Learning with Latent Language

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Abstract

The named concepts and compositional operators present in natural language provide a rich source of information about the kinds of abstractions humans use to navigate the world. Can this linguistic background knowledge improve the generality and efficiency of learned classifiers and control policies? This paper aims to show that using the space of natural language strings as a parameter space is an effective way to capture natural task structure. In a pretraining phase, we learn a language interpretation model that transforms inputs (e.g. images) into outputs (e.g. labels) given natural language descriptions. To learn a new concept (e.g. a classifier), we search directly in the space of descriptions to minimize the interpreter’s loss on training examples. Crucially, our models do not require language data to learn these concepts: language is used only in pretraining to impose structure on subsequent learning. Results on image classification, text editing, and reinforcement learning show that, in all settings, models with a linguistic parameterization outperform those without.

1 Introduction

The structure of natural language reflects the structure of the world. For example, the fact that it is easy for us to communicate the concept left of the circle but comparatively difficult to communicate mean saturation of the first five pixels in the third column reveals something about the kinds of abstractions we find useful for interpreting and navigating our environment (Gopnik and Meltzoff, 1987). In machine learning, efficient automatic discovery of reusable abstract structure remains a major challenge. This paper investigates whether background knowledge from language can provide a useful scaffold for acquiring it. We specifically propose to use language as a latent parameter space for few-shot learning problems of all kinds, including classification, translation and policy search. We aim to show that this linguistic parameterization produces models that are both more accurate and more interpretable than direct approaches to few-shot learning.

Like many recent frameworks for multitask- and meta-learning, our approach consists of three phases: a pretraining phase, a concept-learning phase, and an evaluation phase. Here, the product of pretraining is a language interpretation model that maps from descriptions to predictors (e.g. image classifiers or reinforcement learners). Our thesis that language learning is a powerful, general-purpose kind of pretraining, even for tasks that do not directly involve language.

New concepts are learned by searching directly in the space of natural language strings to minimize the loss incurred by the language interpretation model (Figure 1). Especially on tasks that require...
the learner to successfully model some high-level compositional structure shared by the training examples, natural language hypotheses serve a three-fold purpose: they make it easier to discover these compositional concepts, harder to overfit to few examples, and easier to understand inferred patterns.

Our approach can be implemented using a standard kit of neural components, and is simple and general. In a variety of settings, we find that the structure imposed by a natural-language parameterization is helpful for efficient learning and exploration. The approach outperforms both multitask- and meta-learning approaches that map directly from training examples to outputs by way of a real-valued parameterization, as well as approaches that make use of natural language annotations as an additional supervisory signal rather than an explicit latent parameter. The natural language concept descriptions inferred by our approach often agree with human annotations when they are correct, and provide an interpretable debugging signal when incorrect. In short, by equipping models with the ability to “think out loud” when learning, they become both more comprehensible and more accurate.

2 Background

Suppose we wish to solve an image classification problem like the one shown in Figure 2b−c, mapping from images $x$ to binary labels $y$. One straightforward way to do this is to solve a learning problem of the following form:

$$\arg \min_{\eta \in H} \sum_{x, y} L(f(x; \eta), y),$$

where $L$ is a loss function and $f$ is a richly-parameterized class of models (e.g. convolutional networks) indexed by $\eta$ (e.g. weight matrices) that map from images to labels. Given a new image $x'$, $f(x'; \eta)$ can then be used to predict its label.

In the present work, we are particularly interested in few-shot learning problems where the number of $(x, y)$ pairs is small—on the order of five or ten examples. Under these conditions, directly solving Equation 1 is a risky proposition—any model class powerful enough to capture the true relation between inputs and outputs is also likely to overfit. For few-shot learning to be successful, extra structure must be supplied to the learning algorithm. Existing approaches obtain this structure by either carefully structuring the hypothesis space or providing the learning algorithm with additional kinds of training data. The approach we present in this paper combines elements of both, so we begin with a review of existing work.

