DOMAIN PROMPTS: TOWARDS MEMORY AND COMPUTE EFFICIENT DOMAIN ADAPTATION OF ASR SYSTEMS

Saket Dingliwal*, Ashish Shenoy*, Sravan Bodapati, Ankur Gandhe, Ravi Teja Gadde, Katrin Kirchhoff

{skdin, ashenoy, sravanb, aggandhe, gadderav, katrinki }@amazon.com

ABSTRACT

Automatic Speech Recognition (ASR) systems have found their use in numerous industrial applications in very diverse domains. Since domain-specific systems perform better than their generic counterparts on in-domain evaluation, the need for memory and compute-efficient domain adaptation is obvious. Particularly, adapting parameter-heavy transformerbased language models used for rescoring ASR hypothesis is challenging. In this work, we introduce domain-prompts, a methodology that trains a small number of domain token embedding parameters to prime a transformer-based LM to a particular domain. With just a handful of extra parameters per domain, we achieve 7-14% WER improvement over the baseline of using an unadapted LM. Despite being parameter-efficient, these improvements are comparable to those of fully-fine-tuned models with hundreds of millions of parameters. With ablations on prompt-sizes, dataset sizes, initializations and domains, we provide evidence for the benefits of using domain-prompts in ASR systems.

Index Terms— domain-adaptation, prompt-tuning, multi-domain ASR, parameter-efficiency, low-data setting

1. INTRODUCTION

Automatic Speech Recognition (ASR) systems form a key component of various products across industry. Due to the latest advancements in their performance [1, 2, 3], these have been deployed in wide range of domains, including healthcare, travel reservations, and customer services. A typical technique to further improve the performance of these system is to do a rescoring of the n-best hypotheses with an external Language Model (LM) because of larger availability of textual data as compared to labeled audio data [3, 4]. Recent Transformer-based LMs such as GPT-2 [5] and BERT [6] have shown considerable gains in every language modeling tasks over conventional models. However, these LMs contain millions of parameters and adapting them for low-resource, domain-specific ASR systems poses challenges. Maintaining multiple domain-adapted copies of these LMs is not scalable as it involves large memory, compute, and maintenance costs. On the other hand, a common version of such an LM for all

the domains falls short in performance than domain-specific LM [7, 8]. Therefore, a need for a middle ground between performance and costs is evident.

Recent language modeling literature [9, 10, 11, 12, 13, 8] includes novel methodologies to solve a related problem of efficiently adapting large LMs to specific tasks. Instead of fine-tuning and storing millions of parameters for each task, they propose ideas that involve using a common task-agnostic copies of the LMs with some limited additional parameters per task. Therefore, these methods strike the required balance between costs and the performance on each individual task. For example, AdapterHub [9] introduced new task-specific layers in conjunction to frozen pre-trained weights of LMs, while Leopard [11] proposed a meta-learning-based approach to quickly adapt the pre-trained parameters with very few training examples from an unknown task. More recent models, such as GPT-3 [14], are able to solve new tasks with the help of just words describing the task (called prompts).

Rather than adapting LMs for NLP tasks, we focus on domain adaptation for ASR systems in this work, extending [15]. Our objective is to learn a small set of domain-specific parameters to better score domain-specific ASR hypotheses than an unadapted Transformer-based LM. Drawing ideas from prompt-tuning [10] for task adaptation, we introduce domain-prompts for our goal. We define domain-prompts as a domain-specific embeddings, which when prefixed to token embeddings of any sentence and passed through a vanilla LM, gives the probability of occurrence of the sentence particular to the domain. The number of trainable parameters (the number of prompt tokens times the embedding size) in our domain-adaptation approach are significantly smaller than the size of the LM and yet achieve similar performance to fully fine-tuned domain-specific LM. Our main contributions are summarized as follows: (1) we introduce domain-prompts to prime a Transformer-based LM to a particular domain in a parameter-efficient manner, (2) with small memory and compute overhead, we showcase a 7-14% WER improvement over ASR system with vanilla, out-of-the-box LM, and (3) particularly in low-data settings, our method matches the performance of fully-fine-tuned models and beat other LM adaptation methods even though it uses < 0.3% of parameters of the complete model

