOOK_DOWN(-0.03),         | GRAB + SPIN_UP(-1),  | PULL(-0.5),                     |
| GRAB + LOOK_RIGHT(0.2),          | GRAB + SPIN_FORWARD(1),|                            |
| GRAB + LOOK_RIGHT(-0.2),         | GRAB + SPIN_FORWARD(-1),|                          |
| GRAB + LOOK_RIGHT(0.05),         | GRAB + PULL(1),      |                                 |
| GRAB + LOOK_RIGHT(-0.05),        | GRAB + PULL(-1),     |                                 |

B.2 ShapeNet

ShapeNet contains 3D models of objects with a wide range of complexity and quality. To guarantee that the models are recognizable and of a high quality, we manually filtered the ShapeNet Sem dataset, selecting a subset of everyday semantic classes, ensuring that the selected models had a reasonable number of vertices, and reasonable size and weight dimensions. The selected classes (number of models in each class) were as follows, with a total of 1,437 models across 31 different classes:

- armoire (31), bag (11), bed (65), book (47), bookcase (13), bottle (26), box (37), bunk bed (9), chair (150), chest of drawers (133), coffee table (43), computer (6), floor lamp (68), glass (11), hammer (15), keyboard (5), lamp (100), loudspeaker (37), microwave (16), monitor (58), mug (12), piano (11), plant (31), printer (22), rug (36), soda can (20), sofa (145), stool (25), table (181), vase (66), wine bottle (7).