(Inductive) program synthesis approaches (e.g. Gulwani, 2011) reduce the effective size of the parameter space $H$ by moving the optimization problem out of the continuous space of weight vectors and into a discrete space of formal program descriptors (e.g. regular expressions or Prolog queries). Domain-specific structure like version space algebras (Lau et al., 2003) or type systems (Kitzelmann and Schmid, 2006) can be brought to bear on the search problem, and the bias inherent in the syntax of the formal language provides a strong prior. But while program synthesis techniques are powerful, they are also limited in their application: a human designer must hand-engineer the computational primitives necessary to compactly describe every learnable hypothesis. While reasonable for some applications (like string editing), this is challenging or impossible in others (like computer vision).

An alternative class of multitask learning approaches (Caruana, 1998) attempt to import the relevant structure from other learning problems rather than defining it manually (Figure 2a). Since we may not know a priori what set of learning problems we
ultimately wish to evaluate on, it is useful to think of learning as taking places in three phases:

1. a **pretraining** (or “meta-training”) phase that makes use of various different datasets $i$ with examples $\{(x_1^{(i)}, y_1^{(i)}), \ldots, (x_n^{(i)}, y_n^{(i)})\}$ (Figure 2a)

2. a **concept-learning** phase in which the pretrained model is adapted to fit data $\{(x_1^{(c)}, y_1^{(c)}), \ldots, (x_n^{(c)}, y_n^{(c)})\}$ for a specific new task (Figure 2b)

3. an **evaluation** phase in which the learned concept is applied to a new input $x^{(e)}$ to predict $y^{(e)}$ (Figure 2c)

In these approaches, learning operates over two collections of parameters: shared parameters $\eta$ and task-specific parameters $\theta$. In pretraining, multitask approaches find:

$$\arg\min_{\eta \in \mathbb{R}^a, \theta^{(i)} \in \mathbb{R}^b} \sum_{i,j} L(f(x_j^{(i)}; \eta, \theta^{(i)}), y_j^{(i)}) \quad (2)$$

At concept learning time, they solve for:

$$\arg\min_{\theta^{(c)} \in \mathbb{R}^b} \sum_j L(f(x_j^{(c)}; \eta, \theta^{(c)}), y_j^{(c)}) \quad (3)$$

on the new dataset, then make predictions for new inputs using $f(x^{(e)}; \eta, \theta^{(e)})$.

Closely related meta-learning approaches (e.g. Schmidhuber, 1987; Santoro et al., 2016; Vinyals et al., 2016) make use of the same data, but collapse the inner optimization over $\theta^{(c)}$ and subsequent prediction of $y^{(e)}$ into a single learned model.

### 3 Learning with Language

In this work, we are interested in developing a learning method that enjoys the benefits of both approaches. In particular, we seek an intermediate language of task representations that, like in program synthesis, is both expressive and compact, but like in multitask approaches is learnable directly from training data without domain engineering. We propose to use natural language as this intermediate representation. We call our approach **learning with latent language** (L$^3$).

Natural language shares many structural advantages with the formal languages used in synthesis approaches: it is discrete, has a rich set of compositional operators, and comes equipped with a natural description length prior. But it also has a considerably more flexible semantics. And crucially, plentiful annotated data exists for learning this semantics: we cannot hand-write a computer program to recognize a *small dog*, but we can learn how to do it from image captions. More basically, the set of primitive operators available in language provides a strong prior about the kinds of abstractions that are useful for natural learning problems.

Concretely, we replace the pretraining phase above with a **language-learning** phase. We assume that at language-learning time we additionally have access to natural-language descriptions $w^{(i)}$ (Figure 2a, bottom). We use these $w$ as parameters, in place of the task-specific parameters $\theta$—that is, we learn a language interpretation model $f(x; \eta, w)$ that uses weights $\eta$ to turn a description $w$ into a function from inputs to outputs. For the example in Figure 2, $f$ might be an image rating model (Socher et al., 2014) that outputs a scalar judgment $y$ of how well an image $x$ matches a caption $w$.

Because these natural language parameters are observed at language-learning time, we need only learn the real-valued shared parameters $\eta$ used for their interpretation (e.g. the weights of a neural network that implements the image rating model):

$$\arg\min_{\eta \in \mathbb{R}^a} \sum_{i,j} L(f(x_j^{(i)}; \eta, w^{(i)}), y_j^{(i)}) \quad (4)$$

At concept-learning time, conversely, we solve only the part of the optimization problem over natural language strings:

$$\arg\min_{w^{(e)} \in \Sigma^e} \sum_j L(f(x_j^{(e)}; \eta, w^{(e)}), y_j^{(e)}) \quad (5)$$

This last step presents something of a challenge. When solving the corresponding optimization problem, synthesis techniques can exploit the algebraic structure of the formal language, while end-to-end learning approaches take advantage of differentiability. Here we can’t do either—the language of strings is discrete, and whatever structure the interpretation function has is wrapped up inside the black box of $f$. Inspired by related techniques aimed at making synthesis more efficient (Devlin et al., 2017), we use...
learning to help us develop an effective optimization procedure for natural language parameters.

