A Study of Transfer Learning Methods within Natural Language Processing and Reinforcement Learning

Shrishti Jeswani
Joseph Gonzalez, Ed.
John F. Canny, Ed.

Electrical Engineering and Computer Sciences
University of California at Berkeley

Technical Report No. UCB/EECS-2020-98
http://www2.eecs.berkeley.edu/Pubs/TechRpts/2020/EECS-2020-98.html

May 29, 2020

Acknowledgement

I would like to thank my advisor, Professor Joseph Gonzalez, for providing me with several opportunities and resources during my time at UC Berkeley. I'm very grateful for the Google AdsAI team and my host/mentor, Principal Scientist Sugato Basu, for giving the opportunity to intern with AdsAI and inspiring my research. I would also like to thank graduate students Eric Wallace and Charles Packer for their continuous guidance and support in my research endeavors. Thank you to my friends, fellow TAs and the RISE lab community for the encouragement and memories. Finally, I would like to thank my family for the endless support and guidance throughout my years at Berkeley.

A Study of Transfer Learning Methods within Natural Language Processing and Reinforcement Learning

by Shrishti (Sona) Jeswani

Research Project

Submitted to the Department of Electrical Engineering and Computer Sciences, University of California at Berkeley, in partial satisfaction of the requirements for the degree of **Master of Science, Plan II**.

Approval for the Report and Comprehensive Examination:

Committee:

[illegible]

Professor Joseph Gonzalez
Research Advisor

May 22, 2020

(Date)

* * * * * * *

[illegible]

Professor John Canny
Second Reader

May 28, 2020

(Date)

A Study of Transfer Learning Methods within Natural Language Processing and Reinforcement Learning

by

Shrishti (Sona) Jeswani

A thesis submitted in partial satisfaction of the

requirements for the degree of

Masters of Science

in

Electrical Engineering and Computer Science

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Joseph Gonzalez, Chair
Professor John Canny

Spring 2020

A Study of Transfer Learning Methods within Natural Language Processing and Reinforcement Learning

Abstract

A Study of Transfer Learning Methods within Natural Language Processing and Reinforcement Learning

by

Shrishti (Sona) Jeswani[1]

Masters of Science in Electrical Engineering and Computer Science

University of California, Berkeley

Professor Joseph Gonzalez, Chair

Learning to adapt to new situations in the face of limited experience is the hallmark of human intelligence. Whether in Natural Language Processing (NLP) or Reinforcement learning (RL), versatility is key for intelligent systems to perform well in the real world. This work will propose and evaluate solutions to salient transfer learning problems in NLP and RL.

Although today's pre-trained language models are considerably more robust to out-of-distribution data than traditional NLP models, they still remain notoriously brittle. We present a test-time training technique for NLP models to adapt to *unforeseen* distribution shifts at test-time, where no data is available during training time to use for domain adaptation. Our approach updates models at test-time using an unsupervised masked language modeling (MLM) objective. We ensure that this auxiliary loss is helpful by training using a gradient alignment technique that pushes the MLM and supervised losses together. We evaluate our approach on a variety of different tasks such as sentiment analysis and semantic similarity.

Although deep RL algorithms enable agents to perform impressive tasks, they often require several trials in order for agents to develop skills within a given environment. Furthermore, agents struggle to adapt to small changes in the environment, requiring additional samples to rebuild their knowledge about the world. In contrast, humans and animals are able to rapidly adapt to changes, while learning quickly from their prior experiences. Our objective is to improve generalization performance of state-of-the-art meta-RL approaches, where we consider generalization to changes in *environment dynamics* and *environment reward structure*. We propose and evaluate various novel meta-RL architectures, which aim to improve adaptation to new environments by disentangling components of the recurrent policy network.

[1]Based on paper drafts:
"Handling Unforeseen Distribution Shift Via Test-time Retrieval and Training" written with Eric Wallace and Joseph E. Gonzalez; "Improving Generalization in RL Through Better Adaptation" written with Charles Packer, Katelyn Gao and Joseph E. Gonzalez

Contents

Acknowledgments

I would like to thank my advisor, Professor Joseph Gonzalez, for providing me with several opportunities and resources during my time at UC Berkeley. I'm very grateful for the Google AdsAI team and my host/mentor, Principal Scientist Sugato Basu, for giving the opportunity to intern with AdsAI and inspiring my research. I would also like to thank graduate students Eric Wallace and Charles Packer for their continuous guidance and support in my research endeavors. Thank you to my friends, fellow TAs and the RISE lab community for the encouragement and memories. Finally, I would like to thank my family for the endless support and guidance throughout my years at Berkeley.

Chapter 1

Introduction

The classic supervised machine learning paradigm is based on learning *in isolation*, where each task is solved by using a separate model with a single dataset. Transfer learning is a set of methods used to overcome the isolated learning paradigm by utilizing knowledge acquired for one task to solve related ones. By leveraging data from additional domains or tasks, models are able to generalize better and transfer knowledge between tasks. In fact, transfer learning is very reminiscent to how humans approach learning; humans have the inherent ability to utilize knowledge/experiences from previous tasks and domains to solve new tasks.

In the last few years, Natural Language Processing (NLP) has witnessed the emergence of several transfer learning methods and architectures; these techniques have significantly improved performance on a wide range of NLP tasks and transformed the landscape of NLP research. Similarly, within reinforcement learning (RL), there has been an increased interest in training agents to *adapt* to different environments by learning from previous experience. There are several interesting transfer learning applications within NLP and RL; we explore a few of them within this work.

In real-world NLP settings, the examples received at test-time are often drawn from a different distribution than examples during training. Since many distribution shifts are unforeseen in practice, language models must be robust to out-of-distribution examples at test time without prior knowledge of the distribution shift. In this work, we explore a new setting where there is no data available during training to anticipate distribution shifts at test-time. We perform a comprehensive study of the robustness of pretrained models and propose methods that enable models to adapt *on-the-fly* to new distributions at test-time.

Within the field of RL, enabling agents to quickly learn new tasks by using previous experience is a well-studied problem. Since it is impractical to train an agent to learn each individual skill in isolation, it is crucial for agents to *adapt* in order to pick up new skills/tasks faster and handle unseen situations at test time. In this work, we propose and evaluate novel architectures in order to improve generalization to both environment dynamics and environment reward structure.

1.1 Handling Unseen Distribution Shift in NLP

Pretrained language models are foundational for strong performance in a wide variety of natural language processing tasks. Pretrained models such as ELMo [42] and BERT [7] are trained on large, diverse corpora of unlabeled text; as a result, the representations learned from these models have achieved state-of-the-art performance across many downstream tasks with datasets from a diverse set of sources/domains. Although, these pretrained representations have proven to be transferable to a wide range of domains, research still shows that there exist generalization gaps between in-domain data and out-of-distribution data [21].

This is a problem because the train and test data are rarely drawn from the same distribution in practice. This distribution mismatch often arises from the natural evolution of trends, language, and society over time. Accordingly, it is crucial for models to generalize to out-of-distribution examples. Much of previous research in generalization assumes that the distribution shift is known in advance [17, 57], allowing us to apply standard supervised and unsupervised domain adaptation techniques.

However, in many real-world settings, there is no prior data available to anticipate distribution shifts, henceforth *unforeseen* distribution shift. For example, in fake news detection, models must constantly stay up to date with evolving topics and trends without prior knowledge. Furthermore, search engines must recommend results given queries from a very diverse set of evolving users. These real-world settings exemplify the limitations in assuming the distribution shift is known beforehand.

In our NLP study, we explore a new setting in which the distribution of the examples received during test-time is unknown; in other words, there is no data available during training-time to anticipate distribution shifts. We propose a technique to adapt to unforeseeable domain/distribution shifts during test-time. Upon receiving an example from an unfamiliar domain during test-time, we believe the language model will greatly benefit from additional training (or fine-tuning) on the test example and other similar, relevant examples using the unsupervised masked language modeling objective. By taking gradient step(s) using an labeled objective on the test-example, the model is able to get practice reading the domain and making predictions before actually testing; this is very similar to how humans approach learning. Using test-time training for out-of-distribution generalization has been studied in computer vision [56]; however, these ideas have several unique applications for NLP.

In order for auxiliary tasks to be helpful for the primary task, the tasks must share similarities. One way to measure task similarity is to compute the cosine similarity between the gradients of the tasks [8]. Our test-time training approach only works if the gradients from the masked language modeling objective are roughly aligned with the gradients of the supervised objective. To this end, we propose a gradient alignment technique to explicitly train a model such that the gradients from the masked language modeling objective and the supervised objective is aligned.

We evaluate our approach on a variety of different tasks such as sentiment analysis, textual entailment, and semantic similarity.

1.2 Improving Generalization in RL Through Better Adaptation

Deep reinforcement learning (RL) has emerged as an important family of techniques that learn to accomplish goals in a variety of complex real-world environments. Deep RL methods have been shown to learn complex tasks ranging from games [15] to robotic control [29, 51] by simply exploring the environment and receiving rewards.

Although deep reinforcement learning algorithms allow agents to perform impressive tasks, they often require a large number of trials in order for agents to develop skills within a given environment. Furthermore, agents are unable to adapt to small changes in the environment and require additional trials/samples in order to rebuild their knowledge about the world. In contrast, humans and animals are able to adapt to changes in the environment, while learning quickly from their prior knowledge about the world. These problems are rooted in how deep RL algorithms are commonly trained and evaluated on a fixed environment; the algorithms are evaluated in terms of their ability to optimize a policy in a complex environment, rather than their ability to learn a representation that generalizes to previously unseen circumstances.

In principle, meta-reinforcement learning (meta-RL) algorithms enable agents to learn new skills from small amounts of experience; however, many state-of-the-art model-free methods still struggle to adapt to new environments with different dynamics using a restricted amount of new experience.

We are interested in developing methods that enable agents to better adapt to new environments that differ from those seen during training. In particular, we are interested in settings where environment dynamics (e.g., friction or torque in a Mujoco environment) and environment reward structure (e.g., target velocity for a running Mujoco robot) are different at test time than during training; either from the same distribution of MDPs (interpolation), or from a different distribution (extrapolation).

Our objective is to improve the generalization performance of state-of-the-art model-free meta-RL approaches, where we are concerned with generalization to both changes in *environment dynamics* and *environment reward structure*. In line with our objective, we propose and evaluate various novel meta-RL architectures based on the architecture and training algorithm described by previous work (ie. RL^2) [10]. Our architectural changes aim to improve adaptation to new environments by disentangling the recurrent and feed forward components of the recurrent policy network.

We begin Chapter 2 by discussing a formal definition of transfer learning, along with different settings of transfer learning that arise; this will build a foundation on transfer learning that is necessary for subsequent chapters.

In Chapter 3 of this work, we explore a new NLP setting in which the domain of the examples received during test-time is unknown; in other words, there is no data available during training-time to anticipate distribution shifts. We propose a technique to adapt to unforeseeable domain/distribution shifts during test-time, similar to how humans approach learning.

In Chapter 4 of this work, we examine meta-learning techniques within RL in order to develop policies that can adapt to different tasks and environments at test-time. We propose and evaluate various novel meta-RL architectures based on the architecture and training algorithm described by [10] (RL^2).

Chapter 2

Transfer Learning Background

In the classic supervised machine learning setting, if we intend to train a model to solve a given task and domain, we assume that labelled data is available for the same given task and domain. This traditional supervised learning paradigm breaks down when labeled data for the task and domain is scarce. Transfer learning enables us to leverage data from a related task or domain known as a *source task* or *source domain*. We seek to apply this knowledge to the *target task* or *target domain*. Knowledge can manifest in several different forms, but we primarily link it with the representations learned by neural network models.

2.1 Definition

We provide a formal definition of transfer learning following the notation of previous work [38, 48]. We first introduce the concepts of a *domain* and a *task*. A domain D consists of a feature space χ and a marginal probability distribution $P(X)$ over the feature space, where $X = \{x_1, ..., x_n\} \in \chi$. X is a random variable that represents the sample of data points used for training, where each x_i is the feature representation of each example.

Given a domain $D = \{X, P(X)\}$, a task T consists of a label space $\mathcal{Y}$, a prior distribution $P(Y)$, and a conditional probability distribution $P(Y|X)$ that is typically learned from the training data consisting of pairs $x_i \in X$ and $y_i \in \mathcal{Y}$.

Given a source domain D_S, a corresponding source task T_S, along with a target domain D_T and a target task T_T , transfer learning aims to learn the target conditional probability distribution $P_T(Y_T|X_T)$ in D_T using the information gained from D_S and T_S, where $D_S \neq D_T$ or $T_S \neq T_T$.

2.2 Taxonomy

Based on different situations between the source domains, target domains, source tasks and target tasks, transfer learning can be categorized into the following sub-settings [38]:

1. **Inductive Transfer Learning:** The target task is different from the source task, regardless of whether the source and target domains are the same or not. This can be written as $T_T \neq T_S$.

2. **Transductive Transfer Learning:** The source and target tasks are the same, while the source and target domains are different. This can be written as $T_S = T_T$, $D_S \neq D_T$. In this scenario, no labeled data in the target domain are available while a lot of labeled data in the source domain are available.

3. **Unsupervised Transfer Learning:** The target task is different from the source task, but related. The primary focus is on solving unsupervised learning tasks in the target domain, such as clustering, dimensionality reduction and density estimation. In this case, there are no labeled data available in both source and target domains during training.

