PADA: Example-based Prompt Learning for on-the-fly Adaptation to Unseen Domains

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Abstract

Natural Language Processing algorithms have made incredible progress, but they still struggle when applied to out-of-distribution examples. We address a challenging and underexplored version of this domain adaptation problem, where an algorithm is trained on several source domains, and then applied to examples from unseen domains that are unknown at training time. Particularly, no examples, labeled or unlabeled, or any other knowledge about the target domain are available to the algorithm at training time. We present *PADA*: An example-based autoregressive Prompt learning algorithm for on-the-fly Any-Domain Adaptation, based on the T5 language model. Given a test example, *PADA* first generates a unique prompt for it and then, conditioned on this prompt, labels the example with respect to the NLP prediction task. PADA is trained to generate a prompt which is a token sequence of unrestricted length, consisting of Domain Related Features (DRFs) that characterize each of the source domains. Intuitively, the generated prompt is a unique signature that maps the test example to a semantic space spanned by the source domains. In experiments with 3 tasks (text classification and sequence tagging), for a total of 14 multi-source adaptation scenarios, *PADA* substantially outperforms strong baselines.[1][2]

1 Introduction

Natural Language Processing (NLP) algorithms are gradually achieving remarkable milestones (Devlin et al., 2019; Lewis et al., 2020; Brown et al., 2020). However, such algorithms often rely on the seminal assumption that the training set and the test set come from the same underlying distribution. Unfortunately, this assumption often does not hold since text may emanate from many different sources, each with unique distributional properties. As generalization beyond the training distribution is still a fundamental challenge, NLP algorithms suffer a significant degradation when applied to out-of-distribution examples.

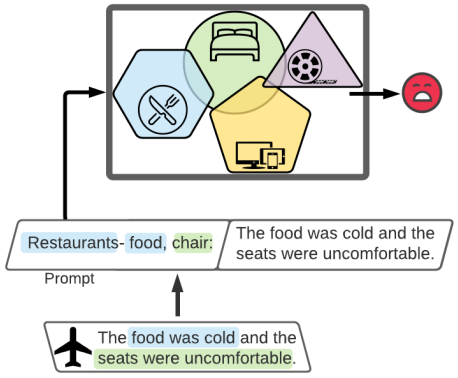

Figure 1: Text classification with PADA. Colored texts signify relation to a specific source domain. *PADA* first generates the domain name, followed by a set of DRFs related to the input example. Then it uses the prompt to predict the task label.

Domain Adaptation (DA) explicitly addresses the above challenge, striving to improve out-of-distribution generalization of NLP algorithms. DA algorithms are trained on annotated data from source domains, to be effectively applied in a variety of target domains. Over the years, considerable efforts have been devoted to the DA challenge, focusing on various scenarios where the target domain is known at training time (e.g. through labeled or unlabeled data) but is yet under-represented (Roark and Bacchiani, 2003; Daumé III and Marcu, 2006; Reichart and Rappoport, 2007; McClosky et al., 2010; Rush et al.,

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[1] Our code and data are available at https://github.com/eyalbd2/PADA.

[2] An earlier version of this paper was previously uploaded to the arxiv under the name: "PADA: A Prompt-based Autoregressive Approach for Adaptation to Unseen Domains"

2012; Schnabel and Schütze, 2014). Still, the challenge of adaptation to *any possible target domain*, that is unknown at training time, is underexplored in DA literature.[3]

In this work, we focus on adaptation to any target domain, which we consider a "Holy Grail" of DA (§3). Apart from the pronounced intellectual challenge, it also presents unique modeling advantages as target-aware algorithms typically require training a separate model for each target domain, leading to an inefficient overall solution.

Intuitively, better generalization to unseen domains can be achieved by integrating knowledge from several source domains. We present *PADA*: An example-based autoregressive Prompt learning algorithm for on-the-fly Any-Domain Adaptation (§4), which utilizes an autoregressive language model (T5, Raffel et al. (2020)), and presents a novel mechanism which learns to generate human-readable prompts that represent multiple source domains. Given a new example, from any unknown domain, the model first generates properties (a sequence of tokens) that belong to familiar (source) domains and relate to the given example. Then, the generated sequence is used as a prompt for the example, while the model performs the downstream task.[4] *PADA* implements a specialized two-stage multi-task protocol which facilitates model parameter sharing between the prompt generation and the downstream tasks. Ultimately, *PADA* performs its adaptation per example, by leveraging (1) an example-specific prompting mechanism and (2) a two-stage multi-task objective.

In order to generate effective prompts, we draw inspiration from previous work on pivot features (Blitzer et al., 2006; Ziser and Reichart, 2018; Ben-David et al., 2020) to define sets of Domain Related Features (DRFs, §4.2). DRFs are tokens which are strongly associated with one of the source domains, encoding domain-specific semantics. We leverage the DRFs of the various source domains in order to span their shared semantic space. Together, these DRFs reflect the similarities and differences between the source domains, in addition to domain-specific knowledge.

Consider the task of review sentiment classification (Figure 1). The model is familiar with four source domains: *restaurants*, *home-furniture*, *electronic-devices*, and *movies*. When the model encounters a review, this time from the *airlines* domain, it uses DRFs to project the example into the shared semantic space, via the prompting mechanism. In the given example the DRFs marked in blue and green relate to the *restaurants* and the *home-furniture* domains, respectively. The DRF-based prompt is then used in classification.

We evaluate *PADA* in the multi-source DA setting, where the target domain is unknown during training (§5, 6). We consider two text classification tasks (Rumour Detection and Multi-Genre Natural Language Inference (MNLI)), and a sequence tagging task (Aspect Prediction), for a total of 14 DA setups. *PADA* outperforms strong baselines, yielding substantial error reductions.

2 Related Work

We first describe research in the setting of unsupervised DA with a focus on pivot-based methods. We then continue with the study of DA methods with multiple sources, focusing on mixture of experts models. Finally, we describe autoregressive language models and prompting mechanisms, and the unique manner in which we employ T5 for DA.

Unsupervised Domain Adaptation (UDA) With the breakthrough of deep neural network (DNN) modeling, attention from the DA community has been directed to representation learning approaches. One line of work employs DNN-based autoencoders to learn latent representations. These models are trained on unlabeled source and target data with an input reconstruction loss (Glorot et al., 2011; Chen et al., 2012; Yang and Eisenstein, 2014; Ganin et al., 2016). Another branch employs pivot features to bridge the gap between a source domain and a target domain (Blitzer et al., 2006, 2007; Pan et al., 2010). Pivot features are prominent to the task of interest and are abundant in the source and target domains. Recently, Ziser and Reichart (2017, 2018, 2019) married the two approaches. Later on, Han and Eisenstein (2019) presented a pre-training method, followed by Ben-David et al. (2020) and Lekhtman et al. (2021) who introduced a pivot-based variant for pre-training contextual

[3] The any-domain adaptation setting is addressed in the model robustness literature. In §3, we discuss the differences between these static methods and our dynamic approach.

[4] We use a language model, pre-trained on massive unlabeled data, and it is possible that this model was exposed to text from the source or target domains. Yet, the downstream task training is based only on examples from the source domains without any knowledge of future target domains.

word embeddings.