In particular, we simply use the language-learning datasets, consisting of pairs \((x_j^{(e)}, y_j^{(e)})\) and descriptions \(w_j\), to fit a reverse proposal model, estimating:

\[
\text{arg max}_x \log q(w_1|x_1^{(e)}, y_1^{(e)}, \ldots, x_n^{(e)}, y_n^{(e)}; \lambda)
\]

where \(q\) provides a (suitably normalized) approximation to the distribution of descriptions given task data. In the running example, this proposal distribution is essentially an image captioning model (Donahue et al., 2015). By sampling from \(q\), we expect to obtain candidate descriptions that are likely to obtain small loss. But our ultimate inference criterion is still the true model \(f\): at evaluation time we perform the minimization in Equation 5 by drawing a fixed number of samples, selecting the hypothesis \(w^{(e)}\) that obtains the lowest loss, and using \(f(x^{(e)}; \eta, w^{(e)})\) to make predictions.

What we have described so far is a generic procedure for equipping collections of related learning problems with a natural language hypothesis space. In Sections 4 and 5, we describe how this procedure can be turned into a concrete algorithm for supervised classification and sequence prediction. In Section 6, we describe how to extend these techniques to reinforcement learning.

4 Few-shot Classification

We begin by investigating whether natural language can be used to support high-dimensional few-shot classification. Our focus is on visual reasoning tasks like the one shown in Figure 3. In these problems, the learner is presented with four images, all positive examples of some visual concept like a blue shape near a yellow triangle, and must decide whether a fifth, held-out image matches the same concept.

These kinds of visual reasoning problems have been well-studied in visual question answering settings (Johnson et al., 2017; Suhr et al., 2017). Our version of the problem, where the input and output feature no text data, but a natural language explanation must be inferred, is similar in spirit to the battery of visual reasoning problems proposed by Raven (1936) and Bongard (1968).

To apply the recipe in Section 2, we need to specify an implementation of the interpretation model \(f\) and the proposal model \(q\). We begin by computing representations of input images \(x\). We start with a pre-trained 16-layer VGGNet (Simonyan and Zisserman, 2014). Because spatial information is important for these tasks, we extract a feature representation from the final convolutional layer of the network. This initial featureization is passed through two fully-connected layers to form a final image representation, as follows:

\[
\begin{align*}
    x & \quad \xrightarrow{\text{VGG-16}} \quad \xrightarrow{\text{FC}} \quad \xrightarrow{\text{ReLU}} \quad \xrightarrow{\text{FC}} \quad \text{rep}(x)
\end{align*}
\]

Then we define interpretation and proposal models:

\[
\begin{align*}
    f(x; w) &= \sigma(\text{rnn-encode}(w)^\top \text{rep}(x)) \\
    q(w | \{x_j\}) &= \text{rnn-decode}(w | \frac{1}{n} \sum_j \text{rep}(x_j))
\end{align*}
\]

The interpretation model \(f\) outputs the probability that \(x\) is assigned a positive class label, and is trained to maximize log-likelihood. Because only positive examples are provided in each language learning set, the proposal model \(q\) can be defined in terms of inputs alone. Details regarding training hyperparameters, RNN implementations, etc. may be found in Appendix A.

Our evaluation aims to answer two questions. First, does the addition of language to the learning process provide any benefit over ordinary multitask or meta-learning? Second, is it specifically better to use language as a hypothesis space for concept

\[\text{\textsuperscript{2}}\text{Suppressing global parameters }\eta \text{ and } \lambda \text{ for clarity.}\]
learning rather than just an additional signal for pre-training? We use several baselines to answer these questions:

1. **Multitask**: a multitask baseline in which the definition of $f$ above is replaced by $\sigma(\theta_i^T \text{rep}(x))$ for task-specific parameters $\theta_i$ that are optimized during both pretraining and concept-learning.