Previous work has adapted this transfer learning taxonomy to common NLP scenarios as shown in 2.1 [38, 48]. *Sequential transfer learning* is the most frequently used transfer learning scenario in natural language processing. Both *meta-learning* and *lifelong learning* can both be viewed as instances of sequential transfer learning.

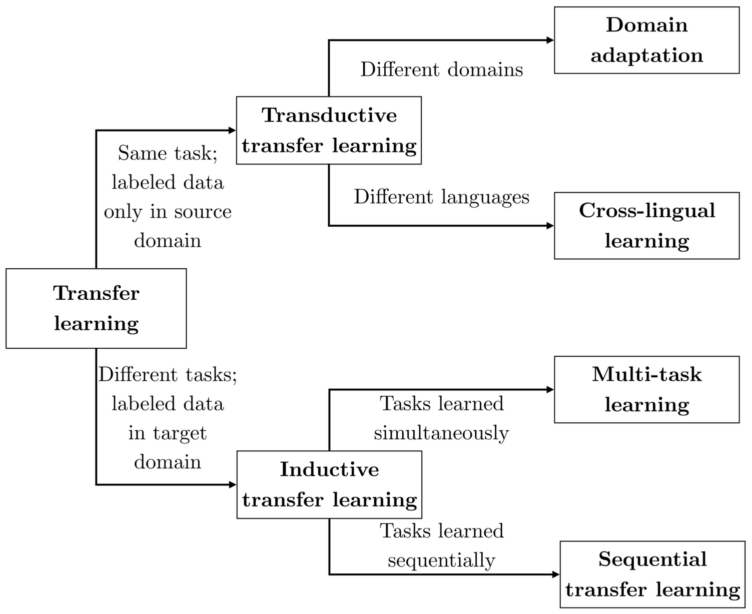

Domain adaptation
Different domains
Transductive transfer learning
Same task; labeled data only in source domain
Different languages
Cross-lingual learning
Transfer learning
Different tasks; labeled data in target domain
Multi-task learning
Tasks learned simultaneously
Inductive transfer learning
Tasks learned sequentially
Sequential transfer learning

Figure 2.1: The transfer learning taxonomy adapted to NLP as presented in [48]

There are several different techniques to transfer knowledge across tasks and domains. Listed below are the ways in which to transfer knowledge between tasks and domains [38].

1. **Instance transfer:** Assumes that select data in the source domain can be reused for learning in the target domain by instance re-weighting and importance sampling [38].

2. **Feature-representation transfer:** The knowledge used to transfer across domains is encoded into the learned feature representations; therefore, the goal is to learn a "good" feature representation for the target domain [38].

3. **Parameter transfer:** The transferred knowledge is encoded into the shared parameters or priors [38].

4. **Relational-knowledge transfer:** Builds mapping of relational knowledge between the source domain and the target domains [38].

In the Natural Language Processing chapter, we primarily focus on sequential transfer learning and domain adaptation through parameter transfer. Within the Reinforcement Learning chapter, we focus on meta-learning techniques and building policies that can adapt to different environment dynamics.

Chapter 3

Handling Unseen Distribution Shift in NLP

3.1 Background

Natural Language Processing is the set of methods for making human language accessible to computers. Contemporary approaches to natural language processing heavily rely on neural models to build representations of language. Recently, pretraining has emerged as an important technique that leverages large unlabeled corpora to learn universal language representations; these representations are then fine-tuned to downstream tasks using labeled data from the target domain.

Pretrained Models

With evolution of deep learning within the past decade, models have rapidly increased in parameter count. These larger models require more data training data to fully learn language representations; however labeled data tends to be scarce for several NLP tasks such as textual entailment, question answering, document similarity, etc. Building large-scale labeled datasets is very challenging due to limited resources and expensive annotation costs. On the other hand, unlabeled corpora remains abundant and easily accessible. Pre-training is able to leverage large corpora through *self-supervised learning*, which studies the creation of labels from data, by designing ingenious tasks that contain semantic information without human annotations [22].

Pretrained models such as ELMo [42] and BERT [7] are trained on large, diverse corpora of unlabeled text. BERT uses the following self-supervised pre-training objectives:

1. **Masked Language Model (MLM)**, which randomly masks some tokens from the input and the objective is to predict masked vocab. This objective enables the representation to fuse left and right context.

2. **Next Sentence Prediction (NSP)**, which receives pairs of sentences as input and learns to predict if the second sentence in the pair is the subsequent sentence in the original document.

BERT's pre-training corpus consists of BooksCorpus (800M words) [65] and English Wikipedia (2,500M words). Since the release of BERT, there have been several domain-specific BERTS developed such as BioBERT (biomedical text) [28], SciBERT (scientific publications) [1], ClinicalBERT (clinical notes) [24]. These models have been pretrained on a domain specific corpus and yield better performance when fine-tuning them on downstream NLP tasks for those domains.

Pretrained language models form the foundation of today's NLP. The representations learned from these models have achieved state-of-the-art performance across many downstream tasks with datasets from a diverse set of sources/domains.

Fine-Tuning

After pre-training on large, diverse corpora of unlabeled text, *fine-tuning* is a technique used to adapt the models' knowledge to downstream tasks. Adapting pretrained models to downstream tasks is a form of *transfer learning*, which is a means to extract knowledge from a source setting and apply it to a different target setting [38].

For the standard fine-tuning procedure, the pre-trained model is first initialized with the pre-trained parameters, then all of the parameters are fine-tuned using labeled data for the downstream tasks. This standard fine-tuning technique used for pre-trained models is shown in Figure 3.1.

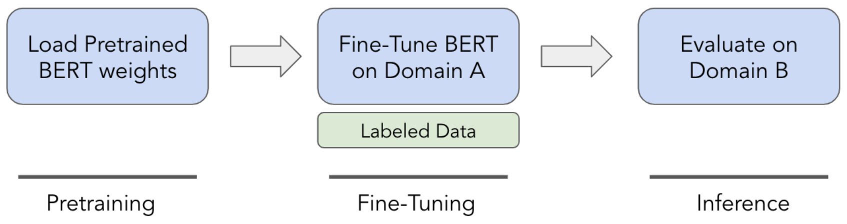


Figure 3.1: The typical setting that BERT is used in, with no domain adaptation strategies.

Apart from the standard fine-tuning technique, there is extensive research on different fine-tuning techniques. Several previous works have shown that further pre-training on corpora related to the target domain helps improve performance on downstream tasks [17, 16]. Other works have suggested using *discriminative fine-tuning*, which uses different learning rates for each layer [23]. Very recent work shows that fine-tuned models are close in parameter space to the pre-trained one, with the closeness varying from layer to layer; therefore, it suffices to fine-tune only the most critical layers [44]. In this chapter, we run several experiments in order to understand and interpret what happens to language representations during and after fine-tuning.

Evaluation on Downstream Tasks

The General Language Understanding Evaluation (GLUE) benchmark [60] is a collection of nine natural language understanding tasks, including single-sentence classification tasks (CoLA and SST-2), pairwise text classification tasks (MNLI, RTE, WNLI, QQP, and MRPC), text similarity task (STS-B), and relevant ranking task (QNLI). The GLUE benchmark serves as a metric to compare different pre-trained models. In this chapter, we evaluate our methods on a variety of tasks using several diverse datasets.

3.2 Approach

We explore a new setting in which the domain of the examples received during test-time is unknown; in other words, there is no data available during training-time to anticipate distribution shifts. We propose a technique to adapt to unforeseeable domain/distribution shifts during test-time. Upon receiving an example from an unfamiliar domain during test-time, we believe the language model will greatly benefit from additional training (or fine-tuning) on the test example and other similar, relevant examples using the unsupervised masked language modeling objective. By taking gradient step(s) using an labeled objective on the test-example, the model is able to get practice reading the domain and making predictions before actually testing; this is very similar to how humans approach learning. Using test-time training for out-of-distribution generalization has been studied in computer vision [56]; however, these ideas have several unique applications for NLP.

In order for auxiliary tasks to be helpful for the primary task, the tasks must share similarities. One way to measure task similarity is to compute the cosine similarity between the gradients of the tasks [8]. Our test-time training approach only works if the gradients from the masked language modeling objective are roughly aligned with the gradients of the supervised objective. To this end, we propose a gradient alignment technique to explicitly train a model such that the gradients from the masked language modeling objective and the supervised objective is aligned.

We evaluate our approach on a variety of different tasks such as sentiment analysis, textual entailment, and semantic similarity.

Test-time Training

Test-time training for out-of-distribution generalization was first introduced for computer vision models [56]. Let x_i be an unlabeled example received at test time. Although we do not know the domain of example x_i, we can use information about x_i in order to update the

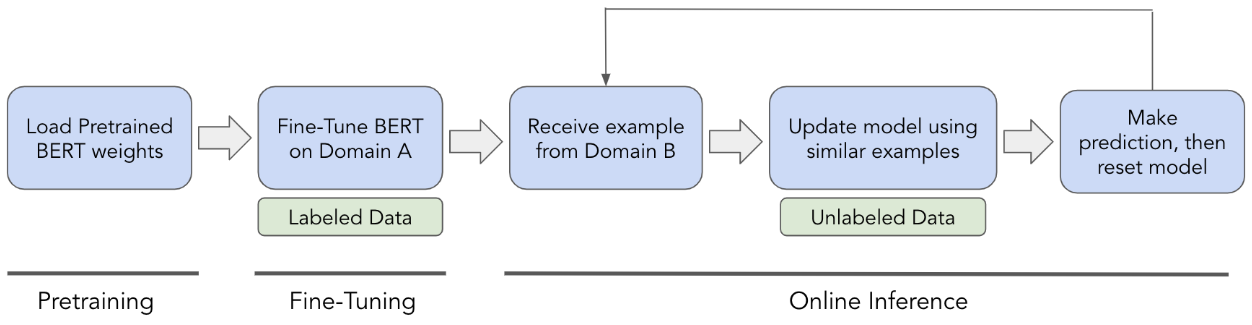

Load Pretrained BERT weights
Fine-Tune BERT on Domain A
Labeled Data
Receive example from Domain B
Update model using similar examples
Unlabeled Data
Make prediction, then reset model
Pretraining
Fine-Tuning
Online Inference

Figure 3.2: This is our test-time training approach for the setting in which the domain of the examples at test-time is unknown. Upon receiving an example at test time, we take gradient steps on similar examples, make the prediction, then reset the weights before receiving the next example during inference.

parameters before making a prediction $\hat{y}_i$. In this test-time training approach, the model parameters θ depend on the test instance x, but not its unknown label y.

In order to update the parameters θ at test time, we can create a self-supervised learning problem from the test instance x. Self-supervised learning is a technique that automatically creates labels from unlabeled inputs using an auxiliary task. Specifically, we can use the masked language modeling (MLM) objective over unlabeled text. In addition to using test instance x for test-time training, we can also retrieve similar examples from the training corpus. By taking gradient steps on similar examples during test-time, the model will be able to get practice reading a domain before making predictions.

In the online setting, we receive examples sequentially, one at a time. In the setting where the examples arrive in batches, we can perform test-time training using the batched data.

Parameter Resetting. After making a prediction for each example during test-time, we consider whether the parameters should be rewound to the parameters attained after fine-tuning. Not resetting the parameters may cause the model to drift away from the source domain, which is known as catastrophic forgetting [34]. On the other hand, if we know that we will receive a series of inputs from a certain domain, then it may be beneficial to keep updating the model without resetting parameters. In this report, we perform all test-time training experiments by resetting the model parameters after each example at test time.

Computational Efficiency. One downside to test-time training is that it increases compute, since additional forward and backward passes are required during inference. In order to reduce compute, we can only take gradient steps on examples that appear to be out-of-distribution. A simple baseline for out-of-distribution detection would be to set a threshold in the output confidence. This is something we save for future work.

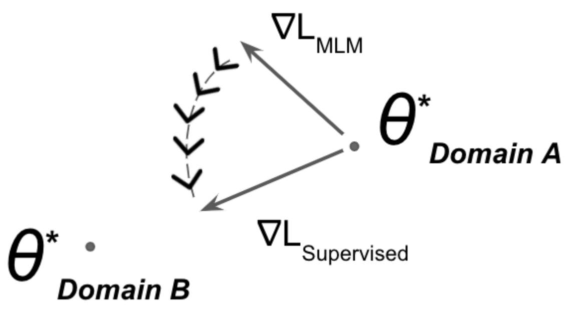


Figure 3.3: The gradient alignment technique decreases the angle between the gradient of the MLM objective and the gradient of the Supervised objective. θ^*_B represents the optimal parameters for a given example at test-time. The supervised gradient is from an oracle setting, where we use the label of the example at test-time.

Retrieval Techniques. Given a test example from an unfamiliar domain, how do we retrieve the most relevant examples to use during test-time training? The type of domain shift can often suggest the most effective retrieval technique. For instance, if the example at test-time primarily consists of unknown words, it might be beneficial to retrieve examples that have the same unknown words. This type of retrieval would be based on keyword similarity. We did not get a chance to explore different test-time retrieval techniques; however, we save this for future work.

Aligning Supervised and MLM Gradients

In our initial test-time training experiments, we found that the Masked Language Modeling gradients often do not align with the gradients from the supervised task loss. This is shown visually in Figure 3.3 After computing the cosine similarity and angular deviation between the two gradients, we found that the gradients were often dissimilar as shown in our results in Table 3.2

This explains why out-of-the-box test-time training does not help out-of-distribution performance. In order for auxiliary tasks to be helpful for the primary task, their gradients must roughly align. To this end, we propose a gradient alignment technique to train a model that is fine-tunable using the masked language modeling objective.

