Not to Overfit or Underfit?
A Study of Domain Generalization in Question Answering

Md Arafat Sultan  Avirup Sil  Radu Florian
IBM Research AI
arafat.sultan@ibm.com, {avi, raduf}@us.ibm.com

Abstract

Machine learning models are prone to overfitting their source (training) distributions, which is commonly believed to be why they falter in novel target domains. Here we examine the contrasting view that multi-source domain generalization (DG) is in fact a problem of mitigating source domain underfitting: models not adequately learning the signal in their multi-domain training data. Experiments on a reading comprehension DG benchmark show that as a model gradually learns its source domains better—using known methods such as knowledge distillation from a larger model—its zero-shot out-of-domain accuracy improves at an even faster rate. Improved source domain learning also demonstrates superior generalization over three popular domain-invariant learning methods that aim to counter overfitting.

1 Introduction

Domain generalization (DG) seeks to train models on a small number of source domains (e.g., datasets) in a way that maximizes their zero-shot out-of-domain (OOD) utility (Blanchard et al., 2011; Muandet et al., 2013). Many existing DG methods are rooted in the premise that weak generalization under domain shift occurs due to model overfitting: the learning of spurious source domain correlations that are unrelated to the actual learning task, and are unlikely to be present in novel target domains. This view has inspired the popular domain-invariant learning (DIL) paradigm, which proposes regularizing the empirical risk minimization (ERM) process over labeled source domain data to achieve improved domain invariance (Wang et al., 2021; Zhou et al., 2021).

In this paper, we take a critical look at this “don’t overfit” formulation of DG and examine the contrasting view that the focus for DG should instead be on not underfitting the training data. Underfitting occurs when a trained model, due to factors such as inadequacies in its capacity or the training procedure, fails to learn training set patterns that are truly representative of the task. In a recent study of DG in computer vision, Gulrajani and Lopez-Paz (2021) find that for large models with sufficiently high capacity, ordinary ERM training can actually outperform DIL when properly configured. Here we study in the NLP context of question answering (QA) how improved supervision of relatively small models, e.g., a BERT-base QA model (Devlin et al., 2019), affects their OOD generalization and how the results compare to DIL. Essentially, we focus on learning the actual signal present in the multi-domain training data, whereas DIL aims to not fit the domain-specific noise in it.

A key advantage of our straightforward formulation is that familiar supervised learning methods such as knowledge distillation (KD) (Hinton et al., 2014) can now be leveraged for DG. KD can generally provide stronger supervision than ERM by minimizing a surrogate risk, which utilizes the soft predictions of a larger teacher model (e.g., a BERT-large QA model) as the learning targets for the smaller model we want to train, now called the student. Additionally, synthesized input in large quantities has been found to further enhance the performance of KD (Chen et al., 2020; Liang et al., 2021). Here we extend the application of these methods to DG for QA.

We evaluate our methods on a multi-dataset reading comprehension benchmark (Fisch et al., 2019) and compare their accuracy with three popular DIL approaches: domain adversarial learning (Ganin et al., 2016; Lee et al., 2019), episodic learning (Li et al., 2019)—for which we propose a novel variant suitable for deep transformer models—and meta learning (Finn et al., 2017; Li et al., 2018). We also design experiments to answer more targeted questions such as: (1) Are the improvements more prominent on in-domain validation data than on out-of-domain test instances, which could be indicative
of weak generalization? (2) Do the proposed methods falter on input cases where domain-invariant approaches thrive, potentially indicating weakness on extremely distant test cases? In all these different evaluations, our methods exhibit far superior DG than the three existing methods, whereas the latter only marginally outperform ERM.

While further experiments with more datasets and baselines are needed before a firm conclusion can be reached on the superiority of our formulation of DG over DIL (or vice versa), our findings do indicate the need for a better understanding of optimal source domain learning as an approach to DG. A primary goal of this paper is to motivate future explorations of this important research question.

## 2 The Reading Comprehension Task

Given a question $q$ and a passage $p$ that answers $q$, reading comprehension (RC) outputs the answer $a$. In extractive RC, which is the form we study in this paper, $a$ is assumed to be a subtext of $p$—the goal is therefore to locate $a$ in $p$.