Crucially, UDA models assume access to unlabeled data from the target domain in-hand during training. We see this as a slight relaxation to the goal of generalization beyond the training distribution. Moreover, this definition has engineering disadvantages, as a new model is required for each target domain. To this end, we pursue the any-domain adaptation setting, where unlabeled target data is unavailable at training time.

We draw inspiration from pivot-based modeling. The pivot definition relies on labeled source domain data and unlabeled source and target domain data (which is unavailable in our setup). Particularly, good pivots are ones that are correlated with the task label. Hence, pivot features are typically applied to tasks which offer meaningful correlations between words and the task label, such as sentiment classification. For other types of tasks, pivots may be difficult to apply. Consider the *MNLI* dataset, where the task is to understand the directional relation between a pair of sentences (entailment, contradiction or neutral). In such a task it is unlikely to find meaningful correlations between single words and the label. Instead, we define task-invariant DRFs, features which are highly correlated with the identity of the domain. Since domains are highly correlated with words, our DRFs are lexical in nature.

Our proposed approach is an important step forward from pivots, as our model generates DRF sequences of unrestricted lengths, instead of focusing on individual words. Moreover, pivots are typically applied in single source setups, and while our method can operate with a single source domain, we utilize multiple source domains to facilitate generalization to unknown target domains.

Multi-Source Domain Adaptation Most existing *multi-source DA* methods follow the setup definitions of unsupervised DA, while considering more than one source domain. A prominent approach is to fuse models from several sources. Early work trained a classifier for each domain and assumed all source domains are equally important for a test example (Li and Zong, 2008; Luo et al., 2008). More recently, adversarial-based methods used unlabeled data to align the source domains to the target domains (Zhao et al., 2018; Chen and Cardie, 2018). Meanwhile, Kim et al. (2017) and Guo et al. (2018) explicitly weighted a Mixture of Experts (MoE) model based on the relationship between a target example and each source domain. However, Wright and Augenstein (2020) followed this work and tested a variety of weighting approaches on a Transfomers-based MoE and found a naive weighting approach to be very effective.

We recognize two limitations in the proposed MoE solution. First, MoE requires training a standalone expert model for each source domain. Hence, the total number of parameters increases (typically linearly) with the number of source domains, which harms the solution's scalability. One possible solution could be to train smaller-scale experts (Pfeiffer et al., 2020; Rücklé et al., 2020), but this approach is likely to lead to degradation in performance. Second, domain experts are tuned towards domain-specific knowledge, at times at the expense of cross-domain knowledge which highlights the relationship between different domains. In practice, test examples may arrive from unknown domains, and may reflect a complicated combination of the sources. To cope with this, MoE ensembles the predictions of the experts using heuristic methods, such as a simple average or a weighted average based on the predictions of a domain-classifier. Our results indicate that this approach is sub-optimal.

Moreover, we view domain partitioning as often somewhat arbitrary (consider for example the differences between the *dvd* and *movie* domains). We do not want to strictly confine our model to a specific partitioning and rather encourage a more lenient approach towards domain boundaries. Hence, in this work, we train only a single model which shares its parameters across all domains. Furthermore, we are interested in adapting to any target domain, such that no information about potential target domains is known at training time. Some of the above works (Wright and Augenstein, 2020) in fact avoid utilizing target data, thus they fit the any-domain setting and form two of our baselines. Yet, in contrast to these works, the *any-domain* objective is a core principle of this study.

Autoregressive LMs and Prompting Recently, a novel approach to language modeling has been proposed, which casts it as a sequence-to-sequence task, by training a full Transformer (encoder-decoder) model (Vaswani et al., 2017) to autoregressively generate masked, missing or perturbed token spans from the input sequence (Raffel et al., 2020; Lewis et al., 2020). Raffel et al.

(2020) present a particularly interesting approach with the T5 model. It treats all tasks as generative (text-to-text), eliminating the need for a task-specific network architecture. This is made possible by prefixing each example with a prompt phrase denoting the specific task being performed.

Recent works have further explored such prompting mechanisms in several avenues: Adapting a language model for different purposes (Brown et al., 2020); eliciting sentiment or topic-related information (Jiang et al., 2020; Sun and Lai, 2020; Shin et al., 2020; Haviv et al., 2021); efficient fine-tuning (Li and Liang, 2021; Scao and Rush, 2021); or as a method for few-shot learning (Gao et al., 2021; Schick and Schütze, 2021).[5] In this work, we make use of T5's prompting mechanism as a way of priming the model to encode domain-specific characteristics relating to each example from an unknown target domain. Borrowing terminology from Liu et al. (2021a), our approach falls under the "Prompt+LM Tuning" training strategy (Liu et al., 2021b; Han et al., 2021). In this strategy, prompt-relevant parameters are fine-tuned together with some or all of the parameters of the pre-trained model (T5 in our case). However, in contrast to prompt tuning approaches which focus on representation level tuning (Liu et al., 2021b; Li and Liang, 2021; Lester et al., 2021), we train T5 to generate human readable prompts consisting of natural language tokens that encode domain-specific information relating to the the given example. To the best of our knowledge, this work is the first to learn to generate textual prompts alongside a downstream prediction task. It is also the first to generate a unique prompt per example. Finally, it is the first to design a prompting mechanism for the purpose of DA.

3 Any-Domain Adaptation

DA and Transfer Learning A prediction task (e.g., Rumour Detection) is defined as $\mathcal{T} = \{\mathcal{Y}\}$, where $\mathcal{Y}$ is the task's label space. We denote $\mathcal{X}$ to be a feature space, $P(X)$ to be the marginal distribution over $\mathcal{X}$, and $P(Y)$ the prior distribution over $\mathcal{Y}$. The domain is then defined by $\mathcal{D}^{\mathcal{T}} = \{\mathcal{X}, P(X), P(Y), P(Y|X)\}$. DA is a particular case of transfer learning, namely *transductive transfer learning* (Ramponi and Plank, 2020), in which $\mathcal{T}_S$ and $\mathcal{T}_T$, the source and target tasks, are the same. However, $\mathcal{D}_S^{\mathcal{T}}$ and $\mathcal{D}_T^{\mathcal{T}}$, the source and target domains, differ in at least one of their underlying probability distributions, $P(X)$, $P(Y)$, or $P(Y|X)$.[6] The goal in DA is to learn a function f from a set of source domains $\{\mathcal{D}_{S_i}\}_{i=1}^{K}$ that generalizes well to a set of target domains $\{\mathcal{D}_{T_i}\}_{i=1}^{M}$.

The Any-Domain Setting We focus on building an algorithm for a given task, that is able to adapt to *any-domain*. To this end, we assume zero knowledge about the target domain, $\mathcal{D}_T$, at training time. Hence, we slightly modify the classic setting of unsupervised multi-source domain adaptation, by assuming we have no knowledge or access to labeled or unlabeled data from the target domains. We only assume access to labeled training data from K source domains $\{\mathcal{D}_{S_i}\}_{i=1}^{K}$, where $\mathcal{D}_{S_i} \triangleq \{(x_t^{S_i}, y_t^{S_i})\}_{t=1}^{n_i}$. The goal is to learn a model using only the source domains data, that generalizes well to unknown target domains.