^{*}equal contribution

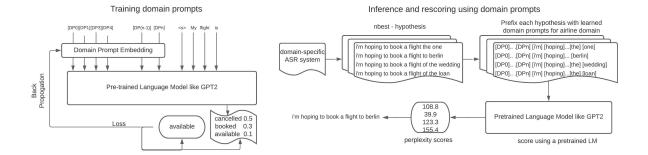


Fig. 1. Domain Prompts: training (left) and inference (right) methodology for domain-adaptation

2. METHODOLOGY

GPT-3 [14] introduced *prompts* as special textual tokens describing a task that helps the model understand it. For example, to solve the machine translation task, instead of fine-tuning the model with a corresponding dataset, one can achieve comparable performance by just adding these prompts while running inference. In prompt-tuning [10], rather than designing these prompts manually for a task, the model directly learns the prompt token embeddings using a few labeled examples from the task. We demonstrate that such embeddings can also be learnt for different domains of a task, i.e., we can prefix a sentence with additional domain-specific tokens such that it improves the score of the sentences from that domain. We hypothesize that the self-attention layer in Transformer-based LMs will create an interaction between the learnt domain embeddings and the tokens from sentences, thereby improving the score to cater to the domain. We validate our claims in Sect. 3 by evaluating perplexity scores. Fig. 1 summarizes the training and inference steps. During training, we prefix a randomly-initialized domain-prompts embedding to training sentences from the domain, pass it through a vanilla Transformer LM, and predict the next token. We back-propagate the loss to update the domain-specific embeddings, keeping every other parameter fixed. During inference, we prefix the learnt domain-prompts to the test sentence and compute perplexity of the whole input. For an ASR system, we use these perplexity scores to re-rank the hypotheses from the Acoustic Model (AM).

There are two additional details to the methodology described above. First, following prior work [10], rather than initializing the *domain-prompts* embeddings randomly, we begin with token embeddings of the most frequent words in the vocabulary of the domain in some of our experiments. Second, since the same learnt *domain-prompts* are prefixed to every hypothesis in the domain, we pre-compute and save the state of the transformer until k time-steps, where k is the number of *domain-prompts* tokens. We reuse this state while scoring all the hypotheses from the the same domain to save on inference latency of the ASR system.

3. EXPERIMENTAL SETUP

Goals: To test the effectiveness of the proposed *domain-prompts* in domain adaptation, we run extensive experimentation with different domains, prompt-sizes, initializations and training set sizes. One of our goals is to establish the ability of *domain-prompts* to learn domain specific knowledge, and investigate the impact of prompt token sizes on performance and costs. For this, we show perplexity numbers on domain-specific sentences and provide qualitative examples of generated text by prompting the model. Next, we show the importance of domain-specific LMs in ASR systems and compare the effectiveness of various domain-adaptation methods based on performance and parameter efficiency.

Methodologies: We evaluate the following approaches for our experiments. In each of the methods, we update different sets of weights of the Transformer LM using domain-specific data and keep others fixed: (1) no-adaptation: no parameter is updated and hence, a vanilla LM. This is used as a baseline for all our experiments, (2) prompt-designing: no parameter is updated but prefix manually created prompts to the input sentences. These prompts are summaries of 15-20 words describing each domain, (3) full fine-tuning: updating all the parameters of the LM, (4) domain-prompts: update only the domain prompt token embeddings, (5) tuning last-layer: update the weights of the last decoder layer of the Transformer LM, and (6) tuning embedding-layer: update only the token embedding weights of the Transformer LM

Dataset: For our initial experiments to compute perplexity scores on domain-specific datasets, we use textual data of the publicly available MultiDoGo [16] dataset. We add and learn *domain-prompts* on top of a pretrained LM using the training set, tune the hyper-parameters using a development set, and compute the perplexity numbers on a test set. We report the numbers on fast food domain with 6748, 1446 and 1446 training, dev and test dialogues respectively. Each dialogue consists of 10 turns of agent-customer conversation on average. For the next experiment with ASR system, we use in-house datasets for both domain-adaptation of the LM and running evaluations after rescoring. The data has all PII