## 3 Methods

Here we describe the different DG approaches evaluated in this paper: the proposed methods for improved source domain learning as well as the three domain-invariant learning baselines.

### 3.1 Multi-Dataset Knowledge Distillation

For improved multi-domain training, we rely on knowledge distillation (KD), which naturally trains small yet powerful models by leveraging the predictions of a larger teacher model. We first train a single teacher using ERM on labeled RC data from all source domains. We follow the standard RC training procedure for this step, which separately trains an answer start and end predictor, as described in (Devlin et al., 2019).

The knowledge of this teacher is then distilled into a smaller student model—equal in size with the baselines—by minimizing the following MSE loss on the same set of training examples:

$$\mathcal{L}_{KD} = \|z_s(x) - z_t(x)/T\|_2^2$$  \hspace{1cm} (1)

where $z_s(x)$ and $z_t(x)$ are the logits computed for an input question-passage pair $x$ by the student and the teacher, respectively, and $T$ is the temperature. Similar to the training of the teacher, two KD losses are minimized per training example, one each for the start and the end of the answer.

### 3.2 Augmenting KD with Synthetic Questions

To facilitate KD from the same teacher on a larger scale, we synthesize additional questions using a sequence-to-sequence model. An encoder-decoder language model (Lewis et al., 2020; Raffel et al., 2020) is first fine-tuned for each source domain, where question-passage pairs from the corresponding dataset constitute the training examples: the passage is the source and the question is the target. Note that we use the teacher’s soft answer predictions as targets during KD (Eq. 1), and therefore do not need to provide any answers as part of the synthesized data.

Sultan et al. (2020) show that sampling-based generation, e.g., with a top-$p$ top-$k$ sampler, produces more useful synthetic training data than deterministic greedy or beam search decoding. Moreover, Chen et al. (2020) find that large amounts of diverse synthetic data can be more effective at supporting KD than typically smaller amounts of human-labeled gold examples, although using both yields the best results. We incorporate these suggestions into our work by sampling examples from our generators and performing KD with first synthesized and then gold training data ($\S$3.1). Unlike those earlier studies, however, we apply the above procedure to the multi-source DG problem.

### 3.3 Domain-Invariant Learning

These existing DG methods impose additional requirements on top of ERM to incorporate domain invariance into the trained models.

For domain-adversarial learning (Ganin et al., 2016), that added requirement is for the model to learn domain-agnostic hidden representations of the training inputs. This is accomplished by training a domain classifier in parallel with the RC model and teaching the shared feature extractor to produce adversarial representations for the domain classifier (Lee et al., 2019).

Given a model with parameters $\Theta$ to be optimized on multi-domain training data, episodic learning (Li et al., 2019) trains a random subset $\Theta'$ in each iteration; values for the remaining parameters $\Theta \setminus \Theta'$ are copied over from a weaker model trained on one of the source domains other than that of the current example. This procedure effectively forces the $\Theta'$ subnetwork to become more robust to domain shift as it learns to work with an OOD companion $\Theta \setminus \Theta'$. While Li et al. (2019) use a fixed breakdown of $\Theta$ into a feature extractor
We run our experiments on the public subset (345 OOD parameters) fine-tuned using large teacher models to allow a split after a randomly chosen transformer layer.

Finally, meta learning (Finn et al., 2017) for DG (Li et al., 2018) (MLDG) uses disjoint subsets of the source domains as meta-train and meta-test domains at each training step. It uses the meta-train set to update model parameters in a way that improves performance on the meta-test set. This is accomplished using a second-order differentiation through the parameter updates of the model.

### Table 1: Performance (F1 score) of different training methods on OOD test data. Each score is a mean±SD over six models, each trained on a unique five-set combination of the six source datasets. While the domain-invariant methods provide small gains over plain ERM, improved source domain learning demonstrates by far the best results.