The NLP and ML literature addresses several settings that are similar to any-domain adaptation. However, our on-the-fly example-based approach is novel. Below, we discuss these settings and the differences between their proposed solution approaches and ours.

The goal of any-domain adaptation was previously explored through the notion of *domain robustness*. Algorithms from this line of work seek generalization to unknown distributions through optimization methods which favor robustness over specification (Hu et al., 2018; Oren et al., 2019; Sagawa et al., 2020; Koh et al., 2020; Wald et al., 2021). This is typically achieved by training the model to focus on domain-invariant features, which are considered fundamental to the task and general across domains (Muandet et al., 2013; Ganin et al., 2016; Arjovsky et al., 2019; Müller et al., 2020). In contrast, this work proposes to achieve this goal through on-the-fly example-based adaptation, utilizing both domain-invariant and domain-specific features, as the latter often proves relevant to the new domain (Blitzer et al., 2006; Ziser and Reichart, 2017). For instance, consider the example presented in Figure 1. The expression "food was cold" would be considered as domain-specific, considering the *restaurants* domain. Despite it not being a domain-invariant feature, it may serve as a valuable feature for the target domain (*airlines*).

[5] For a comprehensive discussion of the research on prompting mechanisms, we refer to Liu et al. (2021a).

[6] In *inductive transfer learning* $\mathcal{T}_S$ differs from $\mathcal{T}_T$.

Any-domain adaptation also draws some similarities with the *continual learning* (Ring, 1995) and *zero-shot learning* (Palatucci et al., 2009) paradigms. *Continual learning* systems seek to transfer knowledge from a number of known tasks to a new one, while in our proposed setting new domains arrive during inference, and as opposed to continual learning, we do not update the parameters of the model when a new domain is presented (we actually do not even know the domains of the test examples).[7] The *zero-shot* setting also does not update the parameters of the model given a new task, yet its definition is less consistent across different models: GPT-3 (Brown et al., 2020) attempts to transfer knowledge to an unknown target task $\mathcal{T}_T$ and unknown domain $\mathcal{D}_T$; Blitzer et al. (2009) assume access to unlabeled data from various domains including the target domain; and Peng et al. (2018) use data of a different task from the target domain. In contrast, our problem setting specifically focuses on domain adaptation, while assuming no prior knowledge of the target domain.

The any-domain adaptation setting naturally calls for an example-level adaptation approach. Since the model does not have any knowledge about the target domain during training, each example it encounters during inference should be aligned with the source domains.

4 Example-based Adaptation through Prompt Learning

In this work we propose a single model that encodes information from multiple domains. Our model is designed such that test examples from new unknown domains can trigger the most relevant parameters in the model. This way we allow our model to share information between domains and use the most relevant information at test time. Our model is inspired by recent research on prompting mechanisms for autoregressive language models. We start (§4.1) by describing the general architecture of our model, and continue (§4.2) with the domain related features that form our prompts.

4.1 The Model

We present our example-based autoregressive Prompt learning algorithm for on-the-fly Any-Domain Adaptation (*PADA*, Figure 2). *PADA* employs a pre-trained T5 language model and learns to generate example-specific Domain Related Features (DRFs) in order to facilitate accurate task predictions. This is implemented through a two-step multi-task mechanism, where first a DRF set is generated to form a prompt, and then the task label is predicted.

Formally, assume an input example $(x_i, y_i) \sim S_i$, such that x_i is the input text, y_i is the task label and S_i is the domain of this example. For the input x_i, *PADA* is trained to first generate N_i, the domain name, followed by R_i, the DRF signature of x_i, and given this prompt to predict the label y_i. At test time, when the model encounters an example from an unknown domain, it generates a prompt that may consist of one or more domain names as well as features from the DRF sets of one or more source domains, and based on this prompt it predicts the task label.

Test-time Inference Consider the example in Figure 1, which describes a sentiment classification model, trained on the *restaurants*, *home-furniture*, *electronic-devices*, and *movies* source domains. The model observes a test example from the *airlines* domain, a previously unseen domain whose name is not known to the model. The model first generates the name of the domain which is most appropriate for this example, *restaurants* in this case. Then, it continues to generate the words "food" and "chair", features related to the *restaurants* and *home-furniture* domains, respectively. Finally, given this prompt, the model predicts the example's (negative) sentiment.

Training In order to separate the prompt generation task from the discriminative classification task, we train our model within a multi-task framework. *PADA* is trained to perform two tasks, one for generating a prompt, consisting of features from the DRF set of the example's domain, and another for predicting the example's label. For the first, generative task, the model receives examples with the special prompt '*Domain:*', which primes the model to generate N_i and R_i (see examples for prompts generated by *PADA* in Table 1). Note that R_i is a set of features derived from the DRF set of S_i, and training examples are automatically annotated with their R_i, as described in §4.2. For the second, discriminative task, the model receives a prompt, consisting of N_i and R_i, and its task is to predict y_i.

[7] von Oswald et al. (2020) explore the notion of inferring the new example's task out of the training tasks.

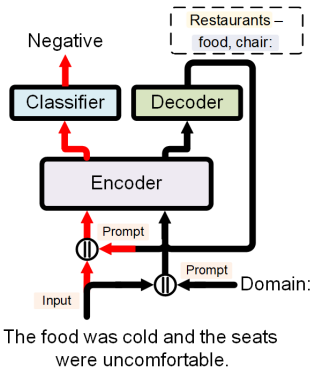


Figure 2: *PADA* during test time inference. An autoregressive model with a generative head trained for DRF generation and a discriminative head for sentiment classification. *PADA* conditions the classification on the generated prompt. Text marked with blue signifies the DRFs and text marked with yellow signifies the domain name. Black arrows (→) mark the first inference step and red arrows (→) mark the second inference step.

Following the multi-task training protocol of T5, we mix examples from each task. To this end, we define a task proportion mixture parameter α. Each example from the training set forms an example for the generative task with probability α, and an example for the discriminative task with probability $1 - \alpha$. The greater the value of α, the more the model will train for the generative task.

At the heart of our method is the clever selection of the DRF set of each domain, and the prompt annotation process for the training examples. We next discuss these features and their selection process.

4.2 Domain Related Features

For each domain we define the DRF set such that these features provide a semantic signature for the domain. Importantly, if two domains have shared semantics, for example the *restaurants* and the *cooking* domains, we expect their DRFs to semantically overlap. Since the prompt of each training example consists of a subset of features from the DRF set of its domain, we should also decide on a prompt generation rule that can annotate these training examples with their relevant features.

In order to reflect the semantics of the domain, DRFs should occur frequently in this domain. Moreover, they should be substantially more common in that specific domain relative to all other domains. Despite their prominence in a specific domain, DRFs can also relate to other domains. For instance, consider the top example presented in Table 1. The word "attack" is highly associated with the "Ottawa Shooting" domain and is indeed one of its DRFs. However, this word is also associated with "Sydney Siege", which is another domain in the Rumour Detection dataset (Zubiaga et al., 2016). Moreover, since both domains are related to similar events, it is not surprising that the DRF set of the former contains the feature *suspect* and the DRF set of the latter contains the feature *taker* (see Table 3). The similarity of these features facilitates parameter sharing in our model.