2. **Meta**: a meta-learning baseline in which $f$ is defined by $\sigma(\left[\frac{1}{n} \sum_j \text{rep}(x_j)\right]^T \text{rep}(x))$.

3. **Meta+Joint**: as in Meta, but the pretraining objective includes an additional term for predicting $q$ (discarded at concept-learning time).

We report results on a dataset derived from the ShapeWorld corpus of Kuhnle and Copestake (2017). In this dataset the held-out image matches the target concept 50% of the time. In the validation and test folds, half of learning problems feature a concept that also appears in the language learning set (but with different exemplar images), while the other half feature both new images and a new concept. Images feature two or three distractor shapes unrelated to the objects that define the target concept. Captions in this dataset were generated from DMRS representations using an HPS grammar (Copestake et al., 2016). (Our remaining experiments use human annotators.) The dataset contains a total of 9000 pretraining tasks and 1000 of each validation and test tasks. More dataset statistics are provided in Appendix B.

Results are shown in Table 1. It can be seen that $L^3$ provides consistent improvements over the baselines, and that these improvements are present both when identifying new instances of previously-learned concepts and when discovering new ones. Some example model predictions are shown in Figure 4. The model often succeeds in making correct predictions, even though its inferred descriptions rarely match the ground truth. Sometimes this is because of inherent ambiguity in the description language (Figure 4a), and sometimes because the model is able to rule out candidates on the basis of partial captions alone (Figure 4b, where it is sufficient to recognize that the target concept involves a circle). More examples are provided in Appendix C.

Table 1: Evaluation on image classification. Val (old) and Val (new) denote subsets of the validation set that contain only previously-used and novel visual concepts respectively. $L^3$ consistently outperforms alternative learning methods based on multitask learning, meta-learning, and meta-learning jointly trained to predict descriptions (Meta+Joint). The last row of the table shows results when the model is given a ground-truth concept description rather than having to infer it from examples.

![Examples of model predictions](image)

**Figure 4**: Example predictions for image classification. The model achieves high accuracy even though predicted descriptions rarely match the ground truth. High-level structure like the presence of certain shapes or spatial relations is consistently recovered. Best viewed in color.
Programming by Demonstration

Next we explore whether the same technique can be applied to tasks that involve more than binary similarity judgments. We focus on structured prediction: specifically a family of string processing tasks. In these tasks, the model is presented with five strings being transformed according to some rule; it must then apply an appropriate transformation to a sixth (Figure 5). Learning proceeds more or less as in the previous section, with the following definitions:

\[
\text{rep}(x, y) = \text{rnn-encode}([x, y])
\]

\[
f(y \mid x; w) = \text{rnn-decode}(y \mid [\text{rnn-encode}(x), \text{rnn-encode}(w)])
\]

\[
q(w \mid \{(x_j, y_j)\}) = \text{rnn-decode}(w \mid \frac{1}{n} \sum_j \text{rep}(x_j, y_j))
\]

Baselines are analogous to those for classification.

While string editing tasks of the kind shown in Figure 5 are popular in both the programming by demonstration literature (Singh and Gulwani, 2012) and the semantic parsing literature (Kushman and Barzilay, 2013), we are unaware of any datasets that support both learning paradigms at the same time. We have thus created a new dataset of string editing tasks by (1) sampling random regular transducers, (2) applying these transducers to collections of dictionary words, and (3) showing the collected examples to Mechanical Turk users and asking them to provide a natural language explanation with their best guess about the underlying rule. The dataset thus features both multi-example learning problems, as well as structured and unstructured annotations for each target concept. There are 3000 tasks for language learning and 500 tasks for each of validation and testing. The human-generated data exhibits comparatively diverse explanatory strategies and word choices; details are in Appendix B. Annotations are included in the code release for this paper.

Results are shown in Table 2. In these experiments, all models that use descriptions have been trained on the natural language supplied by human annotators. While we did find that the Meta+Joint model converges considerably faster than all the others, its final performance is somewhat lower than the baseline Meta model. As before, L3 outperforms alternative approaches for learning directly from examples with or without descriptions.