| Method               | Test Set       | Avg.          |
|----------------------|----------------|---------------|
|                      | BioASQ | DROP | DuoRC | RACE | ReLex | TextbookQA |
| ERM                  | 51.7±1.4 | 37.8±0.2 | 55.1±1.5 | 39.0±1.0 | 83.3±0.3 | 51.6±1.8 |
| Domain-invariant learning to counter overfitting: |
| Domain-Adv           | 51.7±1.9 | 38.4±1.1 | 56.0±1.0 | 39.3±0.6 | 83.5±0.7 | 52.2±1.7 |
| Episodic             | 52.0±1.6 | 38.4±1.4 | 56.4±1.1 | 40.1±0.5 | 83.3±0.4 | 52.3±1.9 |
| MLDG                 | 52.7±0.9 | 38.0±1.1 | 56.1±1.5 | 39.5±0.9 | 83.9±0.3 | 51.1±2.0 |
| KD (gold-only)       | 53.2±0.7 | 42.2±1.3 | 58.4±1.6 | 42.9±0.9 | 84.1±0.9 | 56.1±2.6 |
| KD (augmented)       | 53.4±0.9 | 45.2±1.7 | 60.3±1.2 | 44.2±0.8 | 84.8±0.6 | 58.0±1.4 |

Improved source domain learning to counter underfitting:

| Method               | Test Set       | Avg.          |
|----------------------|----------------|---------------|
|                      | BioASQ | DROP | DuoRC | RACE | ReLex | TextbookQA |
| ERM                  | 51.7±1.4 | 37.8±0.2 | 55.1±1.5 | 39.0±1.0 | 83.3±0.3 | 51.6±1.8 |
| Domain-Adv           | 51.7±1.9 | 38.4±1.1 | 56.0±1.0 | 39.3±0.6 | 83.5±0.7 | 52.2±1.7 |
| Episodic             | 52.0±1.6 | 38.4±1.4 | 56.4±1.1 | 40.1±0.5 | 83.3±0.4 | 52.3±1.9 |
| MLDG                 | 52.7±0.9 | 38.0±1.1 | 56.1±1.5 | 39.5±0.9 | 83.9±0.3 | 51.1±2.0 |
| KD (gold-only)       | 53.2±0.7 | 42.2±1.3 | 58.4±1.6 | 42.9±0.9 | 84.1±0.9 | 56.1±2.6 |
| KD (augmented)       | 53.4±0.9 | 45.2±1.7 | 60.3±1.2 | 44.2±0.8 | 84.8±0.6 | 58.0±1.4 |

and a task head, we relax this condition for multilayer transformer models to allow a split after a randomly chosen transformer layer.

Finally, meta learning (Finn et al., 2017) for DG (Li et al., 2018) (MLDG) uses disjoint subsets of the source domains as meta-train and meta-test domains at each training step. It uses the meta-train set to update model parameters in a way that improves performance on the meta-test set. This is accomplished using a second-order differentiation through the parameter updates of the model.

### 4 Experiments

#### 4.1 Setup

We run our experiments on the the public subset of the DG benchmark by Fisch et al. (2019)\(^1\). It consists of (a) training and in-domain validation data from six source datasets, and (b) six target datasets for evaluation. Table 2 shows some key statistics. We refer the reader to the original paper for a detailed description of each dataset.

Table 2: Dataset statistics (Fisch et al., 2019): # of examples.

| Source               | Train | Dev |
|----------------------|-------|-----|
| BioASQ (Tsatsaronis et al., 2015) | 1,504 |
| DROP (Dua et al., 2019)        | 1,503 |
| DuoRC (Saha et al., 2018)      | 1,501 |
| RACE (Lai et al., 2017)        | 674   |
| ReLex (Levy et al., 2017)      | 2,948 |
| TextbookQA (Kembhavi et al., 2017) | 1,503 |

For synthetic data generation, we fine-tune separate BART-large models (Lewis et al., 2020) on the individual source datasets. We generate 500k questions per dataset from Wikipedia contexts using top-p top-k sampling (p=.95, k=10).

#### 4.2 Results

In Table 3 (column 1), we show the in-domain dev set performance of ERM and the two variants of KD: ERM clearly exhibits some underfitting as evidenced by its lower source domain score, which KD helps to mitigate to some extent. Moreover, augmented KD with additional synthesized questions improves results over gold-only distillation.