Input. *A sad day for France, for journalism, for free speech, and those whose beliefs the attackers pretend to represent.* **Prompt.** *Ottawa Shooting - french, attack, shootings*
Input. *Picture of explosion in Dammartin-en-Goele. all happened suddenly.* **Prompt.** *Germanwings Crash - explosion, goele, german*
Input. *At least 5 hostages in kosher supermarket in eastern Paris, according to reports.* **Prompt.** *Paris Siege - hostages, reports, taker*

Table 1: Examples for DRF-based prompts generated by *PADA*, from the Charlie-Hebdo (C) target domain, which is unknown to *PADA* during training (source domains are FR, GW, OS, and S. See Table 4). *PADA* generates prompts which are semantically related to the input example by combining DRFs from source domains along with non-DRF yet relevant words. Moreover, it can also generate new domain names (*Paris Siege*).

Automatically Extracting DRFs There can be several ways of implementing a DRF extraction method that are in line with the above DRF definition. We experimented with several different extraction criteria (Correlation, class-based TF-IDF,[8] and Mutual Information), and observed high similarity (82% overlap) between their resulting DRF sets. However, we observed a qualitative advantage for Mutual Information (MI), which successfully extracted DRFs that hold domain-specific semantic meaning.

We present the following MI-based method: Let examples (texts) from the jth source domain ($\mathcal{S}_j$) be labeled with 1, and examples from all other do-

[8] https://github.com/MaartenGr/cTFIDF

$\rho = 0$	$\rho = 1$	$\rho = 10$	$\rho = 100$
ferguson	*police*	*know*	*breaking*
mikebrown	*officer*	*report*	
robbery	*killing*	*just*	

Table 2: A sample of DRFs extracted for the Ferguson domain (rumour detection) with different ρ values. Each column represents DRFs which are filtered in DRF sets of lower ρ value. DRFs of lower ρ values are more domain specific.

mains ($\mathcal{S}\backslash\mathcal{S}_j$) be labeled with 0. We first calculate the *mutual-information* (MI) between all tokens and this binary variable, and choose the l tokens with the highest MI score. Note, that the MI criterion might promote tokens which are highly associated with ($\mathcal{S}\backslash\mathcal{S}_j$) rather than with $\mathcal{S}_j$. Thus, we filter the l tokens according to the following condition:

$$\frac{C_{\mathcal{S}\backslash\mathcal{S}_j}(n)}{C_{\mathcal{S}_j}(n)} \leq \rho, \;\; C_{\mathcal{S}_j}(n) > 0$$

where $C_{\mathcal{S}_j}(n)$ is the count of the n-gram n in $\mathcal{S}_j$, $C_{\mathcal{S}\backslash\mathcal{S}_j}(n)$ is the count of this n-gram in all source domains except for $\mathcal{S}_j$, and ρ is an n-gram frequency ratio hyper-parameter.

Intuitively, the smaller ρ is, the more certain we are that the n-gram is especially associated with $\mathcal{S}_j$, compared to other domains. Since the number of examples in $\mathcal{S}_j$ is much smaller than the number of examples in $\mathcal{S}\backslash\mathcal{S}_j$, we choose $\rho \geq 1$ but do not allow it to be too large. As a result, this criterion allows for features which are associated with $\mathcal{S}_j$ but also related to other source domains, to be part of the DRF set of $\mathcal{S}_j$. This is demonstrated in Table 2, where we present examples of DRFs extracted for the *Ferguson* domain of the rumour detection task, by using different values of ρ. Using $\rho = 0$, domain-specific DRFs such as "mikebrown" are extracted for the domain's DRF set. By increasing the value of ρ to 1, we add DRFs which are highly associated with the domain, but are also prevalent in other domains (e.g., "killing" is also related to the *Ottawa-shooting* domain). However, when increasing the value of ρ to 10, we extract DRFs which are less associated with the domain ("know"). This is further exacerbated when increasing ρ to higher values.

Annotating DRF-based Prompts for Training We denote the DRF set of the jth domain with R_j. Given a training example i from domain j, we select the m features from R_j which are most associated with this example to form its prompt. To do that, we compute the Euclidean distance between the T5 embeddings of the DRF features and the T5 embeddings of each of the example's tokens. We then rank this list of pairs by their scores and select the top m features.[9] In Table 3 we provide a sample of DRFs from the DRF sets associated with each domain in the rumor detection task (§ 5), alongside their frequency statistics for being annotated in a training example's prompt.

To conclude, our methods for domain-specific DRF set extraction and for prompt annotation of training examples, demonstrate three attractive properties. First, every example has its own unique prompt. Second, our prompts map each training example to the semantic space of its domain. Lastly, the domain-specific DRF sets may overlap in their semantics, either by including the same tokens or by including tokens with similar meanings. This way they provide a more nuanced domain signature compared to the domain name alone. This is later used during the inference phase when the model can generate an example-specific prompt that consists of features from the DRF sets of the various source domains.

5 Experimental Setup

5.1 Task and Datasets

We experiment with three multi-source DA tasks, where a model is trained on several domains and applied to a new one. We consider two text classification tasks, Rumour Detection and Multi-Genre Natural Language Inference (MNLI), and one sequence tagging task – Aspect Prediction. The details of the training, development and test sets of each domain are provided in Table 4. Our experiments are performed in a leave-one-out fashion: We train the model on all domains but one, and keep the held-out domain for testing. Particularly, training is done on the training data of the source domains and development on their development data, while the test data is taken from the target domain, which is unknown at training time. We repeat the experiments in each task such that each domain is used as a target domain.

[9] In this computation we consider the non-contextual embeddings learned by T5 during its pre-training. In our experiments we consider only unigrams (words) as DRFs.

Rumour Detection The PHEME dataset of rumourous tweets (Zubiaga et al., 2016, 2017) contains 5,802 tweets, which followed 5 different real-world events, and are labelled as rumourous or non-rumourous.[10] We treat each event as a separate domain: Charlie-Hebdo (C), Ferguson (FR), Germanwings-crash (GW), Ottawa-shooting (OS), and Sydney-siege (S).

We follow the data processing procedure of Wright and Augenstein (2020) and split each domain (event) corpus by a 4:1 ratio, establishing training and development sets. Since the corpora are relatively small, we want to avoid further shrinking the size of the test set. Hence, we include all examples available from the target domain to form the test set.[11]

MNLI This corpus (Williams et al., 2018) is an extension of the SNLI dataset (Bowman et al., 2015).[12] Each example consists of a pair of sentences, a premise and a hypothesis. The relationship between the two may be entailment, contradiction, or neutral. The corpus includes data from 10 domains: 5 are matched, with training, development and test sets, and 5 are mismatched, without a training set. We experiment only with the five matched domains: Fiction (F), Government (G), Slate (SL), Telephone (TL) and Travel (TR).