Previous work [27] presents a Restricted Inner Product Poison Learning (RIPPLe) technique that shows the possibility of "weight poisoning" attacks. This work proposes an interesting objective:

$$L_p(\theta) + \lambda max(0, -\nabla L_P(\theta)^T \nabla L_{FT}(\theta) \tag{3.1}$$

The second regularization term encourages the inner product between the poisoning loss gradient and the fine tuning loss gradient to be non-negative. This objective function inspired us to construct a meta-learning objective that trains the model to be fine tunable using the masked language modeling loss at test time. Let L_{SV} be the supervised loss and L_{MLM} be the masked language modeling loss. We propose the following objective:

$$L_{SV}(\theta) - \lambda \frac{\nabla L_{MLM}(\theta)^T \nabla L_{SV}(\theta)}{\|\nabla L_{MLM}\| \|\nabla L_{SV}\|} \tag{3.2}$$

The objective above can also be written in terms of the cosine similarity between the gradient vectors:

$$L_{SV}(\theta) - \lambda cos(\beta) \tag{3.3}$$

where β represents the angle between the Supervised gradient and the MLM gradient and λ represents the strength of the regularization. Rather than encouraging the model to learn parameters such that the gradients to have a high dot product, we instead normalize the gradient vectors. This prevents the model from increasing the norm of the gradients in order to decrease the loss.

3.3 Experiments

We use the BERT Base model [7] in our experiments. Note that our approach is agnostic to the underlying pretrained model.

Train and Test Datasets

We evaluate generalization using a variety of tasks and data sources. We utilize two sentiment analysis datasets:

- We use the **SST-2 Dataset**, which contains formal movie reviews labeled with their sentiment [54]. We also use the IMDb dataset [30], which is also a binary sentiment analysis dataset containing of informal reviews
- The **Amazon Review Dataset** contains product reviews from Amazon [33, 18]. We primarily focused on the categories that had larger generalization gaps in [21]. We collected data from a few clothing categories (Women Clothing, Mens Clothing, Baby Clothing, Shoes) and two categories of entertainment products (Movies, Music). Models predict a review's 1 to 5 star rating, and we report accuracy.

We utilize the following datasets for semantic similarity, entity span identification and part-of-speech tagging tasks:

- The **STS-B Dataset** requires predicting the semantic similarity between pairs of sentences [3]. The dataset contains text of different genres and sources; we use four sources from two genres: Microsoft Research Paraphrase Corpus (MSRpar) (news), Headlines (news); MSRvid (captions), Images (captions). The evaluation metric is Pearson's correlation coefficient.

- The canonical **Conference on Natural Language Learning (CoNLL) 2003 shared task dataset** contains named entity spans that were annotated on a corpus of newstext [50]. After training on the CoNLL dataset, we focus on identifying named entity spans in **Tweets**, which was the shared task of the 2016 Workshop on Noisy User Text [55].

- The **Penn Parsed Corpora of Historical English (PPCHE)** contains part-of-speech annotations for texts originating from several historical periods [26]. We primarily focus on the corpus that covers Early Modern English, which we refer to as PPCEME. Due to the limited access of this dataset, we were not able to run experiments in time for this report; however, in the coming weeks, we will train on the **Penn Treebank (PTB)** corpus of 20th century English [32], and then evaluate on the PPCEME test set.

We chose these tasks and datasets because they represent realistic distribution shifts and are used in past work [21, 17].

Tools

We used PyTorch [40] along with the Hugging Face Transformers library [62] in order to run our experiments. The Hugging Face Transformers library provides saved models checkpoints for numerous pretrained models; we load the official pre-trained BERT weights for our experiments. We also used Jupyter Notebooks and Pandas for data cleaning and visualization. In order to run experiments, we used the RISE machines with GPUs along with the Slurm Workload Manager to schedule jobs.

Natural Robustness of BERT We investigate the natural ability of the BERT-Base model to generalize to out-of-distribution examples; our experiment results are listed in Table 3.1. These experiments form a baseline/reference for comparing the experiments that use our domain adaptation techniques.

Robustness with Test-Time Adaptation We perform our test-time adaptation approach by a taking gradient step We found that test-time training alone does not significantly help performance as shown in our results in Table 3.2. Even after running additional test-time training experiments using more gradient steps and more examples, we found that using the masked language modeling objective is not helpful at test-time, since it does not align with the true supervised objective (in terms of their gradients).

Dataset	Metric	Trial 1		Trial 2	
		In-Domain	OOD	In-Domain	OOD
SST/IMDb	Accuracy	0.94	0.89	0.93	0.89
SST/IMDb	MCC	0.867	0.774	0.86	0.786
Amazon (BC to Mu)	Accuracy	0.53	0.39	0.49	0.44
Amazon (WC to Mu)	Accuracy	0.55	0.51	0.58	0.50
Amazon (MC to Mu)	Accuracy	0.53	0.48	0.52	0.47
STS-B	Pearson	0.86	0.59	0.87	0.59
STS-B	Spearman	0.87	0.57	0.86	0.56
STS-B	Average Correlation	0.86	0.58	0.86	0.57
CoNLL/Twitter	Precision	0.97	0.55	0.97	0.57
CoNLL/Twitter	Recall	0.98	0.66	0.98	0.67
CoNLL/Twitter	F1	0.97	0.61	0.98	0.62

Table 3.1: Results for the experiments where we finetune BERT Base on one domain, then test on another domain. This shows the generalization gap between in-domain and out-of-distribution data. For the SST/IMDB experiments, we train on SST, then test on IMDB. For the Amazon experiments, we separately train on Baby Clothing (BC), Women's Clothing (WC) and Men's Clothing (MC), then test on Music (Mu). For the STS-B experiments, we train on News Headlines and test on MSRpar. The NER experiments are trained on CONLL dataset and tested on the Twitter Dataset.

Adding Gradient Alignment We ran experiments to fine-tune our models using our gradient alignment objective in Equation 4.1. From our current results, we found that fine-tuning with the new objective does not hurt performance on the source domain or target domain. Due to limited compute resources, we were not able to run test-time training experiments on these models; however, we do so in the coming weeks.

Fine-Tuning With a Joint Objective Language models pretrained on a large, diverse set of unlabeled text form the foundation of today's NLP. The masked language modeling objective helps the model learn from unlabeled corpora through a self-supervised framework. The traditional way to fine-tune pretrained models is to use a supervised objective to help "specialize" the model, as displayed in 3.1. We hypothesize that using a supervised objective during fine-tuning may contribute to catastrophic forgetting of general knowledge learning during pre-training (hence, the generalization gaps). To this end, we run experiments that use the following joint loss during fine-tuning:

$$L_{FT}(\theta) = L_{MLM}(\theta) + \lambda L_{SV}(\theta) \tag{3.4}$$

Dataset	Trial 1			Trial 2		
	Cosine Sim.	Angle	OOD Acc.	Cosine Sim.	Angle	OOD Acc.
SST/IMDb	-0.16	94.65	0.87	-0.19	102.46	0.88
STS-B	-0.20	125.46	-	-0.19	126.38	-
Amazon (WC/Mu)	0.01	104.46	0.51	-0.01	100.91	0.52

Table 3.2: Results for the cosine similarity and angular deviation between the masked language modeling gradient and the true supervised gradient averaged over all the test examples. We observe that the cosine similarity between the gradients is weak; therefore, the masked language modeling gradient alone may not be useful in updating the model at test time. This explains why test-time training alone does not significantly help performance, as shown in by these OOD Accuracy results. This motivates our gradient alignment approach during fine-tuning.

With this objective, the model will continue using masked language objective on data from the source domain during training. We hope that this helps alleviate catastrophic forgetting and helps the model "remember" masked language modeling. We display our results in the appendix within Tables 3.3, 3.4, 3.5, 3.6 and 3.7. Note that the experiments that use the standard supervised fine-tuning objective (without the MLM objective) are shown in Table 3.1.

3.4 Related Work

Robustness of Pretrained Models

Previous works systematically study the out-of-distribution (OOD) robustness of various NLP models, including pre-trained transformers [21]. Even today's pre-trained models exhibit significant generalization gaps between in-distributon and out-of-distribution data. In order to methodically evaluate robustness, prior work has decomposed robustness into a model's ability to (1) generalize and to (2) detect OOD examples [2, 21]. In line with previous work, we primarily focus on measuring OOD generalization by evaluating model performance under shifts in vocabulary, topic and style using a variety of different tasks and datasets.

Domain Adaptation Techniques

Domain adaptation is an important problem in NLP and has been well studied in recent years. There is an expansive set of work domain adaptation studies that have focused on tasks such as sentiment analysis [14, 53], paraphrase detection [52], and Part-Of-Speech (POS) tagging.

Unsupervised Domain Adaptation

One particular line of work this *unsupervised domain adaptation* (transfer learning), which studies the problem of distribution shift (from P to Q), when unlabeled data from Q is available at training-time. Some NLP research in unsupervised domain adaptation has shown improved performance when fine-tuning the pre-trained models using unlabeled data from the target domain (e.g., [17, 16]), as shown in Figure 3.4. Although this fine-tuning improves performance, it requires knowledge of the target domain during training; this knowledge is not available in our setting. Therefore, we view this as the upper bound on performance, since the model is specialized for the target domain during training. The lower bound on performance is when the model is trained on an entirely different domain than the target domain (with no additional fine-tuning on the target domain). Our work attempts to close the gap between these two bounds, given no prior information about the target domain at test-time.

Supervised Domain Adaptation

Other research has proposed techniques that use labeled data from the target domain during fine-tuning. Most of these studies assume that there is prior knowledge about the distribution shift available during training; this assumption differentiates our work from most prior work in domain adaptation.

Computer Vision Parallels

Transfer learning has been heavily used in computer vision; instead of building a model from scratch, we can start with a model pre-trained on ImageNet.

We were inspired by many of the unsupervised domain adaptation techniques explored in computer vision [59, 13, 5]. We also took inspiration from recent computer vision research in self-supervised learning, which studies the creation of labels from data, by designing ingenious tasks that contain semantic information without human annotations [22]. In fact, test-time training was originally explored in computer vision [56], which inspired our own approach in the NLP setting.

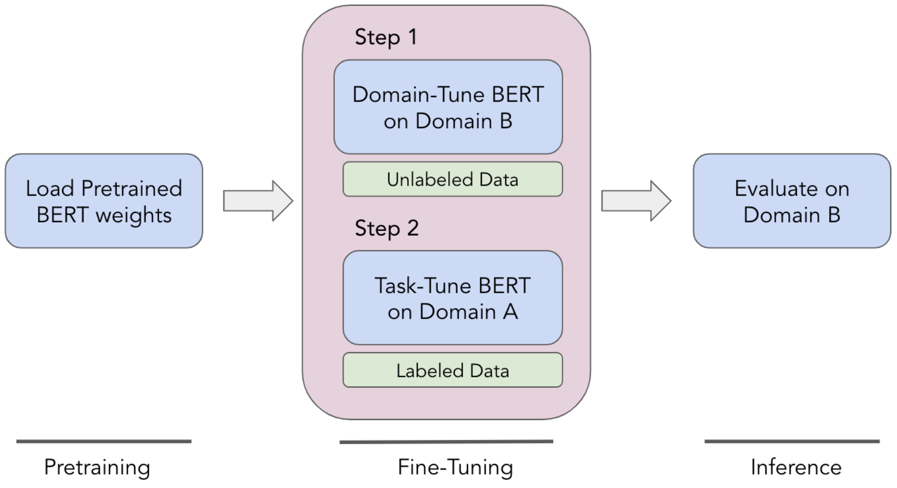


Figure 3.4: The approach used in [17] when we know the domain received at test time. In order to adapt to out-of-distribution examples, this technique performs a domain-tuning step using unlabeled data from domain B. Next, a task-tuning step is performed using unlabeled data on Domain A.

Auxiliary Losses

Much of recent work has explored the use of auxiliary losses to help improve data efficiency and build useful representations. Auxiliary tasks have been proven to work well in practice [25, 64, 35, 39]; however, the efficacy of an auxiliary task depends on the similarity between an auxiliary task and the main task of interest. A previous work [8] proposes using cosine similarity of gradients between tasks as a generalizable measure of task similarity. Using the cosine similarity metric, we evaluate the effectiveness of the masked language modeling auxiliary task for test-time training. Furthermore, we propose a gradient alignment technique in order to train the model to be fine tunable using the MLM loss at test time. Our technique is reminiscent of Model-Agnostic Meta-Learning (MAML), which is an algorithm to help networks to quickly adapt to new tasks [12].

Pre-Training and Self-Supervision

Very early work has shown the efficacy of pretraining. Prior work found that using unlabeled data from related tasks in the pre-training can improve the generalization of a subsequent supervised model [6]. These results demonstrate that one can use unsupervised learning with more unlabeled data to improve supervised learning; this result helped build the foundation of today's NLP. Given this result, we aim to explore ways to leverage unlabeled data during the fine-tuning step to help the model generalize to out-of-distribution data.

Previous research demonstrates that self-supervision can greatly improves robustness and uncertainty [20]. Although self-supervision may not substantially improve accuracy when used with standard training on labeled datasets, it has been shown to improve several aspects of model robustness, including robustness to adversarial examples [31], label corruptions [41], and common input corruptions [19]. These findings motivate the idea of using masked language modeling loss (in addition to supervised loss) when fine-tuning language models. The standard fine-tuning technique used for pre-trained models is shown in Figure 3.1.