Table 1 summarizes the performance of different training methods on the OOD test sets. The DIL

\(^1\)https://github.com/mrqa/MRQA-Shared-Task-2019#datasets
Table 3: F1 score (and relative gain over ERM) for each proposed KD-based method. Gains on the OOD test sets outpace those on the in-domain dev sets, indicating strong generalization.

| Method   | ID-Dev | OOD-Test |
|----------|--------|----------|
| ERM      | 75.0   | 53.1     |
| KD (gold-only) | 76.4 (1.9%) | 56.2 (5.8%) |
| KD (augmented) | 77.2 (2.9%) | 57.6 (8.5%) |

Table 4: Domain-invariant learning does not complement KD-based source domain learning in OOD tests.

| Method                  | Avg. F1 |
|-------------------------|---------|
| KD + Domain-Adv         | 55.4    |
| KD + Episodic           | 55.5    |
| KD + MLDG               | 55.8    |

Although the KD-based methods exhibit stronger overall OOD generalization, it is still possible that DIL teaches certain DG-inducing patterns that even powerful source domain supervision fails to provide, in which case the former should complement the latter well. To test this effect, we train three models using each of the three DIL methods, but replace ERM with KD (gold instances only) as the underlying training mechanism for RC. As Table 4 shows, none of the three combinations does better than KD alone, which, along with the results of Table 1, indicates that as a learner is exposed to stronger source domain supervision, DIL starts to lose its relevance.

As a final test of the sufficiency of multi-source KD as a DG method, we look at its ability to function as a proxy for the different DIL methods. Let $\mathcal{E}$ be the set of examples for which a training method $M$ has a higher F1 score than ERM, representing the DG capabilities of $M$. We define the coverage of $M$ by another method $M'$ as the relative F1 score of $M'$ as a fraction (%) of the F1 score of $M$ on $\mathcal{E}$. This metric essentially quantifies the degree to which the DG capabilities of $M$ is retained by $M'$. As the bar charts of Figure 1 show, the KD-based methods provide the best coverage of all three DIL methods; the latter, while providing considerably better coverage of one another than ERM, lag behind KD in all three cases. These results again suggest that strong source domain learning may potentially be a sufficiently optimal policy for multi-source DG, without the need for an explicit enforcement of domain invariance.

5 Conclusion

This paper puts forward the view with empirical evidence for QA that contrary to popular belief, multi-source domain generalization (DG) is better modeled as a problem of addressing model underfitting than overfitting. Our experimental results show that by simply learning the training domains well, even when the number of such domains is relatively small, strong out-of-domain generalization can be achieved without the need for cross-domain regularization. We rely on knowledge distillation in our experiments for improved source domain learning over ERM. In light of these findings, we believe that focusing our efforts on adequately fitting the source domain patterns might be a more reasonable path forward for DG. That said, further research is needed on the topic before a definitive conclusion can be reached; we hope that our work...
will inspire future explorations of this problem.

6 Ethics

6.1 Limitations

We explore the problem of multi-source domain generalization (DG) in QA with new and existing methods. We believe that our findings will generalize to more baselines and datasets, but here we only show proof of concept for a select set of existing baselines and a single DG benchmark (which consists of multiple datasets from various domains).

6.2 Risks

A reading comprehension (RC) system can be made to give offensive answers, given such passages or even adversarially designed questions by malicious actors. That is not our intent, and we do not believe our work introduces any additional risks over existing approaches to RC.

References

Gilles Blanchard, Gyemin Lee, and Clayton Scott. 2011. Generalizing from Several Related Classification Tasks to a New Unlabeled Sample. In NeurIPS.

Yanda Chen, Md Arafat Sultan, and Vittorio Castelli. 2020. Improved Synthetic Training for Reading Comprehension. arXiv prePrint arXiv:2010.12776.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In NAACL.

Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. 2019. DROP: A Reading Comprehension Benchmark Requiring Discrete Reasoning Over Paragraphs. In NAACL.

Matthew Dunn, Levent Sagun, Mike Higgins, V. Ugur Guney, Volkan Cirik, and Kyunghyun Cho. 2017. SearchQA: A New Q&A Dataset Augmented with Context from a Search Engine. arXiv prePrint arXiv:1704.05179.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. 2017. Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. In ICML.

Adam Fisch, Alon Talmor, Robin Jia, Minjoon Seo, Eunsol Choi, and Danqi Chen. 2019. MRQA 2019 Shared Task: Evaluating Generalization in Reading Comprehension. In EMNLP-IJCNLP MRQA Workshop.

Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. 2016. Domain-Adversarial Training of Neural Networks. Journal of Machine Learning Research.

Ishaan Gulrajani and David Lopez-Paz. 2021. In Search of Lost Domain Generalization. In ICLR.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2014. Distilling the Knowledge in a Neural Network. In NeurIPS Deep Learning Workso.

Mandar Joshi, Eunsol Choi, Daniel Weld, and Luke Zettlemoyer. 2017. TriviaQA: A Large Scale Distantly Supervised Challenge Dataset for Reading Comprehension. In ACL.

Aniruddha Kemblavi, Minjoon Seo, Dustin Schwenk, Jonghyun Choi, Ali Farhadi, and Hannaneh Hajishirzi. 2017. Are You Smarter Than a Sixth Grader? Textbook Question Answering for Multimodal Machine Comprehension. In CVPR.

Tom Kwiatkowski, Jennamaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural Questions: A Benchmark for Question Answering Research. Transactions of the ACL.

Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard Hovy. 2017. RACE: Large-scale ReAding Comprehension Dataset From Examinations. In EMNLP.

Seanie Lee, Donggyu Kim, and Jangwon Park. 2019. Domain-agnostic Question-Answering with Adversarial Training. In EMNLP-IJCNLP MRQA Workshop.

Omer Levy, Minjoon Seo, Eunsol Choi, and Luke Zettlemoyer. 2017. Zero-Shot Relation Extraction via Reading Comprehension. In CoNLL.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising Sequence-to-Sequence Pretraining for Natural Language Generation, Translation, and Comprehension. In ACL.

Da Li, Yongxin Yang, Yi-Zhe Song, and Timothy M. Hospedales. 2018. Learning to Generalize: Meta-learning for Domain Generalization. In AAAI.

Da Li, Jianshu Zhang, Yongxin Yang, Cong Liu, Yi-Zhe Song, and Timothy M. Hospedales. 2019. Episodic Training for Domain Generalization. In ICCV.

Kevin J Liang, Weituo Hao, Dinghan Shen, Yufan Zhou, Weizhu Chen, Changyou Chen, and Lawrence Carin. 2021. MixKD: Towards Efficient Distillation of Large-scale Language Models. In ICLR.
Krikamol Muandet, David Balduzzi, and Bernhard Schölkopf. 2013. Domain Generalization via Invariant Feature Representation. In ICML.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. JMLR.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. SQuAD: 100,000+ Questions for Machine Comprehension of Text. In EMNLP.

Amrita Saha, Rahul Aralikatte, Mitesh M. Khapra, and Karthik Sankaranarayanan. 2018. DuoRC: Towards Complex Language Understanding with Paraphrased Reading Comprehension. In ACL.

Md Arafat Sultan, Shubham Chandel, Ramón Fernández Astudillo, and Vittorio Castelli. 2020. On the Importance of Diversity in Question Generation for QA. In ACL.

Adam Trischler, Tong Wang, Xingdi Yuan, Justin Harris, Alessandro Sordoni, Philip Bachman, and Kaheer Suleman. 2017. NewsQA: A Machine Comprehension Dataset. In 2nd Workshop on Representation Learning for NLP.

George Tsatsaronis, Georgios Balikas, Prodromos Malakasiotis, Ioannis Partalas, Matthias Zschunke, Michael R Alvers, Dirk Weissenborn, Anastasia Krithara, Sergios Petridis, and Dimitris Polychronopoulos et al. 2015. An Overview of the BioASQ Large-Scale Biomedical Semantic Indexing and Question Answering Competition. BMC Bioinformatics.

Jindong Wang, Cuiling Lan, Chang Liu, Yidong Ouyang, and Tao Qin. 2021. Generalizing to Unseen Domains: A Survey on Domain Generalization. In IJCAI (Survey Track).

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, and Remi Louf et al. 2020. Transformers: State-of-the-Art Natural Language Processing. In EMNLP System Demonstrations.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. HotpotQA: A Dataset for Diverse, Explainable Multi-hop Question Answering. In EMNLP.