Comparing prompt-tuning vs fine-tuning vs no-adaptation

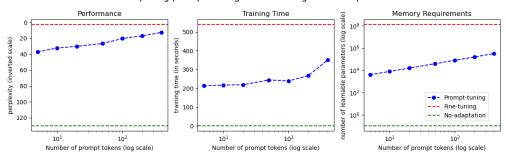


Fig. 2. Comparing the performance, computation, and memory costs of different methods of domain adaptation

info removed without having any user identification. The domain-adaptation data is text-only dataset with dialog utterances from the domains discussed in Sec. 4. We use a random sample of 800 or 10000 such utterances for all the domains in our experiments. The hypothesis rescoring is done on 8kHz conversational dataset which consists of 500 audios and its transcriptions per domain. This dataset is representative of the common ASR application in task-oriented dialogue systems.

Experimental setting: We use GPT-2 model [5] as the base Transformer-based LM. We conduct all our experiments using a machine with 16 Tesla K80 GPUs and report times in wall clock times in seconds. The n-best hypotheses used for evaluation are outputs from the lattice produced by a hybrid ASR system (consisting of first-pass AM and LM) with $n \leq 50$. The first pass LM consisted of a standard 4-gram language model, trained on heterogeneous corpus of text. It uses Kneser-Ney (KN) [17] smoothing and has a vocabulary size of 500k words. All the numbers reported in this paper are WER Relative % (WERR) which represent improvement in WER over the baseline of rescoring with out-of-the-box GPT-2 (i.e., no-adaptation baseline).

4. RESULTS AND DISCUSSION

4.1. Perplexity evaluation

We summarize the results in Fig. 2 for fast food domain from the MultiDoGo dataset. Here, we compare the perplexity, training-time, and memory used to save the updated parameters for additional domain. The x-axis represents the size of the *domain-prompts* used while the y-axis is the metric value. We also add horizontal lines for *no-adaptation* baseline (green) and *full-fine-tuning* (red) for reference. The former requires no additional memory or training-time for a new domain but performs poorly while latter updates millions of parameters. On the other hand, our methodology (blue) is a middle ground between the two extremes, controlled by size of the domain prompts. With as little as 5 prompt-tokens, the perplexity improves from 130 in *no-adaptation* baseline

Input prompt	"hello how are you"				
no-adaptation	hello how are you doing?				
	I'm really happy with the results.				
full-fine-tuning	hello how are you able to get a new flight				
	I'm flying from London Heathrow to Dubai				
domain-prompts	hello how are you able to get a refund on the flight				
	I'm flying from Glasgow to Madrid today				

Table 1. Generated text for airlines domain

to 37, while with 400 prompt-tokens, we achieve a similar perplexity to *fully-fine-tuned* model. Along with these perplexity scores, we also provide text generated from our model for airlines domain in Table 1 to validate that *domain-prompts* is able to generate coherent sentences related to the domain.

4.2. WER evaluation

Table 2 summarizes our experimental results for use of domain-prompts in ASR systems. We evaluate the WER in two different data settings: low-data and large data (as highlighted at the top of the Table 2). In the low-data setting, we use only 800 examples for all the domain-adaptation methods. In the large data setting, we use roughly 12 times more examples. Next, we use four different domains for extensive comparison. We have sufficient relevant domainspecific fine-tuning data for these domains and using that data can yield reasonable positive gains (9-18% WER improvement) over the vanilla Transformer model. Table 3 shows some qualitative examples from our dataset, where learning domain-specific knowledge proves to be useful for rescoring. The amount of improvement varies for different domains based on the quality of n-best lists from an ASR system. In the first column of the table, we also highlight the number of additional training parameters that is learned per domain for each of the domain-adaptation methods, where M represents millions. Note that the goal of the experiments is not to find the best performing method, but to discover settings that achieve optimal performance with minimal number of additional parameters, thereby finding practical utility.