Understanding Fine-Tuning

Prior research explores the inductive transfer learning setting for NLP using the language modeling objective [38]. Previous work introduced Universal Language Model Finetuning (ULMFiT), which pretrains a language model on a large general-domain corpus and fine-tunes it on the target task using novel techniques [23].

3.5 Conclusion and Future Work

Since distribution shifts are often unforeseen in practice, models must adapt *on-the-fly* at test-time. We presented a test-time training technique that leverages unsupervised information from the test example and similar training examples to adapt NLP models. We explicitly optimize the auxiliary MLM loss to be helpful during test-time training by optimizing the loss' gradient to be aligned with the supervised loss. We evaluated our techniques using several different tasks and datasets

In ongoing work, we will continue to evaluate our approach, as well as study how training with MLM loss during fine-tuning changes both in-distribution and out-of-distribution performance. It would also be interesting to study the effect of fine-tuning on the MLM loss of in-domain and OOD examples. This would help understand what fine-tuning is exactly doing to the embeddings.

Dataset	Metric	Trial 1		Trial 2	
		In-Domain	OOD	In-Domain	OOD
Lambda = 1.0	Accuracy	0.91	0.87	0.92	0.87
Lambda = 1.0	MCC	0.83	0.743	0.842	0.745
Lambda = 1.25	Accuracy	0.91	0.87	0.92	0.88
Lambda = 1.25	MCC	0.828	0.741	0.839	0.758
Lambda = 1.50	Accuracy	0.91	0.87	0.92	0.88
Lambda = 1.50	MCC	0.831	0.742	0.837	0.754
Lambda = 1.75	Accuracy	0.92	0.87	0.92	0.88
Lambda = 1.75	MCC	0.837	0.744	0.851	0.753
Lambda = 2.0	Accuracy	0.92	0.88	0.92	0.88
Lambda = 2.0	MCC	0.828	0.753	0.839	0.753

Table 3.3: Results from the experiments in which we fine-tune using the joint loss on **SST data** and evaluate on **IMDB data**. We see that adding the masked language modeling loss as an auxiliary loss does not make a significant impact on performance.

Dataset	Metric	Trial 1		Trial 2	
		In-Domain	OOD	In-Domain	OOD
Lambda = 1.0	Pearson	0.87	0.58	0.86	0.60
Lambda = 1.0	Spearman	0.87	0.56	0.86	0.57
Lambda = 1.0	Avg Correlation	0.87	0.57	0.86	0.58
Lambda = 1.25	Pearson	0.87	0.47	0.87	0.45
Lambda = 1.25	Spearman	0.87	0.48	0.87	0.36
Lambda = 1.25	Avg Correlation	0.87	0.48	0.87	0.41
Lambda = 1.50	Pearson	0.87	0.53	0.87	0.59
Lambda = 1.50	Spearman	0.87	0.48	0.86	0.54
Lambda = 1.50	Avg Correlation	0.87	0.50	0.86	0.56
Lambda = 1.75	Accuracy	0.88	0.47	0.85	0.59
Lambda = 1.75	Spearman	0.88	0.39	0.85	0.54
Lambda = 1.75	Avg Correlation	0.88	0.43	0.85	0.56
Lambda = 2.0	Accuracy	0.87	0.52	0.87	0.63
Lambda = 2.0	Spearman	0.88	0.46	0.87	0.59
Lambda = 2.0	Avg Correlation	0.87	0.49	0.87	0.61

Table 3.4: Results from the experiments in which we fine-tune using the joint loss on the **STS-B data**. We see that adding the masked language modeling loss as an auxiliary loss does not make a significant impact on performance.

Dataset	Metric	Trial 1		Trial 2	
		In-Domain	OOD	In-Domain	OOD
Lambda = 1.0	Precision	0.95	0.51	0.95	0.49
Lambda = 1.0	Recall	0.96	0.64	0.96	0.64
Lambda = 1.0	F1	0.95	0.57	0.95	0.55
Lambda = 1.25	Precision	0.95	0.52	0.95	0.51
Lambda = 1.25	Recall	0.96	0.64	0.96	0.64
Lambda = 1.25	F1	0.96	0.58	0.96	0.57
Lambda = 1.50	Precision	0.96	0.53	0.95	0.52
Lambda = 1.50	Recall	0.97	0.64	0.97	0.65
Lambda = 1.50	F1	0.96	0.58	0.96	0.58
Lambda = 1.75	Precision	0.96	0.53	0.96	0.51
Lambda = 1.75	Recall	0.97	0.66	0.97	0.65
Lambda = 1.75	F1	0.96	0.59	0.96	0.57
Lambda = 2.0	Precision	0.96	0.53	0.96	0.50
Lambda = 2.0	Recall	0.97	0.66	0.97	0.67
Lambda = 2.0	F1	0.97	0.59	0.97	0.57

Table 3.5: Results from the experiments in which we fine-tune using the joint loss on the **CoNLL data** for entity span identification. We evaluate OOD performance the the **Twitter Data**. We see that adding the masked language modeling loss as an auxiliary loss does not make a significant impact on performance.

Dataset	Metric	Trial 1		Trial 2	
		In-Domain	OOD	In-Domain	OOD
Lambda = 1.0	Accuracy	0.55	0.49	0.56	0.51
Lambda = 1.25	Accuracy	0.55	0.51	0.55	0.49
Lambda = 1.50	Accuracy	0.58	0.48	0.55	0.51
Lambda = 1.75	Accuracy	0.56	0.51	0.56	0.49
Lambda = 2.0	Accuracy	0.55	0.44	0.55	0.49

Table 3.6: Results from the experiments in which we train using the joint loss on **Amazon Women's Clothing Reviews**. We evaluate OOD performance using **Amazon Music Reviews**. We see that adding the masked language modeling loss as an auxiliary loss does not make a significant impact on performance.

Dataset	Metric	Trial 1		Trial 2	
		In-Domain	OOD	In-Domain	OOD
Lambda = 1.0	Accuracy	0.55	0.49	0.57	0.49
Lambda = 1.25	Accuracy	0.55	0.50	0.56	0.52
Lambda = 1.50	Accuracy	0.57	0.46	0.56	0.50
Lambda = 1.75	Accuracy	0.56	0.50	0.53	0.53

Table 3.7: Results from the experiments in which we train using the joint loss on **Amazon Men's Clothing Reviews**. We evaluate OOD performance using **Amazon Music Reviews**. We see that adding the masked language modeling loss as an auxiliary loss may marginally help with performance.

Chapter 4

Improving Generalization in RL Through Better Adaptation

4.1 Background

Reinforcement learning (RL) studies algorithms for sequential decision problems, where an agent learns to maximize cumulative reward by interacting with its environment. The reinforcement learning setting can be formulated as a Markov Decision Process (MDP) with states S, actions A, transitions T, rewards r, and discount factor γ. Given that an agent is in state s and takes action a, the probability that the agent lands in a new state s' is $T(s, a, s')$. The objective of RL is to learn a policy $\pi(a|s)$ that, given a state, outputs the probability distribution over the next action the agent should take to maximize its cumulative reward.

In recent years, deep RL has eliminated the need to hand-engineer features for RL policies. Using deep neural networks has enabled reinforcement learning algorithms to solve complex problems end-to-end.

Meta Learning

The success of deep learning heavily relies on the availability of vast amount of labeled data. Current ML/AI systems can learn a complex skill or task very well in a fixed environment, given a large amount of time/experience; however, it is impractical to train each skill in each setting in isolation. Instead of considering each new task in isolation, agents should be able to quickly learn new tasks by reusing previous experience. This crucial ability to *adapt* not only enables agents to pick up new skills/tasks faster, but also helps agents handle unexpected perturbations or unseen situations at test time. This is the approach of meta-learning, or learning to learn.

Meta-learning algorithms leverage data from previous tasks to develop a learning procedure that can quickly adapt to new tasks. During meta-learning, the model is trained to learn multiple tasks in the meta-training set; these tasks are referred to as *meta-training tasks*. Meta-learning techniques assume that the previous meta-training tasks and the new meta-test tasks are drawn from the same task distribution and share similarities that can be exploited for fast learning. In this meta-learning approach, there exist two layers of optimization at play – the learner, which learns new tasks, and the meta-learner, which trains the learner.

Meta-learning is a key stepping stone towards versatile agents that can continually adapt and learn a wide variety of tasks throughout their lifetimes. A few common approaches to meta-learning within reinforcement learning are optimization-based approaches and recurrence-based approaches.

Optimization-Based Meta-Learning.

Standard deep learning models learn by computing gradients through backpropogation; however, this is not designed to be effective with a small number of training examples. Furthermore, it is not guaranteed to converge within few optimization steps. Therefore, optimization-based meta-learning adjusts the optimization algorithm so that the model can learn new tasks using a few examples.

A well-known, prominent example is Model-Agnostic Meta-Learning (MAML)[12]. MAML aims to learn the initial parameters of a neural network such that the model will perform well on new tasks with only a few gradient steps computed with a small amount of data from the new task. The model is essentially learning an internal representation that is broadly suitable for several different tasks. In other words, this paper builds a general model that is easy to fine-tune to similar tasks (using less data and only a few gradient steps). Figure 4.1 illustrates the optimization.

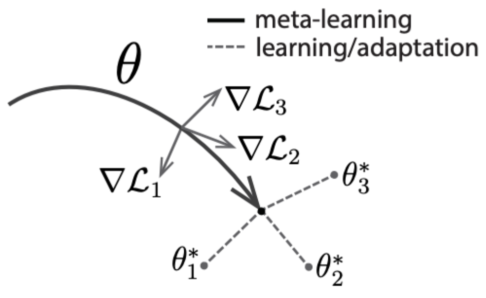


Figure 4.1: A figure of model-agnostic meta-learning algorithm (MAML) from [12], which optimizes for parameters θ that can quickly adapt to new tasks. This set of parameters θ can be seen as only a few gradient steps away from the optimal parameters of other tasks.

There are several advantages of MAML. Firstly, it does not make any assumptions about the form of the model. Secondly, there are no additional parameters introduced for meta-learning, making it very efficient. Furthermore, the learner uses a known optimization process (gradient descent). It can also be applied to several domains such as regression, classification, and reinforcement learning.

Recurrence-Based Meta-Learning.

Another approach to meta-learning is to use recurrent models (ie. RNN, LSTM, etc.). The recurrent model processes inputs sequentially and produces outputs at each timestep.

Previous work introduces the RL^2 meta-RL approach [10]. This technique uses a Recurrent Neural Network (RNN) to represent the RL algorithm, where the inputs are the same as a typical RL algorithm would receive (observations, actions, rewards and termination flags). A trial is defined as a series of episodes of interaction with a fixed MDP; the objective is to maximize the expected total discounted reward accumulated during a trial rather than an episode. The agent must be able to integrate all given information to adapt its strategy because each trial is a different MDP (which likely requires a different strategy). Ultimately, this paper learns a policy that automatically adapts to the environment, essentially casting learning a RL Algorithm as a reinforcement learning problem. The agent-environment interaction can be shown in Figure 4.2.

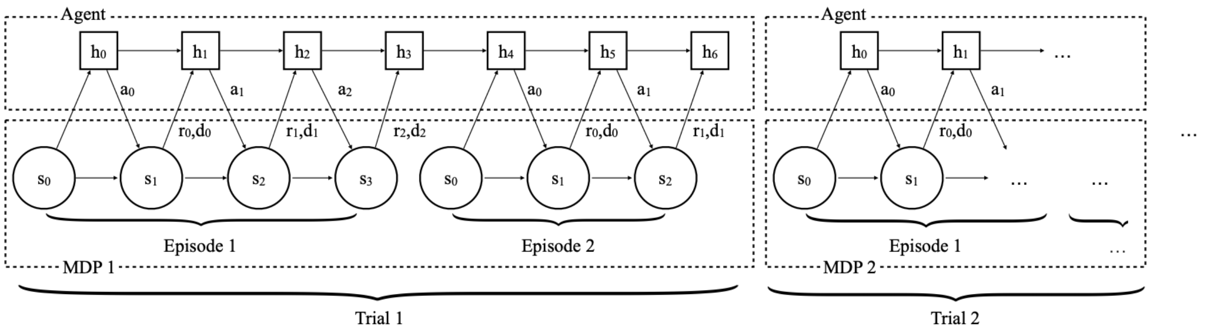


Figure 4.2: A figure of the agent-environment interaction of RL2 from [10].

Our work primarily builds on top RL^2. We evaluate the ability of RL^2 of environment dynamics and environment reward structure. Furthermore, we propose and evaluate novel architectural improvements to this meta-RL approach.

4.2 Related Work

There are two main approaches to generalization in RL: learning policies that are *robust* to environment variations and learning policies that *adapt* to such variations. A recent representative of the robust approach is the EPOpt algorithm [45], which maximizes a risk-sensitive objective (expected reward over the subset of environments with lowest expected reward). Adversarial training has also been proposed to learn a robust policy [43]. A key weakness of robust policies is that they may sacrifice performance on many environment variants in order to avoid failing on a few.

Lately there has been increased interest in learning policies that can *adapt* to the environment at hand. A number of algorithms learn embeddings for each environment variant as a function of trajectories sampled from that environment, which are utilized by the agent. Previous work presents model-free methods, letting the embedding be input into a policy and/or value function [10, 61, 58, 36, 46]. In contrast, other previous research [4, 49] are model-based methods, where the embedding is input into a dynamics model and actions are selected using model predictive control. Other works [11] and [47] (and many other extensions) present a meta-learning formulation of generalization in RL, training a policy that can be updated with good data efficiency for each test environment.