Kaiyang Zhou, Ziwei Liu, Yu Qiao, Tao Xiang, and Chen Change Loy. 2021. Domain Generalization in Vision: A Survey. arXiv preprint arXiv: 2103.02503.
A Appendix

A.1 Qualitative Analysis

To better understand what new patterns the proposed method of augmented knowledge distillation (KD-Aug) teaches, we take a closer look at a random sample of the test instances where the baseline model has an F1 score of zero and the student has an F1 score greater than .5. Table 5 shows four such examples from four different test sets. Even in this very small sample, we observe a number of different ways in which the KD-Aug student is better than the plain ERM baseline:

- **BioASQ**: The student has learned that synonyms are commonly mentioned in parentheses, especially in the beginning of a sentence.

- **DUOREC**: The word “overdose” can be difficult to model in context as the subject of the verb “overdose” becomes the object in the expression “giving someone an overdose”. The student appears to have learned this nuanced semantics, which the baseline model has not.

- **Relation Extraction**: Unlike the baseline, the student knows that a fictional universe is not a time period, and the word “Universe” at the end of the phrase “DC Universe” is a strong hint to capitalize on in this particular case. Crucially, it has also learned to ignore the spurious surface-level match in this example between the question and the phrase “from the 30th century” in the passage.

- **DROP**: This one is a somewhat harder case to analyze, where a plausible explanation could be that the student has better knowledge about people’s names and only the last name “Gostkowski” was sufficient for it to recognize it as a player’s name.

Even though these patterns were taught by KD-Aug using a small number of source domains, their domain-agnostic importance is quite clear and intuitive, which is also supported by the experiments reported in this paper.

A.2 Further Commentary on KD Results

The BERT-base model fine-tuned using ERM has an F1 score of 75.0 on the in-domain dev set; the corresponding number for the BERT-large teacher is 77.3. As Table 3 shows, the augmented KD student has an F1 score of 77.2, indicating that additional synthetic questions facilitated almost perfect distillation from large to base on our source domains.

A.3 Model Selection

We use a training batch size of 32 for all models (with gradient accumulation when necessary). To ensure fair comparison, we train and validate all methods on a large set of learning rates: \( \{1, 3, 5, 7, 9\} \times 10^{-6}, \{1, 3, 5, 7, 9\} \times 10^{-5} \) and \( \{1, 3, 5\} \times 10^{-4} \), as the optimal learning rate varied drastically across different methods in our validation experiments. All models are trained for two epochs; we select the best of the epoch 1 and the epoch 2 checkpoint on the validation set for final evaluation on the OOD test set. In Table 6 we provide the optimal values of these two hyperparameters for all models.

Table 7 provides the optimal combinations of method-specific hyperparameters. Below is a brief description of each:

1. \( \lambda_{\text{adv}} \) (Domain-Adv): This is the weight of the adversarial loss of the domain classifier. The main ERM loss has a fixed weight of 1.

2. \( \lambda_{\text{erm}}, \lambda_{\text{episodic}} \) (Episodic): The relative weights of the ERM loss and the episodic learning loss in their convex combination.

3. \( \beta \) (MLDG): The weight of the meta-test loss during meta-optimization (second-order differentiation). The meta-train loss has a fixed weight of 1.

4. \( \tau \) (KD): Temperature (Eq. 1).

A.4 Infrastructure and Computation

We run all experiments on a single V100 GPU with 32gb memory. A vast majority of the runs take less than a day; the longest ones take less than 48h.
**Dataset:** BioASQ
**Question:** Name synonym of Acrokeratosis paraneoplastica.
**Passage:** Acrokeratosis paraneoplastica (Bazex 'syndrome') is a rare but clinically distinctive dermatosis that has been associated in all reported cases, to our knowledge, with either a primary malignant neoplasm of the upper aerodigestive tract or metastatic cancer to the lymph nodes of the neck. Acrokeratosis paraneoplastica was found in a 53-year-old black man with squamous cell carcinoma of the tonsil. A distinctive series of changes was found on histopathologic examination of biopsy specimens taken from his skin lesions, and direct immunofluorescence microscopy of both lesional and nonlesional skin specimens showed immunoglobulin and complement deposition on the epidermal basement membrane. The skin lesions largely resolved following radiation therapy of the neoplasm and of the presumably involved lymph nodes.
**GT:** ['Bazex syndrome']
**ERM Answer:** dermatosis
**KD-Aug Answer:** Bazex ‘syndrome’