Because all of the transduction rules in this dataset were generated from known formal descriptors, these tasks provide an opportunity to perform additional analysis comparing natural language to more structured forms of annotation (since we have access to ground-truth regular expressions) and more conventional synthesis-based methods (since we have access to a ground-truth regular expression execution engine). We additionally investigate the effect of the number of samples drawn from the process of inference and representation experiments for string editing. Italicized numbers correspond to entries in Table 2. Allowing the model to use multiple samples rather than the 1-best decoder output substantially improves performance. The full model does better with inferred natural language descriptions than either regular expressions or ground-truth natural language.
positional model. These results are shown in Table 3.

A few interesting facts stand out. Under the ordinary evaluation condition (with no ground-truth annotations provided), language-learning with natural language data is actually better than language-learning with regular expressions. This might be because the extra diversity helps the model figure out the relevant axes of variation and avoid overfitting to individual strings. Allowing the model to do its own inference is also better than providing ground-truth natural language descriptions, suggesting that it is actually better at generalizing from the relevant concepts than our human annotators (who occasionally write things like I have no idea for the inferred rule).

Unsurprisingly, with ground truth REs (which unlike the human data are always correct) we can do better than any of the models that have to do inference. Coupling our inference procedure with an oracle RE evaluator, we essentially recover the synthesis-based approach of Devlin et al. (2017). Our findings are consistent with theirs: when a complete and accurate execution engine is available, there is no reason not to use it. But we can get almost 90% of the way there with an execution model learned from scratch. Some examples of model behavior are shown in Figure 6; more may be found in Appendix D.

6 Policy Search

The previous two sections examined supervised settings where the learning signal comes from few examples but is readily accessible. In this section, we move to a set of reinforcement learning problems, where the learning signal is instead sparse and time-consuming to obtain. We evaluate on a collection of 2-D treasure hunting tasks. These tasks require the agent to discover a rule that determines the location of buried treasure in a large collection of environments of the kind shown in Figure 7. To recover the treasure, the agent must navigate (while avoiding water) to its goal location, then perform a DIG action. At this point the episode ends; if the treasure is located in the agent’s current position, it receives a reward, otherwise it does not. In every task, the treasure has consistently been buried at a fixed position relative to some landmark (like the heart in Figure 7). Both the offset and the identity of the target landmark are unknown to the agent, and the location landmark itself varies across maps. Indeed, there is nothing about the agent’s observations or action space to suggest that landmarks and offsets are even the relevant axis of variation across tasks, but this structure is made clear in the natural language annotations. The high-level structure of these tasks is similar to one used by Hermer-Vazquez et al. (2001) to study concept learning in humans.

The interaction between language and learning in these tasks is rather different than in the supervised settings. In the supervised case, language served mostly as a guard against overfitting, and could...
be generated conditioned on a set of pre-provided concept-learning observations. Here, agents are free to interact with the environment as much as they need, but receive observations only during interaction. Thus our goal here will be to build agents that can *adapt quickly* to new environments, rather than requiring them to immediately perform well on held-out data.

Why should we expect $L^3$ to help in this setting? In reinforcement learning, we typically encourage our models to explore by injecting randomness into either the agent’s action space or its underlying parameterization. But most random random policies exhibit nonsensical behaviors; as a result, it is quite inefficient both to sample in the space of network weights and to perform policy optimization from a random starting point. Our hope is that when parameters are instead chosen from within a structured family, a stochastic search in this structured space will only ever consider behaviors corresponding to some reasonable final policy, and in this way discover good behavior much faster than ordinary RL.

Here the interpretation model $f$ describes a policy that chooses actions conditioned on the current environment state and its linguistic parameterization. As the agent initially has no observations at all, we simply design the proposal model to generate unconditional samples from a prior over descriptions. Taking $x$ to be an agent’s current observation of the environment state, we define a state representation network:

$$x \xrightarrow{\text{FC}} \xrightarrow{\text{tanh}} \xrightarrow{\text{FC}} \xrightarrow{\text{tanh}} \text{rep}(x)$$

and models:

$$f(a | x; w) \propto \text{rnn-encode}(w)^\top W_a \text{rep}(x)$$

$$q(w) = \text{rnn-decode}(w)$$

This parameterization assumes a discrete action space, and assigns to each action a probability proportional to a bilinear function of the encoded description and world state. $f$ is effectively an instruction following model of a kind well-studied in the natural language processing literature (Branavan et al., 2009); the proposal model allows it to generate its own instructions without external direction.