Since the test sets of the MNLI dataset are not publicly available, we use the original development sets as our test sets for each target domain, while source domains use these sets for development. We explore a lightly supervised scenario, which emphasizes the need for a DA algorithm. Thus, we randomly downsample each of the training sets by a factor of 30, resulting in $2,000 - 3,000$ examples per set.

Aspect Prediction The Aspect Prediction dataset is based on aspect-based sentiment analysis (ABSA) corpora from four domains: Device (D), Laptops (L), Restaurant (R), and Service (SE). The D data consists of reviews from Toprak et al. (2010), the SE data includes web service reviews (Hu and Liu, 2004), and the L and R domains consist of reviews from the SemEval-2014 ABSA challenge (Pontiki et al., 2014).

We follow the training and test splits defined by Gong et al. (2020) for the D and SE domains, while the splits for the L and R domains are taken from the SemEval-2014 ABSA challenge. To establish our development set, we randomly sample 10% out of the training data.

[10] https://figshare.com/articles/dataset/PHEME_dataset_of_rumours_and_non-rumours/4010619

[11] This does not harm the integrity of our experiments, since the training and development sets are sampled from the source domains while the test set is sampled only from the target domain.

[12] https://cims.nyu.edu/~sbowman/multinli/

C	GW	OS	S
hebdo (88%)	lufthansa (86%)	ottawa (83%)	australians (75%)
ahmed (48%)	germanwings (33%)	cdnpoli (36%)	monis (69%)
terrorists (22%)	crash (25%)	shooting (30%)	isis (21%)
attack (19%)	plane (24%)	soldier (12%)	cafe (18%)
victims (4%)	barcelona (23%)	suspect (5%)	taker (16%)

Table 3: A sample of DRFs from four rumour detection domains along with their frequency for being annotated in a training example's prompt.

Rumour Detection			
Domain	**Training (src)**	**Dev (src)**	**Test (trg)**
Charlie-Hebdo (C)	1,663	416	2,079
Ferguson (FR)	914	229	1,143
Germanwings-crash (GW)	375	94	469
Ottawa-shooting (OS)	712	178	890
Sydney-siege (S)	976	245	1,221
MNLI			
Domain	**Training (src)**	**Dev (src)**	**Test (trg)**
Fiction (F)	2,547	1,972	1,972
Government (G)	2,541	1,944	1,944
Slate (SL)	2,605	1,954	1,954
Telephone(TL)	2,754	1,965	1,965
Travel (TR)	2,541	1,975	1,975
Aspect			
Domain	**Training (src)**	**Dev (src)**	**Test (trg)**
Device (D)	2,302	255	1,279
Laptops (L)	2,726	303	800
Restaurants (R)	3,487	388	800
Service(SE)	1,343	149	747

Table 4: The number of examples in each domain of our three tasks. We denote the examples used when a domain is included as a source domain (src), and when it is the target domain (trg).

5.2 Evaluated Models

Our main model is ***PADA***: The multi-task model that first generates the domain name and domain related features to form a prompt, and then uses this prompt to predict the task label (§4.1, Figure 2). We compare it to two types of models: (a) T5-based baselines corresponding to ideas presented in multi-source DA work, as well as other recent state-of-the-art models (§2); and (b) Ablation models that use specific parts of *PADA*, to highlight the importance of its components.

5.2.1 Baseline Models

Transformer-based Mixture of Experts (Tr-MoE) For each source domain, a separate transformer-based DistilBERT expert model (Sanh et al., 2019) is trained on the domain's training set, and an additional model is trained on the union of training sets from all source domains. At test time, the average of the class probabilities of these models is calculated and the highest probability class is selected. This model is named *MoE-avg* by Wright and Augenstein (2020) and has demonstrated to achieve state-of-the-art performance for Rumour Detection.

T5-MoE A T5-based MoE ensemble model. For each source domain, a separate pre-trained T5 model is fine-tuned on the domain's training set (i.e. a domain expert model). During inference, the final predictions of the model are decided using the same averaging procedure as in *Tr-MoE*.

T5-No-Domain-Adaptation (T5-NoDA) A pre-trained T5 model, which feeds the same task classifier used in *PADA* (see below) to predict the task label. In each DA setting, the model is trained on the training data from all source domains.

We also experiment with an in-domain version of this model, ***T5-UpperBound (T5-UB)***, which is tested on the development data of each domain. We treat *T5-UB* performance as an upper bound for the average target performance across all DA settings, for any T5-based model in our setup.

T5-Domain-Adversarial-Network (T5-DAN) A model that integrates *T5-NoDA* with an adversarial domain classifier to learn domain invariant representations.[13]

T5-Invariant-Risk-Minimization (T5-IRM) A T5-based model which penalizes feature distributions that have different optimal linear classifiers for each domain. The model is trained on the training data from all source domains.

IRM (Arjovsky et al., 2019) and DAN (Ganin et al., 2016) are established algorithms in the domain robustness literature, for generalization to unseen distributions (Koh et al., 2020).

5.2.2 Ablation Models

Prompt-DN A simplified version of our *PADA* model, which assigns only a *domain name* as a prompt to the input text. Since the domain name is unknown at test time, we create multiple variants of each test example, each with one of the training domain names as a prompt. For the final predictions of the model we follow the same averaging procedure as in *Tr-MoE* and *T5-MoE*.

Prompt-RDW* and *Prompt-REW Two simplified versions of *PADA* which form prompts from *Random-Domain-Words* and *Random-Example-Words*, respectively. For *Prompt-RDW*, we sample $m = 5$ domain words (according to their distribution in the joint vocabulary of all source domains) for each example. For *Prompt-REW*, we randomly select $m = 5$ words from the example's text. At both training and test times, we follow the same prompt formation procedures.

PADA-NP (No Prompt) A multi-task model similar to *PADA*, except that it simultaneously generates the example-specific domain name and DRF-based prompt, and predicts the task label (Figure 3a). Since this model does not condition the task prediction on the generated prompt, it sheds light on the effect of the autoregressive nature of *PADA*.

PADA-NM (No Multi-task) A pipeline of two independent models which emulates *PADA*. Given an input example, the first model generates a unique prompt for it. Then, the second model predicts the task label given the input and its generated prompt (Figure 3b). Since the prediction and prompt generation tasks are not performed jointly, nor are the model parameters shared between the tasks, this pipeline sheds light on the effect of the multi-task nature of *PADA*.

5.3 Implementation Details

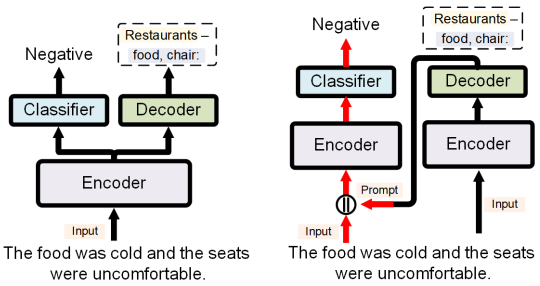
For all implemented models we use the *HuggingFace Transformers* library (Wolf et al., 2020).[14]

The T5-based text classification models do not follow the same procedure originally described in Raffel et al. (2020). Instead, we add a simple *1D-CNN* classifier on top of the T5 encoder to predict the task label (Figure 2). The number of filters in this classifier is 32 with a filter size of 9.[15] The generative component of the T5-based models is identical to that of the original T5. Our T5-based

[13] We also experimented with *BERT-NoDA* and *BERT-DAN* models. We do not report their results since they were consistently outperformed by *T5-NoDA* and *T5-DAN*.