---

**Dataset:** DuoRC
**Question:** Who overdoses on insulin?
**Passage:** The film tells the story of a psychiatrist, Dr. Cross (Vincent Price), who is treating a young woman, Janet Stewart (Anabel Shaw), who is in a coma-state, brought on when she heard loud arguing, went to her window and saw a man strike his wife with a candlestick and kill her. It also stars Lynn Bari as Dr. Cross’s nurse/lover, Elaine Jordan. As Stewart comes out of her shock, she recognizes Dr. Cross as the killer. He then takes her to his sanitarium and at Elaine’s urging, gives Janet an overdose of insulin under the pretense of administering insulin shock therapy. He can’t bring himself to murder her in cold blood, though, and asks Elaine to get the medicine to save her. Elaine refuses, they argue, and he strangles her. A colleague of Dr. Cross, Dr. Harvey, saves Janet’s life and Dr. Cross is taken into custody by a lawyer from the District Attorney’s office.
**GT:** ['Janet.', 'Janet']
**ERM Answer:** Dr. Cross
**KD-Aug Answer:** Janet Stewart

---

**Dataset:** RelationExtraction
**Question:** What is the name of the fictional universe that Polar Boy is from?
**Passage:** Polar Boy is a fictional character from the 30th century of the DC Universe, initially suggested by reader Buddy Lavigne of Northbrook, Illinois in the letters page of Adventure Comics # 304, January, 1963.
**GT:** ['DC Universe']
**ERM Answer:** 30th century
**KD-Aug Answer:** DC Universe

---

**Dataset:** DROP
**Question:** Which player scored the first points of the game?
**Passage:** The Patriots clinched their fourth straight AFC East title with a close road win. After a scoreless first quarter, the Jaguars responded to a Gostkowski field goal with a Maurice Jones - Drew touchdown run. The Patriots challenged the play, as Jones - Drew appeared to fall down at the line of scrimmage, but the ruling on the field was upheld. New England came back before the halftime to retake the lead at 10 - 7 on a Dillan one-yard touchdown run. The Patriots maintained their lead as the teams traded touchdowns in the second half, including another touchdown by Jones - Drew. A David Garrard fumble with 1:55 left in the fourth quarter, recovered by safety Rodney Harrison, sealed the Patriots’ 11th win of the season.
**GT:** ['Gostkowski']
**ERM Answer:** Maurice Jones
**KD-Aug Answer:** Gostkowski