Domain prompts achieves at-par performance in low-

		Low data setting (~800 sentences)				Large data setting (~10000 sentences)			
domain adaptation methods	# param	WER Relative %				WER Relative %			
		retail	airlines	healthcare	travel	retail	airlines	healthcare	travel
no-adaptation (vanilla GPT-2)	0	-	-	-	-	-	-	-	-
prompt-designing	0	3.23	0	2.05	0.64	3.23	0	2.05	0.64
tuning-last-layer	7M	8.6	11.54	4.62	1.27	10.75	12.18	6.15	2.55
tuning-embedding-layer	40M	5.91	11.54	3.59	3.82	9.14	13.46	6.15	3.82
domain-prompts: 50 size, random init	0.04M	8.06	11.54	4.62	5.1	10.22	10.26	5.64	5.73
domain-prompts: 50 size, vocab init	0.04M	9.68	13.46	5.64	4.46	10.75	14.1	6.67	6.37
domain-prompts: 500 size, vocab init	0.4M	10.22	12.82	6.15	5.73	14.52	14.1	7.18	7.64
full-fine-tuning	120M	9.14	14.1	7.18	4.46	13.98	17.95	10.26	8.92

Table 2. Comparison of different domain-adaptation methods for different domains in parameter count and WERR% metric

retail	
baseline: have you got any cable in stock	
prompt-tuned : have you got any kale in stock	
- !!!	

baseline: what's the point to tell you for my frequent flyer number prompt-tuned: what's the points tally for my frequent flyer number

healthcare

baseline: i require four packs of adrenaline pence **prompt-tuned**: i require four packs of adrenaline pens

Table 3. Qualitative examples: comparing outputs from prompt-tuned GPT-2 with vanilla GPT-2 (baseline)

data setting This setting represents very common practical applications where limited amount of conversational domain-specific data is available for the ASR systems in dialog management. Under this setting, we observed that domain-prompts models almost match the performance of the fully-fine-tuned models with significantly smaller number of parameters. We attribute this finding to the fact that domain-prompts are capable enough to capture all the information from the limited domain-specific examples without overfitting. Therefore, domain-prompts become an obvious choice in this setting as it achieve at-par performance but with the least number of trainable parameters among all other methods and thus saving memory and compute costs.

Domain prompts are very parameter efficient As shown in right half of the table, when we have sufficient fine-tuning data, we see that *domain-prompts* can achieve 7-14% WER improvement over the vanilla GPT-2 model with very small memory overhead. Although fine-tuned models perform better in this setting, their small performance improvement as compared to the *domain-prompts* method comes at the cost of storing and updating roughly 300 times more parameters than domain prompt embeddings. *domain-prompts* with 40k parameters perform consistently better when compared to adaptation methods that involve updating a single layer and freezing the rest of the model which use 7M-40M parameters. This is expected as it is difficult to manually select a subset of all high impact parameters to tune within the big model architecture and therefore such methods lose their parameter ef-

ficiency. In contrast, *domain-prompts* provide a better way by fixing the entire model architecture but prefixing the input to the model with additional trainable parameters. Further, manually creating these prompts in *prompt-designing* do not bring good improvements over the baseline suggesting that these prompts must be learnt using domain-specific data.

Ablations The table also contains some ablations on the prompt-size and the initialization method to understand their contribution to the performance. As mentioned in Sec. 2, we initialized the *domain-prompts* with most common vocabulary words. This gives us marginal improvements over random initialization of prompt-embeddings. Since these words are representative of the domain, they prove to be a useful starting point to learn the domain-specific embeddings. Further, we also observe small improvements on increasing the size of the *domain-prompts* from 50 to 500, which comes with additional memory costs as well. Therefore, such hyperparameters provide flexibility to an ASR system developer to effectively trade-off costs and performance as needed.

5. CONCLUSION

We propose a memory and compute efficient domain adaptation method called domain-prompts for Transformer-based LMs like GPT-2 for their use in rescoring ASR hypotheses. By prefixing these prompts to input sentences, we bias the model towards a particular domain and hence better score the sentences from that domain. Using just 0.3% of additional parameters per domain, our methodology achieves comparable perplexity and WER numbers on domain-specific datasets as a fully-fine-tuned model. With very small memory overhead, our method achieves 7-14% WER improvements over using vanilla GPT-2 model. Particularly, our method performs atpar with fine-tuning in low-data setting. This setting has industrial significance as it allows ASR systems to adapt to lowresource domains in a scalable manner. Domain prompts represents one case where a technique developed for efficiently adapting to language modelling tasks can yield positive results for domain adaptation in ASR systems. We plan to adapt more such ideas like AdapterHub [9], Side-tuning [18] for ASR systems in the future.