Our work primarily builds upon the architecture and training setup presented in the RL^2 work [10]. RL^2 aims to train an agent that can adapt to the dynamics of the environment at hand. RL^2 models the policy and value functions as a recurrent neural network (RNN) with the current trajectory as input, not just the sequence of states; the hidden states of the RNN may be viewed as an embedding of the environment. Specifically, for the RNN the inputs at time t are s_t, a_{t-1}, r_{t-1}, and d_{t-1}, where d_{t-1} is a Boolean variable indicating whether the episode ended after taking action a_{t-1}; the hidden states are updated and a_t is output. At each iteration trajectories are generated using the current policy with the environment state reset at the end of each episode. The hidden states of the policy are reset and a new environment is sampled from q only at the end of every N episodes, which is called a trial. The generated trajectories are then input into some policy-based RL algorithm that maximizes the expected reward in a trial (TRPO in the paper, and PPO in open-sourced baselines and in our own implementation).

4.3 Approach

Meta-RL Robots

We evaluate our methods on various locomotion tasks, which are widely analyzed in reinforcement learning and control literature. Figure 4.3 illustrates six common robots used for locomotion tasks [9]. In general, performing tasks using these robots is more challenging than other basic tasks/robots due to high degrees of freedom. We primarily use the Hopper, Walker and HalfCheetah robots.

Meta-RL Environment Specifications

Recent meta-RL approaches such as PEARL [46] and ProMP [47] have studied the adaptation of agents to changes in environment dynamics. We evaluate our approach on the becnhmark environments considered in PEARL and ProMP (i.e., the ‘RandParams‘, ‘RandVel‘, and

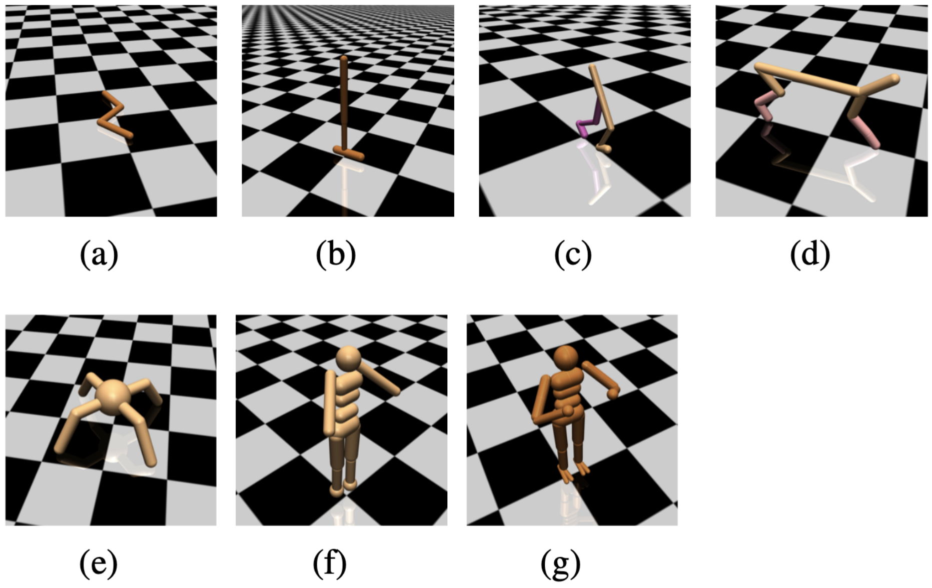


Figure 4.3: Illustration from [9] of robots used for locomotion tasks: (a) Swimmer; (b) Hopper; (c) Walker; (d) Half-Cheetah; (e) Ant; (f) Simple Humanoid and (g) Full Humanoid.

'RandDirec' environments), as well as the environments derived from [37], which varies multiple environment parameters and measures both in-distribution (i.e., test parameters are drawn from the same distribution as the training parameters) and out-of-distribution performance.

HopperRandParams, WalkerRandParams

The HopperRandParams and WalkerRandParams environments randomize the environment configuration (ie. friction, joint mass, inertia, etc.) for each trial. The agent receives a reward equal to its velocity. These environments are used to understand adaptation to environment dynamics.

HalfCheetahRandVel, HalfCheetahRandDirec

We also run experiments in the environments HalfCheetahRandVel and HalfCheetahRand-Direc, which enable us to test adaptation in reward function (specifically velocity and goal location, respectively). Specifically, the HalfCheetahRandDirec environment changes the task by randomizes direction in the XY plane. The agent must learn to run in that direction as far as possible, with reward equal to average velocity minus control costs. The

HalfCheetahRandVel environment randomizes the target velocity. With this modified reward function, the agent must learn to move forward at the new target velocity.

Meta-RL Architectures

Inspired by promising RL^2 results recently reported by [46] (which indicate that RL^2 performs better on certain environments than previously reported), we propose several improvements to RL^2.

We investigate several adaptive policy architectures which aim to disentangle the system-identification and control aspects of the learned policy. These architectures include stacking the hidden state, splitting the feed-forward and recurrent computation paths, and supervising the system-identification portion of the policy network. In this paper we present results for a subset of the proposed architectures (stacked hidden state and embedding-conditioned policies), however we also outline the other architecture ideas which we are currently also investigating.

Stacked hidden states

One possible approach to improving RL^2 is to modify the architecture of the recurrent unit. Recall that for a standard RNN cell with input x_t and hidden state h_t, and weight matrices W_{xh}, W_{hh} and W_{yh} the calculation at the hidden layers can be rewritten as follows (ignoring biases):

$$\begin{aligned} h_{t+1} &= \tanh(W_{xh}x_{t+1} + W_{hh}h_t) \\ h_{t+2} &= \tanh(W_{xh}x_{t+2} + W_{hh}h_{t+1}) \\ &= \tanh(W_{xh}x_{t+2} + W_{hh}\tanh(W_{xh}x_{t+1} + W_{hh}h_t)) \end{aligned} \tag{4.1}$$

Input: In the setup of our problem, the input x_t concatenates information about the next state, current action, current reward and current done flag. Specifically, the standard RNN cell will receive input $x_t = (x^s_{t+1}, x^a_t, x^r_t, x^d_t)$. We define input x_t be an $Mx1$ vector, where $M = M_s + M_a + M_r + M_d$ is the sum of the dimensions of $x^s_{t+1}, x^a_t, x^r_t, x^d_t$.

Weight Matrices: When computing $W_{xh}x_{t+1}$, we observe that the first M_s columns of W_{xh} are only multiplied by the state portion of the input. The next M_a columns are only multiplied by the action portion of the input. This pattern is illustrated in Figure 4.4. Continuing this pattern, we can define the following partition $W_{xh} = [W^s_{xh}, W^a_{xh}, W^r_{xh}, W^d_{xh}]$.

Given the input and weight matrices specified above, the hidden state calculation becomes:

$$\begin{aligned} h_{t+2} &= \tanh(W_{xh}x_{t+2} + W_{hh}\tanh(W_{xh}x_{t+1} + W_{hh}h_t)) \\ &= \tanh(W^s_{xh}x^s_{t+3} + W^a_{xh}x^a_{t+2} + W^r_{xh}x^r_{t+2} + W^d_{xh}x^d_{t+2} \\ &+ W_{hh}\tanh(W^s_{xh}x^s_{t+2} + W^a_{xh}x^a_{t+1} + W^r_{xh}x^r_{t+1} + W^d_{xh}x^d_{t+1} + W_{hh}h_t)) \end{aligned} \tag{4.2}$$

When written out in this form, we see that h_{t+2} measures the error in the time series model with parameter W_{hh} of the quantity $W_s s_{t+1} + W_a a_t + W_r r_t + W_d d_t$. The addition of the (factored) weight matrices seems suboptimal because it does not take into account the MDP structure. Instead of adding the matrices, we can vertically concatenate them, i.e., $[W^s_{xh}, x^s_{t+2}, W^a_{xh} x^a_{t+1}, W^r_{xh} x^r_{t+1}, W^d_{xh} x^d_{t+1}]$. Figure 4.4 illustrates the standard architecture of the RL^2 recurrent unit, while Figure 4.5 illustrates our stacked modification.

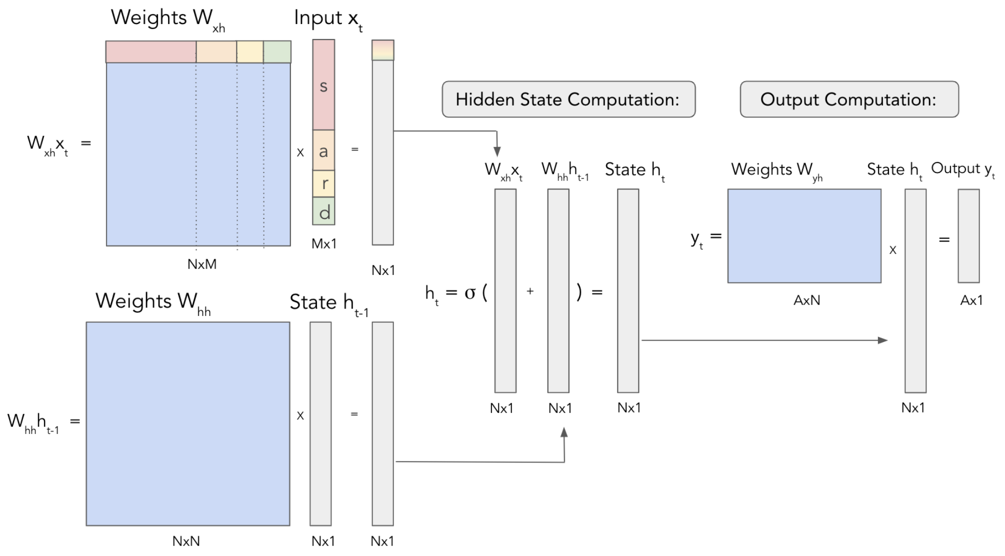


Figure 4.4: The standard RL^2 recurrent unit architecture based on equations 4.1 and 4.1.

4.4 Experiments

Stacked Hidden States

In order to improve the generalization performance of state-of-the-art meta-RL approaches, we propose an extension to the network architecture described by [10] (RL^2) where we concatenate/stack the weight matrices for state, action, reward and done. In this section, we evaluate meta-train and meta-test performance of the stacked architecture. In line with our objective, we have conducted several experiments using both the ordinary LSTM architecture and stacked LSTM architecture sweeping over the following hyperparameters: Number of Hidden Units, Allocation of Hidden Units to [state, action, reward, done], Learning Rate, Random Seed, Rollouts Sampled per MDP (`rollouts_per_meta_task` in the figures).

For evaluating meta-train performance, we have primarily focused our efforts in the Hopper and Walker environments because these environments are also considered in [46] and [47], which allows us to compare against their RL^2 baseline (as a sanity check), MAML,

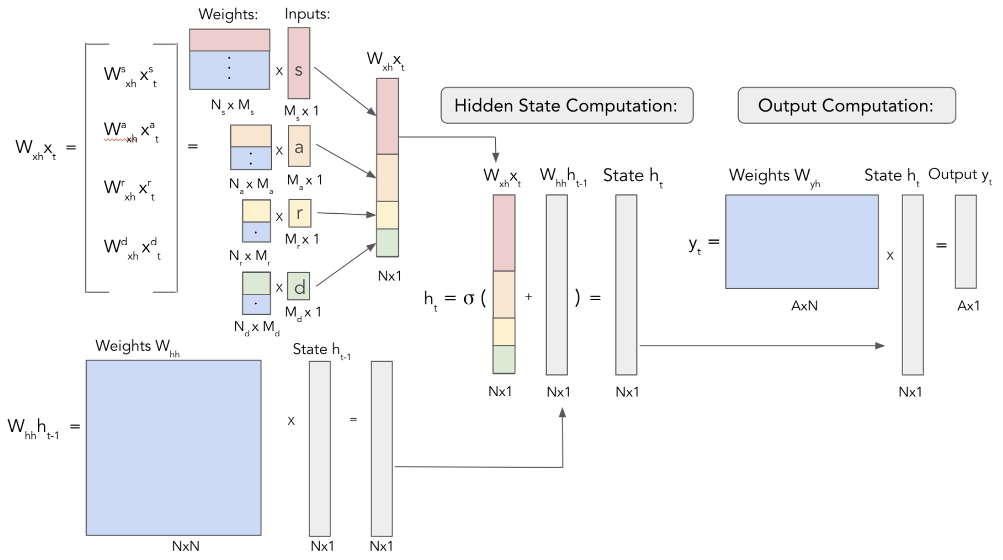
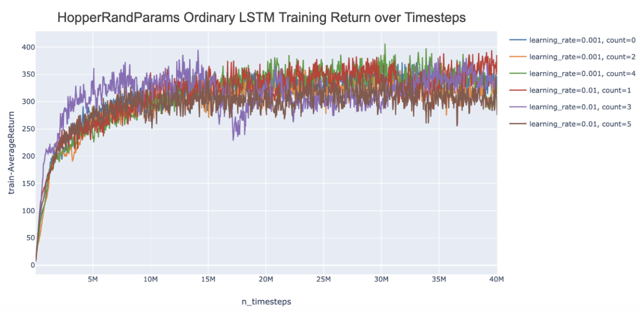


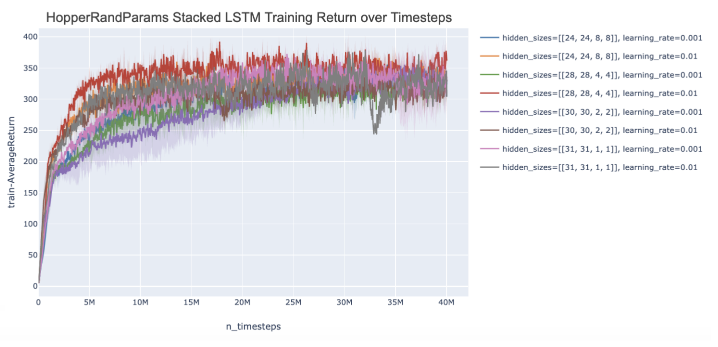
Figure 4.5: Our proposed stacked RL^2 recurrent unit architecture, which accounts for the MDP structure by disentangling the state, action, reward and done inputs.

as well as PEARL and ProMP. In these experiments, we focus on generalization with respect to environment dynamics (i.e., the RandParams environments), where each task/MDP is a different randomization of the simulation parameters, including friction, joint mass, and inertia.