To learn, we sample a fixed number of descriptions $w$ from $q$. For each description, we sample multiple rollouts of the policy it induces to obtain an estimate of the average reward it obtains. Finally, we can take the highest-scoring description and perform additional fine-tuning of its induced policy.

At language-learning time, we assume access to both natural language descriptions of these target locations provided by human annotators, as well as expert policies for navigating to the location of the treasure. The multitask model we compare to replaces these descriptions with trainable task embeddings. The learner is trained from task-specific expert policies using DAgger (Ross et al., 2011) during the language-learning phase, and adapts to individual environments using “vanilla” policy gradient (Williams, 1992) during the concept learning phase.

The environment implementation and linguistic annotations are in this case adapted from a natural language processing literature. Here, the multitask model learns separate embeddings for each task, while the Scratch model trains on each task individually. $L^3$ rapidly discovers high-scoring policies in most environments. The dashed line indicates the end of the concept-learning phase; subsequent performance comes from fine-tuning. The max possible reward for this task is 3 points. Error bands shows 95% confidence intervals for mean performance.

In the case of RL in particular, the contribution from $L^3$ are orthogonal to those of meta-learning—one could imagine using a technique like RL$^2$ (Duan et al., 2016) to generate candidate descriptions more efficiently, or use MAML (Finn et al., 2017) rather than zero-shot reward as the training criterion for the interpretation model.
language navigation dataset originally introduced by Janner et al. (2017). In our version of the problem (Figure 7), the agent begins each episode in a random position on a randomly-chosen map and must attempt to obtain the treasure. Some relational concepts describing target locations are reused between language learning and concept-learning phases, but the environments themselves are distinct. For language learning the agent has access to 250 tasks, and is evaluated on an additional set of 50.

Averaged learning curves for held-out tasks are shown in Figure 8. As expected, reward for the $L^3$ model remains low during the initial exploration period, but once a description is chosen the score improves rapidly. Immediately $L^3$ achieves better reward than the multitask baseline, though it is not perfect; this suggests that the interpretation model is somewhat overfit to the pretraining environments. However, after additional fine-tuning even better results are rapidly obtained. Example rollouts are visualized in Appendix E. These results show that the model has used the structure provided by language to learn a better representation space for policies—one that allows it to sample from a distribution over interesting and meaningful behaviors rather than sequences of random actions.

7 Other Related Work

This is the first approach we are aware of to frame a general learning problem as optimization over a space of natural language strings. However, many closely-related ideas have been explored in the literature. String-valued latent variables are widely used in language processing tasks ranging from morphological analysis (Dreyer and Eisner, 2009) to sentence compression (Miao and Blunsom, 2016). Natural language annotations have been used in conjunction with training examples to guide the discovery of logical descriptions of concepts (Ling et al., 2017; Srivastava et al., 2017), and used as an auxiliary loss for training (Frome et al., 2013), analogously to the Meta+Joint baseline in this paper. Structured language-like annotations have been used to improve learning of generalizable structured policies (Andreas et al., 2017; Denil et al., 2017). Finally, natural language instructions available at concept-learning time (rather than language-learning time) have been used to provide side information to reinforcement learners about high-level strategy (Branavan et al., 2011), environment dynamics (Narasimhan et al., 2017) and exploration (Harrison et al., 2017).

8 Conclusion

We have presented an approach for optimizing models in a space parameterized by natural language. Using standard neural encoder–decoder components to build models for representation and search in this space, we demonstrated that our approach outperforms strong baselines on classification, structured prediction and reinforcement learning tasks. We believe that these results suggest the following general conclusions:

Language encourages compositional generalization: standard deep learning architectures are good at recognizing new instances of previously-encountered concepts, but not always at generalizing to new ones. By forcing decisions to pass through a linguistic bottleneck in which the underlying compositional structure of concepts is explicitly expressed, stronger generalization becomes possible.

Language simplifies structured exploration: relatedly, linguistic scaffolding can provide dramatic advantages in problems like reinforcement learning that require exploration: models with latent linguistic parameterizations can sample in this space, and thus limit exploration to a class of behaviors that are likely a priori to be goal-directed and interpretable.