[14] https://github.com/huggingface/transformers

[15] We experimented with the original T5 classification method as well, but *PADA* consistently outperformed it.



(a) *PADA-NP*. (b) *PADA-NM*.

Figure 3: *PADA* ablation models: (a) *PADA-NP*, which follows a multi-task training protocol, but does not condition its prediction on the generated prompt; (b) *PADA-NM*, which separately trains a prompt generation model (→) and a prompted task prediction model (→).

models for Aspect Prediction cast sequence tagging as a sequence-to-sequence task, employing the text-to-text approach of Raffel et al. (2020) to generate a 'B' (begin), 'I' (in) or 'O' (out) token for each input token. Other than this change, these models are identical to the T5-based models for text classification.

We train all text classification models for 5 epochs and all sequence tagging models for 60 epochs, with an early stopping criterion according to performance on the development data. We use the cross-entropy loss function for all models, optimizing their parameters with the *ADAM* optimizer (Kingma and Ba, 2015). We employ a batch size of 32 for text classification and 24 for sequence tagging, warmup ratio of 0.1, and a learning rate of $5{\cdot}10^{-5}$. The maximum input and output lengths of all T5-based models is set to 128 tokens. We pad shorter sequences and truncate longer ones to the maximum input length.

For *PADA*, we tune the α (example proportion-mixture, see §4.1) parameter considering the value range of $\{0.1, 0.25, 0.5, 0.75, 0.9\}$. The chosen values are: $\alpha_{rumour} = 0.75$, $\alpha_{mnli} = 0.1$ and $\alpha_{absa} = 0.1$. For each training example, we select the top $m = 5$ DRFs most associated with it for its prompt. For the generative component of the T5-based models, we perform inference with the Diverse Beam Search algorithm (Vijayakumar et al., 2016), considering the following hyper-parameters: We generate 5 candidates, using a beam size of 10, with 5 beam groups, and a diversity penalty value of 1.5. The l and ρ parameters of the DRF extraction procedure (§4.2) were tuned to 1000 and 1.5, respectively, for all domains.

6 Results

Text Classification Table 5 presents our results. We report the binary-F1 score for Rumour Detection, and the macro-F1 score for MNLI.[16] *PADA* outperforms all baseline models (§ 5.2.1) in 7 of 10 settings and reaches the highest result in another setting (with *T5-NoDA*), exhibiting average performance gains of 3.5% and 1.3% in Rumour Detection and MNLI, respectively, over the best performing baseline model. Interestingly, it is *T5-NoDA*, which does not perform any DA, that outperforms (on average and in most model-to-model comparisons) all other baseline model, including the MoE models.

While the performance gains differ between the tasks, they partly stem from the different performance gaps between source and target domains in each of these tasks. Recall, that we consider the *T5-UB* performance on its development sets for Rumour Detection (82.8%) and MNLI (80.8%), to be the upper bound for the average target performance across all DA settings, for any T5-based model. When considering the gaps between this upper bound and *T5-NoDA* (65.8% for Rumour Detection and 78.3% for MNLI), *PADA* reduces the error rate by 21% for Rumour Detection and 52% for MNLI. The improvements gained by *PADA* are in fact substantial in both tasks.

The advantage of *PADA* over MoE goes beyond improved predictions. Particularly, for *PADA* we train a single model while for MoE we train a unique model for each source domain, hence the number of parameters in the MoE framework linearly increases with the number of source domains. For example, in our setups, *Tr-MoE* trains five DistilBERT models (one for each source domain and one for all source domains together), resulting in $5 \cdot 66M = 330M$ parameters. In contrast, the *PADA* models keep the $220M$ parameters of T5, regardless of the number of source domains.

Sequence Tagging In order to demonstrate the wide applicability of our approach, we go beyond text classification (with 2 (Rumour Detection) or 3 (MNLI) classes) and also consider Aspect Prediction: A sequence tagging task. We are particularly curious to see if the aforementioned patterns

[16] Binary-F1 measures the F1 score of the positive class. It is useful in cases of unbalanced datasets where the positive class is of interest (34% of the Rumour Detection dataset).

	Rumour Detection						MNLI					
	All → C	**All → FR**	**All → GW**	**All → OS**	**All → S**	**AVG**	**All → F**	**All → G**	**All → SL**	**All → TE**	**All → TR**	**AVG**
Tr-MoE	68.0	46.1	74.8	58.2	64.9	62.4	64.3	73.9	65.3	62.4	69.8	67.1
T5-MoE	68.1	46.0	73.6	65.3	66.3	63.9	74.0	82.0	73.4	74.6	78.3	76.5
T5-DAN	64.9	52.4	69.1	72.7	64.4	64.7	74.4	76.3	61.0	72.4	77.7	72.4
T5-IRM	63.5	39.4	70.1	44.2	65.7	56.6	72.0	81.5	73.2	69.3	78.9	75.0
T5-NoDA	64.1	46.9	**75.1**	72.0	71.0	65.8	76.4	83.5	75.5	74.9	81.3	78.3
Prompt-DN	66.4	53.7	72.4	71.4	70.1	66.8	**77.0**	**84.4**	75.6	76.3	80.5	78.8
Prompt-RDW	64.1	53.1	71.8	66.0	70.0	65.0	76.0	84.2	76.6	77.0	79.9	78.7
Prompt-REW	64.2	54.3	71.6	70.0	69.1	65.8	75.7	81.4	76.7	78.8	81.2	78.7
PADA-NP	65.8	**54.8**	71.6	72.2	74.0	67.7	76.2	83.6	75.4	77.2	81.4	78.8
PADA-NM	63.6	54.1	74.3	70.1	70.3	66.5	76.0	83.7	76.5	78.0	81.0	79.0
PADA	**68.6**	54.4	73.0	**75.2**	**75.1**	**69.3**	76.4	83.4	**76.9**	**78.9**	**82.5**	**79.6**

Table 5: Binary-F1 scores for the Rumour Detection task and macro-F1 scores for the MNLI task.

	Aspect Prediction				
	All → D	**All → L**	**All → R**	**All → SE**	**AVG**
T5-MoE	39.5	31.4	31.4	30.9	33.3
T5-DAN	28.4	38.0	49.1	33.4	33.2
T5-IRM	37.1	44.6	47.4	41.5	42.7
T5-NoDA	31.1	45.6	40.2	37.9	38.7
Prompt-DN	41.1	42.6	29.0	30.8	35.9
Prompt-RDW	34.6	46.9	**52.9**	41.2	43.9
Prompt-REW	38.2	49.5	45.1	39.6	43.1
PADA-NP	41.7	48.2	50.1	40.1	45.0
PADA-NM	40.3	48.8	50.8	40.2	45.0
PADA	**43.1**	**50.9**	50.8	**45.3**	**47.5**

Table 6: Binary-F1 scores for Aspect Prediction.

replicate in this qualitatively different task. Our results are presented in Table 6, where we report the binary-F1 score (the F1 score of the aspect class). Crucially, the patterns we observe for text classification can also be detected for sequence tagging. Particularly, *PADA* is the best performing model in 4 of 4 settings compared to its baselines. On average, *PADA* outperforms the second-best model, *T5-IRM*, by 3.5% on average. Given the average results of *T5-UB* (69.4%) and *T5-NoDA* (38.7%), the error reduction is 24%.