Ordinary LSTM vs. Stacked LSTM

Our preliminary analysis focuses on comparing average return during training between stacked and unstacked LSTMs. We ran initial experiments on the Hopper environment using 64 hidden units and a variety of different learning rates. The figure below displays the average training return from using an ordinary LSTM (on left) and a stacked LSTM (on right).

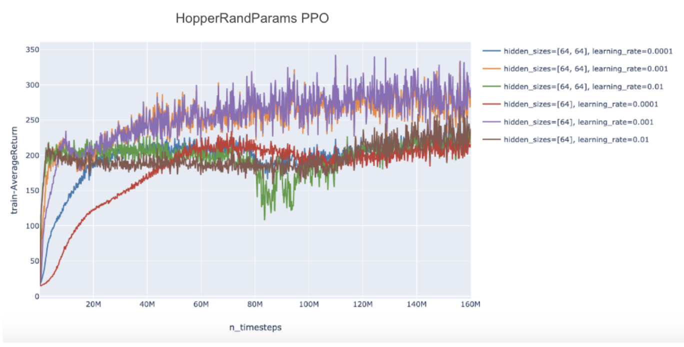


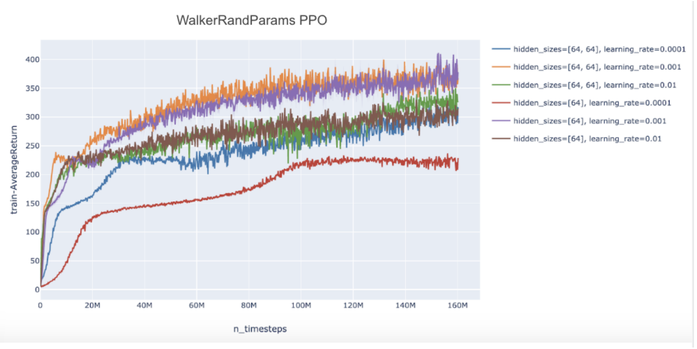


Although we do not see an immediate improvement using the stacked LSTMs, the meta-training curves do not give us the full story as far as adaptation goes, and we do see significant improvements in meta-test. Similar observations hold across a variety of other environments, and base cell types (e.g., with RNNs instead of LSTMs).

PPO Baseline Experiments

As a baseline, we ran experiments using Proximal Policy Optimization (PPO) on the same randomized environments, which corresponds to domain randomization (on a static policy). This domain randomization (DR) baseline is absent from [46] and [47], and is present in [37] however using slightly different environments.



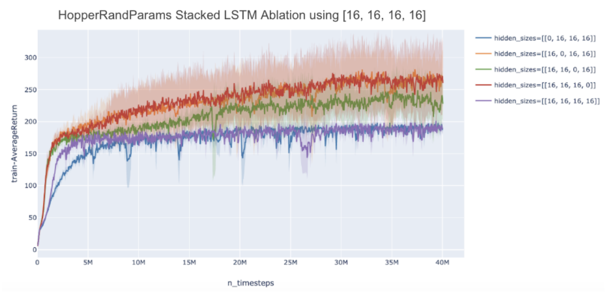


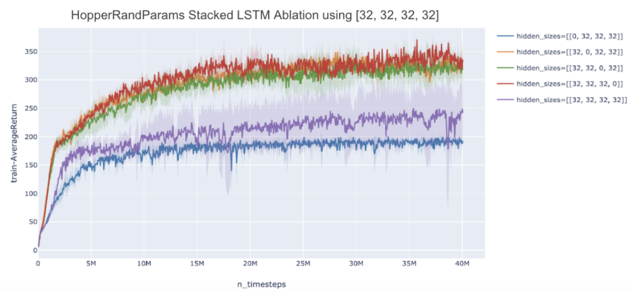
From the DR PPO experiments above, we can conclude that DR PPO performs worse in meta-training as compared to RL2 and PEARL; indicating that adaptation may be beneficial in achieving high average return in these environments. Note that this comparison should be made at the same number of timesteps; for example, PPO on Walker achieves 300 average training return at 40M timesteps, while RL2 achieves 475 average training return at 40M timesteps. Furthermore, we observe that the extra parameters from using [64, 64] do not provide any additional benefit as compared to [64].

Ablation Experiments

The policy architecture in the original RL^2 paper takes in the [state, action, reward, done] inputs, however, no ablation is done over the set of inputs to determine if the network is really utilizing the additional information. In our new stacked architecture, each of these inputs is allocated a certain number of hidden units. We first run ablation experiments on the stacked architecture, zeroing out each of the 4 inputs one at a time. These ablation experiments help illustrate which inputs are important per environment, which may inform how to modify/improve the RL^2 architecture.

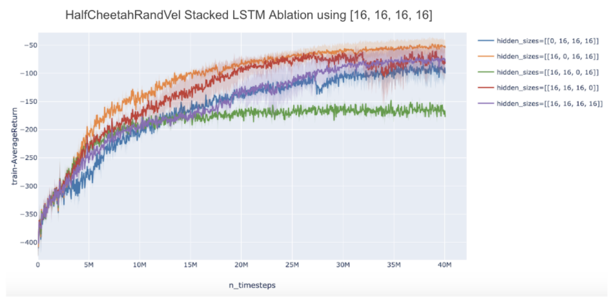
The following graphs display ablation experiments on the HopperRandParams environment using a stacked architecture of [16, 16, 16, 16] nodes in the left plot and [32, 32, 32, 32] in the right plot.

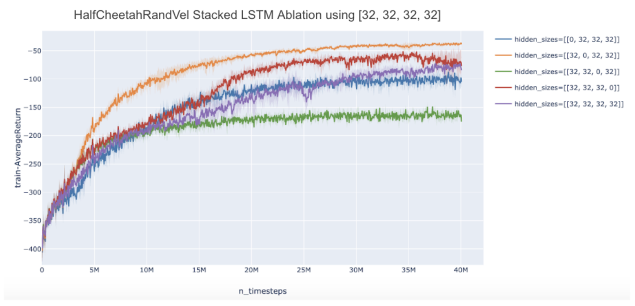




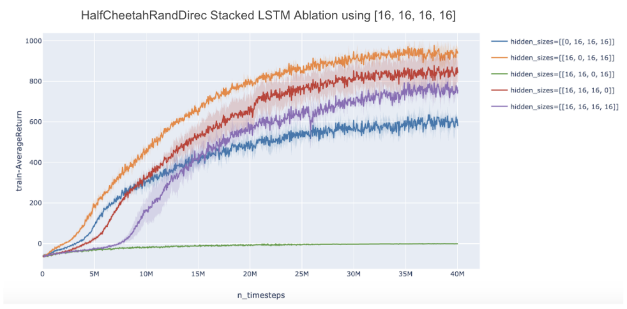
We notice that in both curves, removing the state yields very poor performance. This makes sense; naturally, knowing the state is essential in performing well in both the HopperRandParams and WalkerRandParams environments.

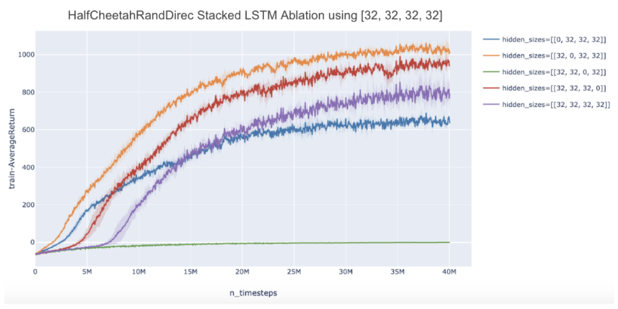
The following graphs show the ablation experiments on the HalfCheetahRandVel using a stacked architecture of [16, 16, 16, 16] nodes in the left plot and [32, 32, 32, 32] in the right plot.





The following graphs show the ablation experiments on the HalfCheetahRandDirec using a stacked architecture of [16, 16, 16, 16] nodes in the left plot and [32, 32, 32, 32] in the right plot.

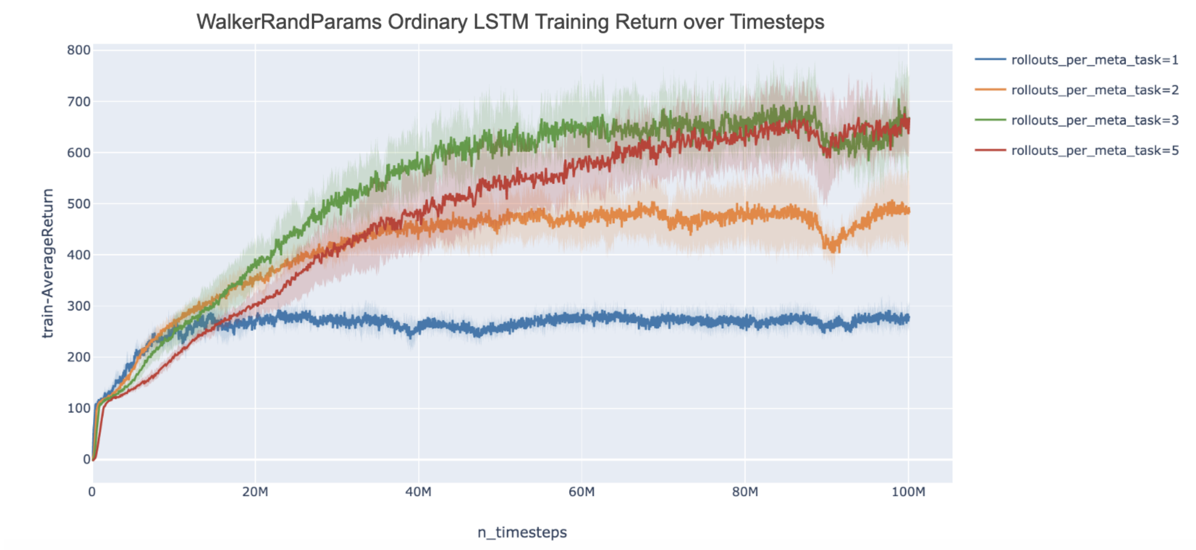




The HalfCheetahRandVel and HalfCheetahRandDirec environments test how well the agent is able to adapt to a changing reward function (specifically, modulated by velocity and goal direction, respectively). This aligns with what is observed in the graphs above; we observe that performance suffers when the reward is ablated. Therefore, knowing the reward is very important for the agent to perform well in the environment. Furthermore, it appears that removing A/D can actually help performance. This indicates that the system-identification component of the network may not be working effectively, or that there is some sort of optimization problem during training.

Rollout Experiments

Previous work in meta-RL that used RL^2 has primarily trained using 2 episodes per trial. Intuitively, the more experience an agent has in a given MDP, the more it should be able to learn about this environment configuration. However, in dense reward environments, it is unclear as to how much additional episodes in a trial can help. The figure below displays the effect of number of rollouts (i.e., episodes) per sampled MDP (papers using RL^2 generally report results with 2). We observe that the average return is higher for 3 and 5 rollouts per MDP vs 2, and that 1 rollout per MDP performs poorly. Note that the return/reward graphed in the plot above is based on the agent's performance in the final episode in the trial.



Meta-test performance: Quantifying Adaptation

The motivation behind using a recurrent policy is to allow the agent to utilize past information in order to adapt to a given environment configuration. Without any adaptation taking place, the recurrence in the policy is superfluous. With this in mind, we seek to devise experiments where adaptation is needed to succeed, and where the level of adaptation can be quantified.

Sparse Reward Environments: In sparse reward environments, the agent only receives a reward at the end of each episode; therefore, we can measure adaptation by observing performance over the course of a trial. For example, in the random-goal-maze environment, the agent should improve from episode 1 to episode 2. [10] accesses the adaptation of the RL^2 agents in this way.

Dense Reward Environments: In dense reward environments, the agent receives a reward at each timestep within the episode. Therefore, measuring adaptation is less clear because the agent can adapt within the first few timesteps of the episode. E.g., [36] claims that '*In contrast, SNAIL and [RL^2] LSTM are able to specialize themselves based on the shared task structure, enabling them to identify the task* ***within the initial timesteps of the first episode****, and then act optimally thereafter.*' In subsequent sections, we discuss ways to measure adaption for dense reward environments, i.e., to test that adaptation is actually happening, and that the learned policy is not just simply a robust policy.