And generally, language can help learning. In multitask settings, it can even improve learning on tasks for which no language data is available at training or test time. While some of these advantages are also provided by techniques like program synthesis that are built on top of formal languages, natural language is at once more expressive and easier to obtain than formal supervision. We believe this work hints at broader opportunities for using naturally-occurring language data to improve machine learning for tasks of all kinds.
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A Model and Training Details

In all models, RNN encoders and decoders use gated recurrent units (Cho et al., 2014).

Few-shot classification Models are trained with the ADAM optimizer (Kingma and Ba, 2015) with a step size of 0.0001 and batch size of 100. The number of pretraining iterations is tuned based on subsequent concept-learning performance on the development set. Neural network hidden states, task parameters, and word vectors are all of size 512. 10 hypotheses are sampled during for each evaluation task in the concept-learning phase.

Programming by demonstration Training as in the classification task, but with a step size of 0.001. Hidden states are of size 512, task parameters of size 128 and word vectors of size 32. 100 hypotheses are sampled for concept learning.

Policy search DAgger (Ross et al., 2011) is used for pre-training and vanilla policy gradient (Williams, 1992) for concept learning. Both learning algorithms use ADAM with a step size of 0.001 and a batch size of 5000 samples. For imitation learning, rollouts are obtained from the expert policy on a schedule with probability $0.95^t$ (for $t$ the current epoch). For reinforcement learning, a discount of 0.9 is used. Because this dataset contains no development data, pretraining is run until performance on the pretraining tasks reaches a plateau. Hidden states and task embeddings are of size 64. 100 hypotheses are sampled for concept learning, and 1000 episodes (divided evenly among samples) are used to estimate hypothesis quality before fine-tuning.

B Dataset Information

ShapeWorld This is the only fully-synthetic dataset used in our experiments. Each scene features 4 or 5 non-overlapping entities. Descriptions refer to spatial relationships between pairs of entities identified by shape, color, or both. There are 8 colors and 8 shapes. The total vocabulary size is only 30 words, but the dataset contains 2643 distinct captions. Descriptions are on average 12.0 words long.

Regular expressions Annotations were collected from Mechanical Turk users. Each user was presented with the same task as the learner in this paper: they observed five strings being transformed, and had to predict how to transform a sixth. Only after they correctly generated the held-out word were they asked for a description of the rule. Workers were additionally presented with hints like “look at the beginning of the word” or “look at the vowels”. Descriptions are automatically preprocessed to strip punctuation and ensure that every character literal appears as a single token.

The regular expression data has a vocabulary of 1015 rules and a total of 1986 distinct descriptions. Descriptions are on average 12.3 words in length but as long as 46 words in some cases.

Navigation The data used was obtained from Janner et al. (2017). We created our own variant of the dataset containing collections of related tasks. Beginning with the “local” tasks in the dataset, we generated alternative goal positions at fixed offsets from landmarks as described in the main section of this paper. Natural-language descriptions were selected for each task collection from the human annotations provided with the dataset. The vocabulary size is 74 and the number of distinct hints 446. The original action space for the environment is also modified slightly: rather than simply reaching the goal cell (achieved with reasonably high frequency by a policy that takes random moves), we require the agent to commit to an individual goal cell and end the episode with a special DIG action.

Data augmentation Due to their comparatively small size, a data augmentation scheme (Jia and Liang, 2016) is employed for the regular expression and navigation datasets. In particular, wherever a description contains a recognizable entity name (i.e. a character literal or a landmark name), a description template is extracted. These templates are then randomly swapped in at training time on other examples with the same high-level semantics. For example, the description replace first b with e is abstracted to replace first CHAR1 with CHAR2, and can subsequently be specialized to, e.g., replace first c with d. This templating is easy to implement because we have access to ground-truth structured concept representations at training time. If these were not available it would be straightforward to employ an automatic template induction system (Kwiatkowski et al., 2011) instead.
C  Examples: ShapeWorld

(Examples in this and the following appendices were not cherry-picked.)