---

Table 5: Examples of test cases where KD-based methods improve over plain ERM.
| Method             | Source Datasets | Learning Rate | # of Epochs |
|--------------------|-----------------|---------------|-------------|
| ERM                | C, D, L, P, V   | 3e-5          | 2           |
|                    | D, L, P, V, W   | 1e-5          | 2           |
|                    | L, P, V, W, C   | 1e-5          | 2           |
|                    | P, V, W, C, D   | 7e-6          | 2           |
|                    | V, W, C, D, L   | 1e-5          | 2           |
|                    | W, C, D, L, P   | 1e-5          | 2           |
| Domain-Adv         | C, D, L, P, V   | 5e-5          | 2           |
|                    | D, L, P, V, W   | 7e-5          | 2           |
|                    | L, P, V, W, C   | 7e-5          | 2           |
|                    | P, V, W, C, D   | 7e-5          | 2           |
|                    | V, W, C, D, L   | 9e-5          | 2           |
|                    | W, C, D, L, P   | 9e-5          | 2           |
| Episodic           | C, D, L, P, V   | 9e-6          | 2           |
|                    | D, L, P, V, W   | 9e-6          | 2           |
|                    | L, P, V, W, C   | 1e-5          | 2           |
|                    | P, V, W, C, D   | 7e-6          | 2           |
|                    | V, W, C, D, L   | 7e-6          | 2           |
|                    | W, C, D, L, P   | 9e-6          | 2           |
| MLDG               | C, D, L, P, V   | 9e-6          | 2           |
|                    | D, L, P, V, W   | 1e-5          | 2           |
|                    | L, P, V, W, C   | 1e-5          | 2           |
|                    | P, V, W, C, D   | 3e-5          | 2           |
|                    | V, W, C, D, L   | 9e-6          | 2           |
|                    | W, C, D, L, P   | 9e-6          | 2           |
| KD (gold-only)     | C, D, L, P, V   | 7e-5          | 2           |
|                    | D, L, P, V, W   | 3e-5          | 2           |
|                    | L, P, V, W, C   | 3e-5          | 2           |
|                    | P, V, W, C, D   | 5e-5          | 2           |
|                    | V, W, C, D, L   | 5e-5          | 2           |
|                    | W, C, D, L, P   | 3e-5          | 2           |
| KD (augmented)     | C, D, L, P, V   | 5e-5          | synthetic: 1, gold: 2 |
|                    | D, L, P, V, W   | 5e-5          | synthetic: 1, gold: 2 |
|                    | L, P, V, W, C   | 3e-5          | synthetic: 1, gold: 1 |
|                    | P, V, W, C, D   | 5e-5          | synthetic: 1, gold: 2 |
|                    | V, W, C, D, L   | 5e-5          | synthetic: 1, gold: 2 |
|                    | W, C, D, L, P   | 9e-6          | synthetic: 1, gold: 2 |
| KD (gold) w/ Domain-Adv | C, D, L, P, V | 7e-5          | 2           |
|                    | D, L, P, V, W   | 9e-5          | 2           |
|                    | L, P, V, W, C   | 9e-5          | 2           |
|                    | P, V, W, C, D   | 7e-5          | 2           |
|                    | V, W, C, D, L   | 1e-4          | 2           |
|                    | W, C, D, L, P   | 1e-4          | 2           |
| KD (gold) w/ Episodic | C, D, L, P, V | 3e-5          | 2           |
|                    | D, L, P, V, W   | 3e-5          | 2           |
|                    | L, P, V, W, C   | 3e-5          | 2           |
|                    | P, V, W, C, D   | 3e-5          | 2           |
|                    | V, W, C, D, L   | 3e-5          | 2           |
|                    | W, C, D, L, P   | 3e-5          | 2           |
| KD (gold) w/ MLDG  | C, D, L, P, V   | 5e-5          | 2           |
|                    | D, L, P, V, W   | 5e-5          | 2           |
|                    | L, P, V, W, C   | 5e-5          | 2           |
|                    | P, V, W, C, D   | 5e-5          | 2           |
|                    | V, W, C, D, L   | 7e-5          | 2           |
|                    | W, C, D, L, P   | 5e-5          | 2           |

Table 6: Optimal values of shared hyperparameters (learning rate, # of epochs). C: SearchQA, D: SQuAD, L: NaturalQuestions (NQ), P: HotpotQA, V: TriviaQA, W: NewsQA.
| Method                        | Hyperparameters          | Grid                          | Optimal                   |
|-------------------------------|--------------------------|-------------------------------|---------------------------|
| Domain-Adv                   | $\lambda_{adv}$          | $\{0.01, 0.1, 1.0\}$         | 0.1                       |
| Episodic                     | $(\lambda_{erm}, \lambda_{episodic})$ | $\lambda_{erm} \in \{0.25, 0.5, 0.75, 0.9\}$ | $\lambda_{episodic} = 1 - \lambda_{erm}$ | $(0.75, 0.25)$ |
| MLDG                          | $\beta$                  | $\{1\}$                      | 1                         |
| KD (gold)                    | $\tau$                   | $\{1, 2, 4\}$                | 2                         |
| KD (augmented)               | $\tau$                   | $\{1\}$                      | 4                         |
| KD (gold) w/ Domain-Adv      | $(\tau, \lambda_{adv})$ | $\{1, 2, 4\} \times \{0.01, 0.1, 1.0\}$ | (1, 0.01)                |
| KD (gold) w/ Episodic        | $(\tau, \lambda_{erm}, \lambda_{episodic})$ | $\{1, 2, 4\} \times \lambda_{erm} \in \{0.25, 0.5, 0.75, 0.9\}$ | $\lambda_{episodic} = 1 - \lambda_{erm}$ | $(1, 0.75, 0.25)$ |
| KD (gold) w/ MLDG            | $(\tau, \beta)$         | $\{1, 2, 4\} \times \{1\}$  | (4, 1)                    |

Table 7: Optimal values of hyperparameters specific to different training methods and the respective search grids.