PADA Ablation Models As shown in Table 5, *PADA* outperforms all of its variants (§ 5.2.2) in 6 out of 10 text classification settings overall. Furthermore, in the sequence tagging task (Table 6), *PADA* outperforms its simpler variants (Prompt-{DN, REW}, PADA-NP) in all 4 setups, and Prompt-RDW, PADA-NM in 3 out of 4 setups. These results highlight the importance of our design choices: (a) including DRFs in the example-specific prompts, tailoring them to express the relation between the source domains and the test example (*PADA* vs *Prompt-{DN, RDW, REW}*); (b) utilizing an autoregressive component, where the generated DRF prompts are used by the task classification component (*PADA* vs *PADA-NP*); and (3) leveraging a multi-task training objective (*PADA* vs *PADA-NM*). A noticeable difference in the aspect prediction results from text classification results is the weakness of *Prompt-DN*, which is outperformed by all baseline models (§ 5.2.1) in 2 setups, and by 2 of these models in a third setup, as well as on average across all setups. This is yet another indication of the importance of the DRFs in the prompt generated by *PADA*.

	BERTScore	*ROUGE-1*	*ROUGE-2*	*ROUGE-L*
Dev F1	0.94	0.64	0.30	0.61

Table 7: Average F1 scores for our automatic evaluation metrics, calculated for generated prompts compared to annotated prompts over all development sets in the rumour detection task.

7 Ablation Analysis

In this section, we analyze several unique aspects of *PADA*. We first evaluate the prompts generated by *PADA*, to gain further insight into its generative capabilities. We then analyze the impact of the number of source domains on *PADA*'s performance. Finally, we examine performance drops due to domain shifts, in order to evaluate *PADA*'s adaptation stability across domains. For the sake of clarity and concision, analyses will henceforth focus on the rumour detection task.

Generated Prompts Analysis We first present an intrinsic evaluation of *PADA*'s prompt generation task (see §4.1) by examining model-generated prompts for examples from the development set, compared to their annotated prompts.[17] We

[17] *PADA* is not restricted to specific structures or vocabulary when generating prompts, hence our annotated prompts

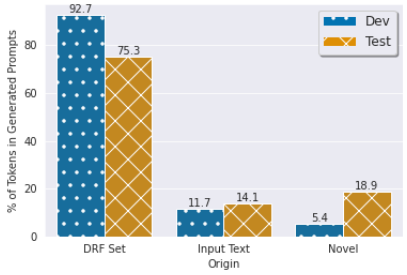


Figure 4: Average token source ratios in generated prompts, calculated over all development and test sets in the rumour detection task.

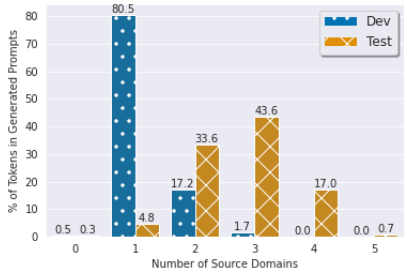


Figure 5: Average ratios of number of domains in generated prompts, calculated over all development and test sets in the rumour detection task.

choose automatic metrics widely used for evaluating NLG tasks, focusing on n-gram overlap by calculating ROUGE (Lin, 2004) scores as well as measuring semantic similarity with BERTScore (Zhang et al., 2020). In Table 7 we present average F1 scores for these metrics, calculated over all DA settings in the rumour detection task. The high average BERTScore (0.94) indicates that the generated prompts share high semantic similarity with their annotated prompts. Yet, the average ROUGE-1 (0.64) and ROUGE-2 (0.3) scores, indicate that the generated prompts vary on their unigram and bigram levels (respectively), compared with their annotated prompts. This evidence suggests that *PADA* learns to leverage the semantic overlaps between DRFs, over memorizing specific n-grams (f.e. an annotated DRF may be *terrorist* while the generated may be *gunman*).

We continue our evaluation by analyzing the origins of words in the *PADA*-generated prompts, specifically, whether they appear in the source domains' DRF sets, the input text, or in neither (Novel). Figure 4 presents the average ratios of different origins for generated prompt tokens, calculated over all DA settings in the rumour detection task. As expected, the overwhelming majority of generated tokens come from the source domains DRF sets, for both development (92.7%) and test (75.3%) sets. However, when introduced to examples from unknown domains (test sets), we observe a significant increase (compared to the development sets) in novel tokens (18.9% vs 5.4%) and a slight increase in tokens from the example's input text (14.1% vs 11.7%).

Furthermore, Figure 5 demonstrates that *PADA* is able to exploit information from its multiple source domains. For test examples *PADA* generates prompts containing DRFs from several domains (95% of prompts contain DRFs from more than 2 source domains), while for development examples it mostly generates prompts with DRFs only from the correct source domain. Together with the examples presented in Table 1, these observations suggest an encouraging finding - *PADA* is successful in generating prompts which leverage and integrate both the source domains and the semantics of the input example.

Number of Source Domains We next turn to study the impact of the number of source domains on *PADA*'s overall performance. Figure 6 presents F1 scores by the number of source domains for *PADA* and two of its baselines, namely *T5-NoDA* and *T5-MoE*. We provide results on two target domains, as well as an average score across all five target domains from the rumour detection dataset.

As indicated in the figure, *PADA*'s performance improves as the number of source domains increases. These results support our claim that *PADA* is able to integrate knowledge from multiple source domains by learning a meaningful domain-mixture, and it then leverages this knowledge when introduced to an example from a new, unknown, domain. Interestingly, for the baseline models *T5-NoDA* and *T5-MoE*, it seems that including more source domains can sometimes harm their ability to generalize to unknown target domains. One of our main hypotheses states that a DA model stands to benefit from incorporating combined knowledge from multiple source domains (§4). *PADA* successfully implements this idea, while *T5-MoE* and *T5-NoDA* fall short.

Performance Drops between Source and Target When a DA method improves model performance on the target domain, this can result in either increasing or decreasing the performance gap be-

only serve as pseudo gold labels for training purposes.

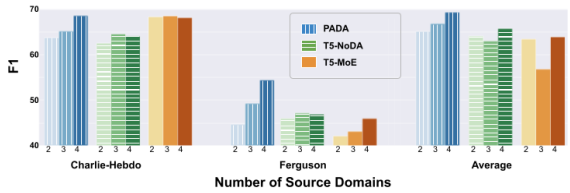


Figure 6: Performance on the Rumour Detection task by the number of source domains the model was trained on. Darker hues represent a larger number of source domains.