Positive examples:

| True description: | Input: | True label: |
|-------------------|--------|-------------|
| a red ellipse is to the right of an ellipse | ![Input Image] | true |

Inferred description:

| a red shape is to the right of a red semicircle |
|--------|

| Input: | Pred. label: |
|--------|-------------|
| ![Input Image] | true |

a shape is below a white ellipse

| ![Input Image] | false |

a white shape is to the left of a yellow ellipse

| ![Input Image] | true |

a magenta triangle is to the left of a magenta pentagon

| ![Input Image] | true |

a magenta triangle is to the left of a pentagon

| ![Input Image] | true |

a green pentagon is to the right of a yellow shape

| ![Input Image] | false |

a green shape is to the right of a red semicircle

| ![Input Image] | false |

a red circle is above a magenta semicircle

| ![Input Image] | false |

a green triangle is above a red circle

| ![Input Image] | true |

a white ellipse is to the left of a green cross

| ![Input Image] | true |

a green cross is to the right of a white ellipse

| ![Input Image] | true |
### D Examples: Regular Expressions

| Example in: | Example out: | Human description: | True out: | Input: | Pred. out: |
|------------|--------------|--------------------|-----------|-------|-----------|
| mediaeval  | ilediaeval   | leading consonant si replaced with i l | ilhaser   | chaser | ilhaser   |
| paneling   | ilaneling    | first consonant of a word is replaced with i l | reballiununusness | stumplight | regulatiunn |
| wafer      | ilafer       | replace every o with u n | regulation | regulation | regulatinun |
| conventions| ilonventions | replace every o with u n | regulation | regulation | regulatinun |
| handsprings| ilandsprings | change all o to u n | regulation | regulation | regulatinun |

| fluffiest   | fluffiest    | the letter m is replaced by ee | chartering | chartering | chartering |
| kidnappers  | kidnappers   | the letter m is replaced by ee | chartering | chartering | chartering |
| matting     | matting      | the letter m is replaced by ee | chartering | chartering | chartering |
| gripping    | gripping     | change every m to ee | chartering | chartering | chartering |
| disagreements| disagreements| change every m to ee | chartering | chartering | chartering |

| clandestine | clandqtine   | e | gratuity |
| limming     | limming      | where e appears, replace it and the following letter with q | gratuity |
| homes       | homq         |  |  |
| lifeblood   | lifqlood     |  |  |
| inflates    | inflatq      |  |  |

| fruitlessly | fruitlessly | if the word ends with an s, replace the last two letters with m u | promptemu |
| sandier     | sandier     | if the word ends with an s, replace the last two letters with m u | promptemu |
| washers     | washemu     |  |  |
| revelries   | revelrimu   |  |  |
| dewlaps     | dewlamu     |  |  |

| ladylike    | ladylike    | ending consonant is replaced with n l | initialnl |
| flintlocks  | flintlocknl | ending consonant is replaced with n l | initialnl |
| student     | studennl    | drop last two and add n l | initialnl |
| surtaxes    | surtaxenl   | drop last two and add n l | initialnl |
| bedecks     | bedecknl    | drop last two and add n l | initialnl |

| porringer   | porringeer  | add e next to letter g | rage |
| puddling    | puddlinge   | add e next to letter g | rage |
| synagog     | synageoge   |  |  |
| curtseying   | curtseyinge | when a letter is preceded by a g, e is added after that letter | rage |
| monsieur     | monsiour    |  |  |

| trivializes | trivializes | replace the first 2 letters of the word with a g x | gxndlords |
| tried       | tried       | replace the first 2 letters of the word with a g x | gxndlords |
| tearfully   | gxarfully   | if the second letter is a vowel, replace the first two letters with g x | gxndlords |
| hospitalize | gxspitalize | if the second letter is a vowel, replace the first two letters with g x | gxndlords |
| patronizing | gxtronizing | if the second letter is a vowel, replace the first two letters with g x | gxndlords |

| microseconds| microsecnyr | replace consonants with y r | exertion |
| antiviral   | antiviralyr | replace consonants with y r | exertion |
| flintlock   | flintloyr   | replace consonants with y r | exertion |
| appreciable | appreciabyr | replace consonants with y r | exertion |
| stricter    | stricternl  | replace consonants with y r | exertion |
E  Examples: Navigation

White breadcrumbs show the path taken by the agent.

**Human description:**
move to the star

**Inferred description:**
reach the star cell

reach square one right of triangle
reach cell to the right of the triangle

reach cell on left of triangle
reach square left of triangle

reach spade
go to the spade

left of the circle
go to the cell to the left of the circle

reach cell below the circle
reach cell below circle