Inspecting the hidden units/activations during testing

One useful method to gain intuition on adaptation performance is to visualize the hidden states. In Figure 4.7, we can see that the hidden states have strong periodicity, which upon further inspection (aligning the x-axis to the timesteps in Mujoco renderings) we can see correspond to the periodicity in the Hopper's movement (see Figure 4.6). However these visualizations alone are not indicative that the hidden state is being used to learn an environment embedding for system identification.

In order to better understand/visualize the patterns within the hidden states, we can additionally perform Principal Component Analysis (PCA) and project the high dimensional states onto a 2D plane. In the simple case where we vary only one free variable (eg friction), if we sample E trajectories from T trials/MDPs, we should expect the activations along each trajectory from the same trial/MDP to be in a cluster. For example, the hidden state activations for trajectories in high friction environments should be clustered together, while low friction trajectories should be in a separate cluster. We are currently implementing cluster visualizations for hidden states at test-time, and will include them in a subsequent iteration of this research paper. Additionally, we are investigating inspecting the gradients during meta-training to better understand what the hidden state is learning.

Continual Adaptation Experiments

In a dense reward environment, the recurrent policy should ostensibly adapt within the first few timesteps of an episode, unlike in a sparse reward environment, where adaptation will occur on the scale of episodes (instead of timesteps). Because adaptation happens within an episode in dense reward environments (e.g., Mujoco locomotion envs), it is hard to discern between an adaptive policy and a robust policy. One way to tell the difference is to deploy the agent in an environment where it needs to continually adapt to changing goals or dynamics. In the subsequent sections, we test the adaptive policies on HalfCheetahRandDirec and RandVel environments where the goal direction and goal/target velocity change mid-episode. For the target velocity envs, we test both interpolation (target velocities within the original [0,3] range), and extrapolation to a new target velocity (4).

For RandVel, we test on three scenarios:

1. **Interpolation:** Goal velocity sequence of [0,1,2,3] at 50 timestep intervals
2. **Extrapolation 1:** Goal velocity sequence of [1,2,3,4] at 50 timestep intervals
3. **Extrapolation 2:** Goal velocity sequence of [3,4] at 100 timestep intervals

For RandDirec, we test on two scenarios:

1. **Backwards-Forwards:** Target direction switches from Backwards to Forwards mid-episode (100 timesteps)
2. **Forwards-Backwards:** Opposite of Backwards-Forwards

In the subsequent sections, we provide high-level conclusions from our results for brevity, but include the full suite of experiments in Section **??** and Section 4.4.

Does RL^2 continually adapt on HalfCheetahRandVel?

We perform experiments to evaluate how well RL^2 adapts on the HalfCheetahRandVel environment. If the agent is adapting perfectly, the graph should look like a sawtooth wave, where the cheetah slows down / speeds up until it hits goal velocity, then cruises at the goal velocity.

We performed continual adaptation experiments using both an Ordinary RNN and Stacked RNN with 64 units. Interpolation and Extrapolation results are shown in Figure 4.8, Figure 4.9 and Figure 4.10. We can draw the following conclusions:

BasicRNNStackInputs (64 units) vs BasicRNN (64 units)

1. Interpolation: The stacked architecture is marginally better. Based on the reward trajectories, the stacked architecture is able to adapt to final goal velocity better.
2. Extrapolation 1 and 2: The stacked architecture is much better, and actually has the best (highest) terminal goal velocity.

Does RL^2 continually adapt on HalfCheetahRandDirec?

In order to measure how RL^2 continually adapts in the HalfCheetahRandDirec environment, we change the direction midway through the episode and analyze how well the agent is able to adapt to this new reward function. We test on both scenarios: changing backwards to forwards and changing forwards to backwards.

We performed continual adaptation experiments using both an Ordinary RNN and Stacked RNN with 64 units. Forward-to-Backward and Backward-to-Forward results are shown in Figure 4.11 and Figure 4.12. We can draw the following conclusions:

BasicRNNStackInputs (64 units) vs BasicRNN (64 units)

1. Back to Forward: Based on the cumulative reward and overall reward trajectories, the stacked architecture performs much better.
2. Forward to Back: Based on the cumulative reward and overall reward trajectories, the stacked architecture performs much better.

Takeaway: In both cases, we can see that the stacked architecture is quite promising, indicating that the stacked hidden states architecture can enable significantly better adaptation to new, changing environments. Additionally, it seems that the stacked architecture has the best extrapolation performance. We are planning on expanding the number of test environments to include environments with continually changing dynamics (in addition to changing goals) to further investigate these results and see if they still hold.

4.5 Conclusion and Future Work

Our preliminary analysis indicates that the stacked hidden states architecture can enable significantly better adaptation to new, changing environments. We are planning on expanding the number of test environments to include environments with continually changing dynamics (in addition to changing goals) to further investigate these results and see if they still hold.

Another direction is to investigate test-time adaptation to environments with sparse rewards, such as mazes with varying goals (a common benchmark in prior work) to see if our preliminary observations still hold, as well as evaluating our new architectures on the recently released Meta-World benchmark. [63].

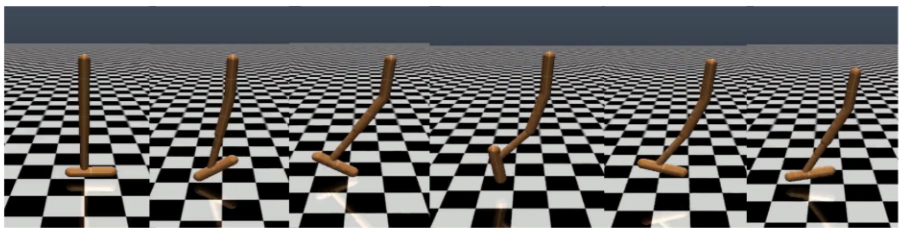


Figure 4.6: Cyclic motion of the Hopper which corresponds to the cyclic patterns in the hidden states heatmap.

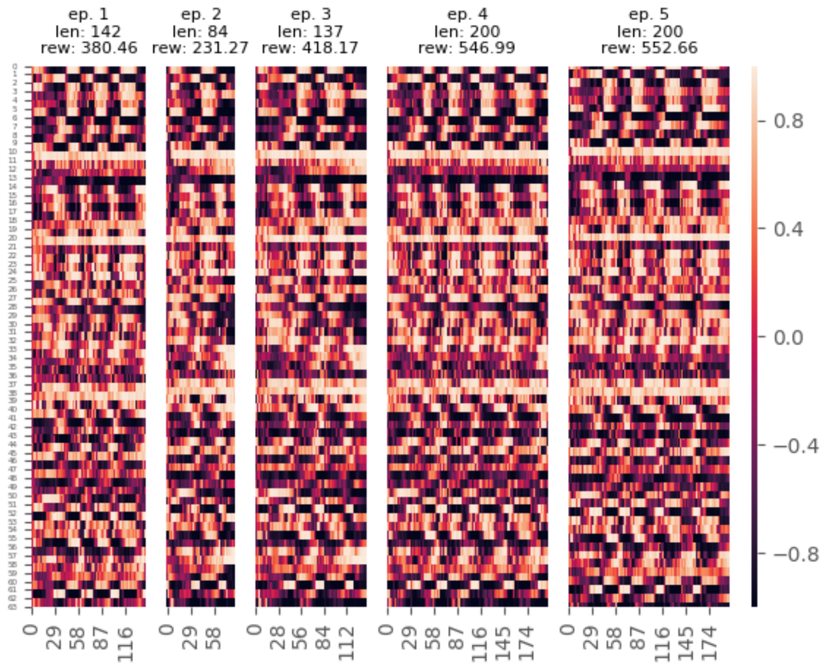


Figure 4.7: Heatmap visualization of the hidden states over the course of a trial (all five episodes) during meta-test (HopperRandParams). The hidden state is represented by a 1×64 column vector (y-axis). The x-axis is time, with extra spacing between episodes. Memory (hidden state) is reset at the beginning of the first episode in the trial, and preserved throughout the rest of the trial.

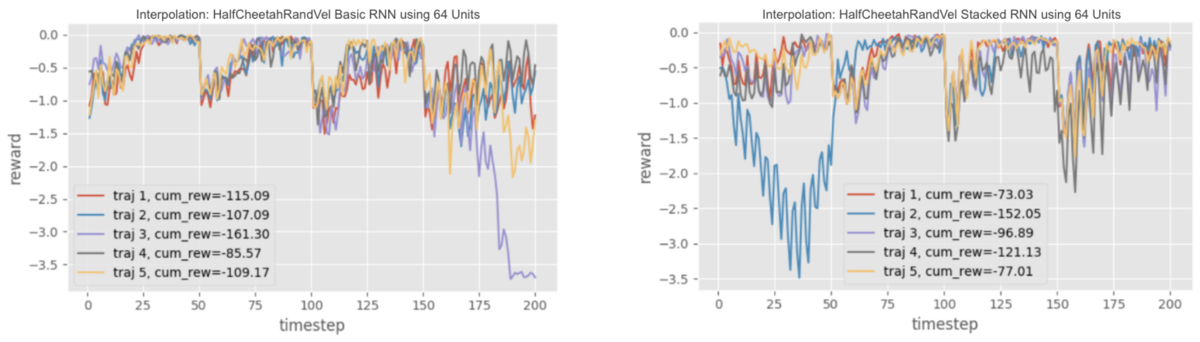


Figure 4.8: HalfCheetahChangingVel (changing target velocity during episode) interpolation results with standard RNN (left) and stacked RNN (right). The stacked RNN performs marginally better than the standard RNN (ideal performance is a sawtooth wave). Using a standard RNN, the agent is unable to adapt to the new velocity, flipping over at the end of trajectory 3.

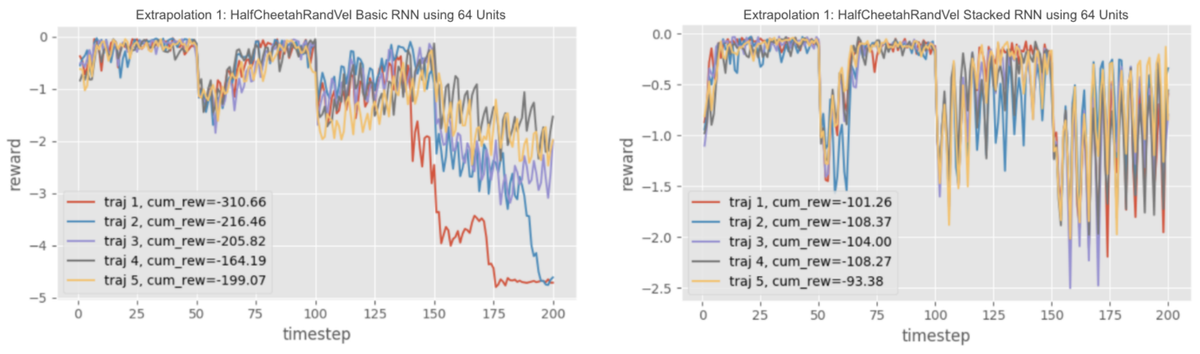


Figure 4.9: HalfCheetahChangingVel (changing target velocity during episode) extrapolation 1 results with standard RNN (left) and stacked RNN (right). The stacked RNN adapts significantly better to changing goals than the standard RNN, based on the cumulative reward and overall reward trajectories. Using a standard RNN, the agent is unable to adapt to the new velocity, flipping over at the end of trajectory 1 and 2.

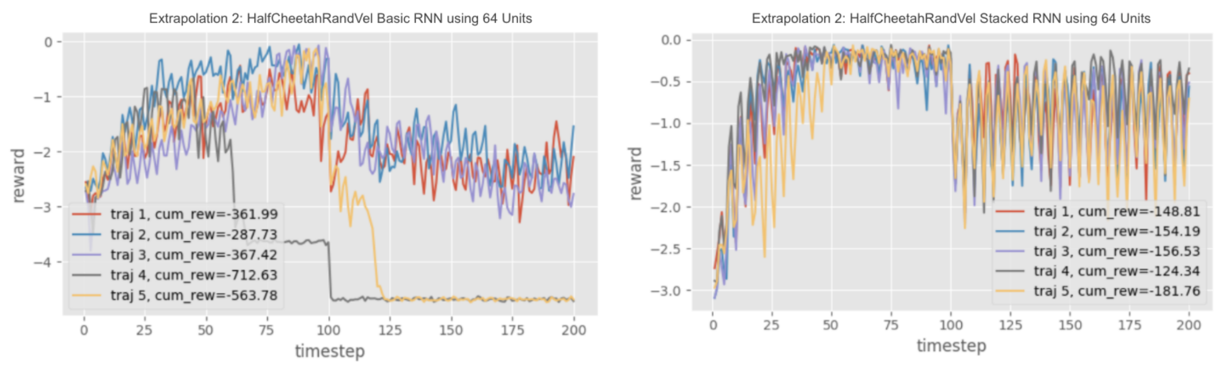


Figure 4.10: HalfCheetahChangingVel (changing target velocity during episode) extrapolation 2 results with standard RNN (left) and stacked RNN (right). The stacked RNN adapts better to changing goals than the standard RNN, based on the cumulative reward and overall reward trajectories. Using a standard RNN, the agent is unable to adapt to the new velocity, flipping over in trajectory 4 and 5.