6. REFERENCES

- [1] Qian Zhang, Han Lu, Hasim Sak, Anshuman Tripathi, Erik McDermott, Stephen Koo, and Shankar Kumar, "Transformer transducer: A streamable speech recognition model with transformer encoders and rnn-t loss," in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 7829–7833.
- [2] Alex Graves, "Sequence transduction with recurrent neural networks," *arXiv preprint arXiv:1211.3711*, 2012.
- [3] William Chan, Navdeep Jaitly, Quoc Le, and Oriol Vinyals, "Listen, attend and spell: A neural network for large vocabulary conversational speech recognition," in 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2016, pp. 4960–4964.
- [4] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Hannemann, Petr Motlicek, Yanmin Qian, Petr Schwarz, et al., "The kaldi speech recognition toolkit," in *IEEE* 2011 workshop on automatic speech recognition and understanding. IEEE Signal Processing Society, 2011, number CONF.
- [5] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al., "Language models are unsupervised multitask learners," *OpenAI blog*, vol. 1, no. 8, pp. 9, 2019.
- [6] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," arXiv preprint arXiv:1810.04805, 2018.
- [7] Ashish Shenoy, Sravan Bodapati, Monica Sunkara, Srikanth Ronanki, and Katrin Kirchhoff, "Adapting Long Context NLM for ASR Rescoring in Conversational Agents," in *Proc. Interspeech 2021*, 2021, pp. 3246–3250.
- [8] Ashish Shenoy, Sravan Bodapati, and Katrin Kirchhoff, "Asr adaptation for e-commerce chatbots using crossutterance context and multi-task language modeling," Proceedings of The 4th Workshop on e-Commerce and NLP, 2021.
- [9] Jonas Pfeiffer, Andreas Rücklé, Clifton Poth, Aishwarya Kamath, Ivan Vulić, Sebastian Ruder, Kyunghyun Cho, and Iryna Gurevych, "Adapterhub: A framework for adapting transformers," arXiv preprint arXiv:2007.07779, 2020.

- [10] Brian Lester, Rami Al-Rfou, and Noah Constant, "The power of scale for parameter-efficient prompt tuning," *arXiv preprint arXiv:2104.08691*, 2021.
- [11] Trapit Bansal, Rishikesh Jha, and Andrew McCallum, "Learning to few-shot learn across diverse natural language classification tasks," *arXiv preprint arXiv:1911.03863*, 2019.
- [12] Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang, "Gpt understands, too," *arXiv preprint arXiv:2103.10385*, 2021.
- [13] Xiang Lisa Li and Percy Liang, "Prefix-tuning: Optimizing continuous prompts for generation," *arXiv* preprint arXiv:2101.00190, 2021.
- [14] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al., "Language models are few-shot learners," *arXiv* preprint arXiv:2005.14165, 2020.
- [15] Saket Dingliwal, Ashish Shenoy, Sravan Bodapati, Ankur Gandhe, Ravi Teja Gadde, and Katrin Kirchhoff, "Efficient domain adaptation of language models in ASR systems using prompt-tuning," *CoRR*, vol. abs/2110.06502, 2021.
- [16] Denis Peskov, Nancy Clarke, Jason Krone, Brigi Fodor, Yi Zhang, Adel Youssef, and Mona Diab, "Multidomain goal-oriented dialogues (MultiDoGO): Strategies toward curating and annotating large scale dialogue data," in Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), Hong Kong, China, Nov. 2019, pp. 4526–4536, Association for Computational Linguistics.
- [17] Reinhard Kneser and Hermann Ney, "Improved backing-off for m-gram language modeling," in 1995 international conference on acoustics, speech, and signal processing. IEEE, 1995, vol. 1, pp. 181–184.
- [18] Jeffrey O Zhang, Alexander Sax, Amir Zamir, Leonidas Guibas, and Jitendra Malik, "Side-tuning: A baseline for network adaptation via additive side networks," in Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16. Springer, 2020, pp. 698–714.