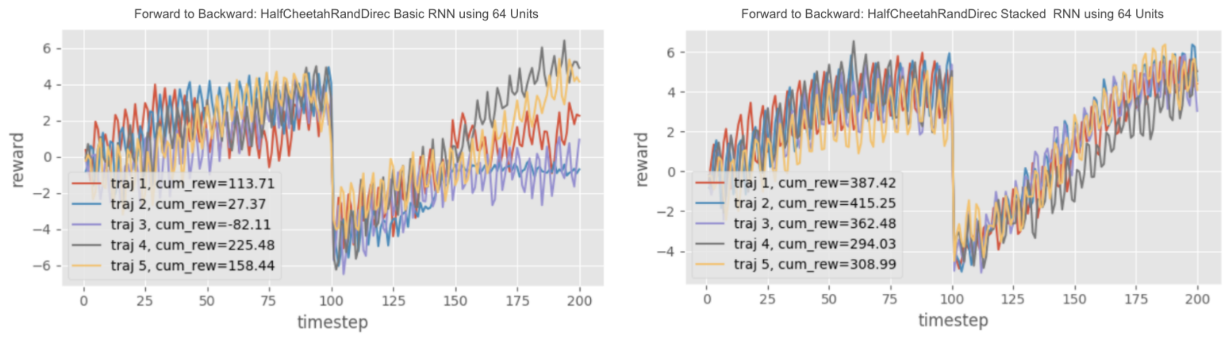
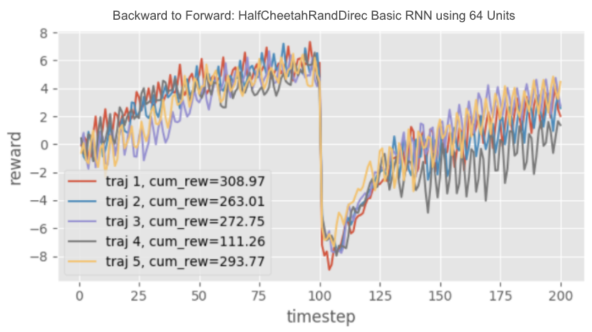


Figure 4.11: HalfCheetahRandDirec results changing the goal direction from forward to backward during the episode. We use a standard RNN (left) and a stacked RNN (right). Based on the cumulative reward and overall reward trajectories, the stacked RNN adapts significantly better to changing goals than the standard RNN. Using a stacked RNN also achieves more consistent results.



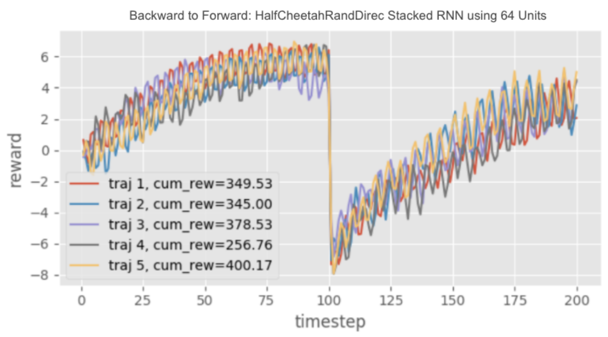


Figure 4.12: HalfCheetahRandDirec results changing the goal direction from backward to forward during the episode. We use a standard RNN (left) and a stacked RNN (right). Based on the cumulative reward and overall reward trajectories, the stacked RNN adapts significantly better to changing goals than the standard RNN. Using a stacked RNN also achieves more consistent results.

Chapter 5

Conclusion and Future Work

In this work, we proposed and evaluated solutions to salient transfer learning problems in both Natural Language Processing and Reinforcement Learning.

In Chapter 3, we presented a test-time training technique that leverages unsupervised information from the test example and similar training examples to adapt NLP models. Further work should focus on how training with MLM loss during fine-tuning changes both in-distribution and out-of-distribution performance. A possible other direction is to study the effect of fine-tuning on the MLM loss of in-domain and OOD examples. This would help understand what fine-tuning is exactly doing to the embeddings.

In Chapter 4, we proposed and evaluated a meta-RL architectures based on the architecture and training algorithm described by previous work (ie. RL^2) [10]. Our architectural changes improves adaptation to new environments by disentangling the recurrent and feed forward components of the recurrent policy network. One direction to investigate is test-time adaptation to environments with sparse rewards, such as mazes with varying goals (a common benchmark in prior work) to see if our preliminary observations still hold, as well as evaluating our new architectures on the recently released Meta-World benchmark.

Bibliography

[1] Iz Beltagy, Arman Cohan, and Kyle Lo. "Scibert: Pretrained contextualized embeddings for scientific text". In: *arXiv preprint arXiv:1903.10676* (2019).

[2] Dallas Card, Michael Zhang, and Noah A. Smith. "Deep Weighted Averaging Classifiers". In: *FAT*. 2018.

[3] Daniel Cer et al. "SemEval-2017 Task 1: Semantic textual similarity-multilingual and cross-lingual focused evaluation". In: *SemEval*. 2017.

[4] Ignasi Clavera et al. "Learning to Adapt: Meta-Learning for Model-Based Control". In: *arXiv:1803.11347* (2018).

[5] Gabriela Csurka. "Domain adaptation for visual applications: A comprehensive survey". In: *arXiv preprint arXiv:1702.05374* (2017).

[6] Andrew M Dai and Quoc V Le. "Semi-supervised sequence learning". In: 2015.

[7] Jacob Devlin et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding". In: *NAACL-HLT*. 2019.

[8] Yunshu Du et al. "Adapting auxiliary losses using gradient similarity". In: *arXiv preprint arXiv:1812.02224* (2018).

[9] Yan Duan et al. "Benchmarking deep reinforcement learning for continuous control". In: *International Conference on Machine Learning*. 2016, pp. 1329–1338.

[10] Yan Duan et al. "RL^2: Fast Reinforcement Learning via Slow Reinforcement Learning". In: *arXiv:1611.02779* (2016).

[11] Chelsea Finn, Pieter Abbeel, and Sergey Levine. "Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks". In: 2017.

[12] Chelsea Finn, Pieter Abbeel, and Sergey Levine. "Model-agnostic meta-learning for fast adaptation of deep networks". In: *ICML*. 2017.

[13] Yaroslav Ganin et al. "Domain-adversarial training of neural networks". In: *The Journal of Machine Learning Research*. 2016.

[14] Xavier Glorot, Antoine Bordes, and Yoshua Bengio. "Domain adaptation for large-scale sentiment classification: A deep learning approach". In: 2011.

[15] Xiaoxiao Guo et al. “Deep learning for real-time Atari game play using offline Monte-Carlo tree search planning”. In: *Advances in neural information processing systems*. 2014, pp. 3338–3346.

[16] Suchin Gururangan et al. “Don’t Stop Pretraining: Adapt Language Models to Domains and Tasks”. In: 2020.

[17] Xiaochuang Han and Jacob Eisenstein. “Unsupervised domain adaptation of contextualized embeddings: A case study in early modern english”. In: *EMNLP*. 2019.

[18] Ruining He and Julian J. McAuley. “Ups and Downs: Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering”. In: *WWW*. 2016.

[19] Dan Hendrycks and Thomas Dietterich. “Benchmarking Neural Network Robustness to Common Corruptions and Perturbations”. In: *ICLR*. 2019.

[20] Dan Hendrycks, Kimin Lee, and Mantas Mazeika. “Using pre-training can improve model robustness and uncertainty”. In: 2019.

[21] Dan Hendrycks et al. “Pretrained Transformers Improve Out-of-Distribution Robustness”. In: 2020.

[22] Dan Hendrycks et al. “Using self-supervised learning can improve model robustness and uncertainty”. In: *NeurIPS*. 2019.

[23] Jeremy Howard and Sebastian Ruder. “Universal language model fine-tuning for text classification”. In: 2018.

[24] Kexin Huang, Jaan Altosaar, and Rajesh Ranganath. “Clinicalbert: Modeling clinical notes and predicting hospital readmission”. In: *arXiv preprint arXiv:1904.05342* (2019).

[25] Max Jaderberg et al. “Reinforcement learning with unsupervised auxiliary tasks”. In: 2017.

[26] Anthony Kroch, Beatrice Santorini, and Ariel Diertani. “Penn-Helsinki Parsed Corpus of Early Modern English”. In: (2004). URL: `http://www.ling.upenn.edu/hist-corpora/PPCEME-RELEASE-2/index.html`.

[27] Keita Kurita, Paul Michel, and Graham Neubig. “Weight Poisoning Attacks on Pre-trained Models”. In: *ACL*. 2020.

[28] Jinhyuk Lee et al. “BioBERT: a pre-trained biomedical language representation model for biomedical text mining”. In: *Bioinformatics* 36.4 (2020), pp. 1234–1240.

[29] Sergey Levine et al. “End-to-end training of deep visuomotor policies”. In: *The Journal of Machine Learning Research* 17.1 (2016), pp. 1334–1373.

[30] Andrew L Maas et al. “Learning word vectors for sentiment analysis”. In: *ACL*. 2011.

[31] Aleksander Madry et al. “Towards deep learning models resistant to adversarial attacks”. In: 2018.

[32] Mitchell P. Marcus, Mary Ann Marcinkiewicz, and Beatrice Santorini. "Building a large annotated corpus of English: The Penn Treebank". In: *Computational Linguistics*. 1993.

[33] Julian J. McAuley et al. "Image-based Recommendations on Styles and Substitutes". In: *SIGIR*. 2015.

[34] Michael McCloskey and Neal J Cohen. "Catastrophic Interference in Connectionist Networks: The Sequential Learning Problem". In: *Psychology of learning and motivation*. 1989.

[35] Piotr Mirowski et al. "Learning to navigate in complex environments". In: 2017.

[36] Nikhil Mishra et al. "A Simple Neural Attentive Meta-Learner". In: 2018.

[37] Charles Packer et al. "Assessing Generalization in Deep Reinforcement Learning". In: *arXiv:1810.12282* (2019).

[38] Sinno Jialin Pan and Qiang Yang. "A survey on transfer learning". In: *IEEE TKDE*. 2009.

[39] Georgios Papoudakis, Kyriakos C. Chatzidimitriou, and Pericles A. Mitkas. "Deep reinforcement learning for doom using unsupervised auxiliary tasks". In: *arXiv preprint arXiv:1807.01960* (2018).

[40] Adam Paszke et al. "PyTorch: An imperative style, high-performance deep learning library". In: 2019.

[41] Giorgio Patrini et al. "Making deep neural networks robust to label noise: A loss correction approach". In: 2017.

[42] Matthew E. Peters et al. "Deep contextualized word representations". In: 2018.

[43] Lerrel Pinto et al. "Robust Adversarial Reinforcement Learning". In: 2017.

[44] Evani Radiya-Dixit and Xin Wang. "How fine can fine-tuning be? Learning efficient language models". In: *arXiv preprint arXiv:2004.14129* (2020).

[45] Aravind Rajeswaran et al. "EPOpt: Learning robust neural network policies using model ensembles". In: 2017.

[46] Kate Rakelly et al. "Efficient Off-Policy Meta-Reinforcement learning via Probabilistic Context Variables". In: 2019.

[47] Jonas Rothfuss et al. "ProMP: Proximal Meta-Policy Search". In: 2019.

[48] Sebastian Ruder. "Neural Transfer Learning for Natural Language Processing". PhD thesis. National University of Ireland, Galway, 2019.

[49] Steindór Sæmundsson, Katja Hofmann, and Marc Peter Deisenroth. "Meta Reinforcement Learning with Latent Variable Gaussian Processes". In: 2018.

[50] Erik F Sang and Fien De Meulder. "Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition". In: *arXiv preprint cs/0306050* (2003).

[51] John Schulman et al. "High-dimensional continuous control using generalized advantage estimation". In: *arXiv preprint arXiv:1506.02438* (2015).

[52] Darsh J Shah et al. "Adversarial domain adaptation for duplicate question detection". In: 2018.

[53] Jian Shen et al. "Wasserstein distance guided representation learning for domain adaptation". In: 2018.

[54] Richard Socher et al. "Recursive deep models for semantic compositionality over a sentiment treebank". In: *EMNLP*. 2013.

[55] Benjamin Strauss et al. "Results of the wnut16 named entity recognition shared task". In: *Proceedings of the 2nd Workshop on Noisy User-generated Text (WNUT)*. 2016, pp. 138–144.

[56] Yu Sun et al. "Test-time training for out-of-distribution generalization". In: *arXiv preprint arXiv:1909.13231* (2019).

[57] Yu Sun et al. "Unsupervised Domain Adaptation through Self-Supervision". In: *arXiv preprint arXiv:1909.11825* (2019).

[58] Flood Sung et al. "Learning to learn: Meta-critic networks for sample efficient learning". In: *arXiv:1706.09529* (2017).

[59] Eric Tzeng et al. "Adversarial discriminative domain adaptation". In: 2017.

[60] Alex Wang et al. "Glue: A multi-task benchmark and analysis platform for natural language understanding". In: *arXiv preprint arXiv:1804.07461* (2018).

[61] Jane X Wang et al. "Learning to reinforcement learn". In: *arXiv:1611.05763* (2016).

[62] Thomas Wolf et al. "Transformers: State-of-the-art Natural Language Processing". In: *arXiv preprint arXiv:1910.03771* (2019).

[63] Tianhe Yu et al. "Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning". In: *arXiv preprint arXiv:1910.10897* (2019).

[64] Yuting Zhang, Kibok Lee, and Honglak Lee. "Augmenting supervised neural networks with unsupervised objectives for large-scale image classification". In: 2016.

[65] Yukun Zhu et al. "Aligning books and movies: Towards story-like visual explanations by watching movies and reading books". In: *Proceedings of the IEEE international conference on computer vision*. 2015, pp. 19–27.