	C	FR	GW	OS	S	AVG
T5-NoDA	20	37	5.2	8.1	13	17
T5-IRM	17	27	2.6	15	4.4	13
Prompt-DN	18	29	9.9	9.9	12	14
PADA-NP	16	28	6.8	5.1	8.7	13
PADA	12	25	1.6	1.8	3.2	8.7

Figure 7: A heatmap presenting performance drops between source domains and target domains (columns), for the rumour detection task. Darker colors represent smaller performance drops.

tween the source and target domains. If a model performs similarly on its source training domains and on unseen target domains, its source domain performance can also provide an important indication for its future performance in such unseen domains. We hence consider such stability in performance as a desired property in our setup where future target domains are unknown (see discussion in Ziser and Reichart (2019)).

Figure 7 presents a heatmap, depicting the performance drop for each model between the source domains and the target domains in rumour detection. We measure each model's in-domain performance by calculating an F1 score across all development examples from its source domains, as well as out-of-domain performance on the target domain test set, as described in §6. We then calculate the difference between the source and the target performance measures, and report results for the best performing models in our experiments (§6). The general trend is clear: *PADA* not only performs better on the target domain, but it also substantially reduces the source-target performance gap. While *T5-NoDA*, which is not a DA model, triggers the largest average absolute performance drop, 17%, the average of *PADA*'s absolute performance drop is 8.7%.

8 Discussion

We addressed the problem of multi-source domain adaptation when the target domain is not known at training time. Effective models for this setup can be applied to any target domain with no data requirements about the target domains and without an increase in the number of model parameters as a function of the number of source or target domains. *PADA*, our algorithm, extends the prompting mechanism of the T5 autoregressive language model to generate a unique textual prompt per example. Each generated prompt maps its test example into a semantic space spanned by the source domains.

Our experimental results with three tasks and fourteen multi-source adaptation settings demonstrate the effectiveness of our approach compared to strong alternatives, as well as the importance of the model components and of our design choices. Moreover, as opposed to the MoE paradigm, where a model is trained separately for each source domain, *PADA* provides a single unified model. Intuitively, this approach also seems more cognitively plausible – a single model attempts to adapt itself to examples from new incoming domains, rather than employing an independent model per domain.

The prompt generation mechanism of *PADA* is naturally limited by the set of source domains it is trained on. This might yield sub-optimal DRFs in prompts generated for examples stemming from target domains which are semantically unrelated to any of the source domains. To alleviate this issue, we allow *PADA* to generate non-DRF words. Still, our prompt generation training process does not directly optimize for the downstream prediction task's objective, which might also contribute to sub-optimally generated prompts. In future work, we hope to improve these aspects of our approach and explore natural extensions that accommodate multiple tasks and domains in a single model.

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References

Martín Arjovsky, Léon Bottou, Ishaan Gulrajani, and David Lopez-Paz. 2019. Invariant risk minimization. *CoRR*, abs/1907.02893.

Eyal Ben-David, Carmel Rabinovitz, and Roi Reichart. 2020. Perl: Pivot-based domain adaptation for pre-trained deep contextualized embedding models. *Transactions of the Association for Computational Linguistics*, 8:504–521.

John Blitzer, Mark Dredze, and Fernando Pereira. 2007. Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification. In *ACL 2007, Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics, June 23-30, 2007, Prague, Czech Republic*. The Association for Computational Linguistics.

John Blitzer, Dean P. Foster, and Sham Machandranath Kakade. 2009. Zero-shot domain adaptation: A multi-view approach.

John Blitzer, Ryan McDonald, and Fernando Pereira. 2006. Domain adaptation with structural correspondence learning. In *EMNLP 2006, Proceedings of the 2006 Conference on Empirical Methods in Natural Language Processing, 22-23 July 2006, Sydney, Australia*, pages 120–128. ACL.

Samuel Bowman, Gabor Angeli, Christopher Potts, and Christopher Manning. 2015. A large annotated corpus for learning natural language inference. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015, Lisbon, Portugal, September 17-21, 2015*, pages 632–642. The Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Minmin Chen, Zhixiang Eddie Xu, Kilian Q. Weinberger, and Fei Sha. 2012. Marginalized denoising autoencoders for domain adaptation. In *Proceedings of the 29th International Conference on Machine Learning, ICML 2012, Edinburgh, Scotland, UK, June 26 - July 1, 2012*. icml.cc / Omnipress.

Xilun Chen and Claire Cardie. 2018. Multinomial adversarial networks for multi-domain text classification. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pages 1226–1240. Association for Computational Linguistics.

Hal Daumé III and Daniel Marcu. 2006. Domain adaptation for statistical classifiers. *Journal of Artificial Intelligence Research*, 26:101–126.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 4171–4186. Association for Computational Linguistics.

Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor S. Lempitsky. 2016. Domain-adversarial training of neural networks. *The Journal of Machine Learning Research*, 17:59:1–59:35.

Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making pre-trained language models better few-shot learners. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume*

1: Long Papers), Virtual Event, August 1-6, 2021, pages 3816–3830. Association for Computational Linguistics.

Xavier Glorot, Antoine Bordes, and Yoshua Bengio. 2011. Domain adaptation for large-scale sentiment classification: A deep learning approach. In *Proceedings of the 28th International Conference on Machine Learning, ICML 2011, Bellevue, Washington, USA, June 28 - July 2, 2011*, pages 513–520. Omnipress.

Chenggong Gong, Jianfei Yu, and Rui Xia. 2020. Unified feature and instance based domain adaptation for aspect-based sentiment analysis. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 7035–7045. Association for Computational Linguistics.

Jiang Guo, Darsh J. Shah, and Regina Barzilay. 2018. Multi-source domain adaptation with mixture of experts. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018*, pages 4694–4703. Association for Computational Linguistics.

Xiaochuang Han and Jacob Eisenstein. 2019. Unsupervised domain adaptation of contextualized embeddings for sequence labeling. 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 2019, Hong Kong, China, November 3-7, 2019*, pages 4237–4247. Association for Computational Linguistics.

Xu Han, Weilin Zhao, Ning Ding, Zhiyuan Liu, and Maosong Sun. 2021. PTR: prompt tuning with rules for text classification. *CoRR*, abs/2105.11259.

Adi Haviv, Jonathan Berant, and Amir Globerson. 2021. Bertese: Learning to speak to BERT. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, EACL 2021, Online, April 19 - 23, 2021*, pages 3618–3623. Association for Computational Linguistics.

Minqing Hu and Bing Liu. 2004. Mining and summarizing customer reviews. In *Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, Washington, USA, August 22-25, 2004*, pages 168–177. ACM.

Weihua Hu, Gang Niu, Issei Sato, and Masashi Sugiyama. 2018. Does distributionally robust supervised learning give robust classifiers? In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 2034–2042. PMLR.

Zhengbao Jiang, Frank F. Xu, Jun Araki, and Graham Neubig. 2020. How can we know what language models know. *Transactions of the Association for Computational Linguistics*, 8:423–438.

Young-Bum Kim, Karl Stratos, and Dongchan Kim. 2017. Domain attention with an ensemble of experts. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers*, pages 643–653. Association for Computational Linguistics.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*.

Pang Wei Koh, Shiori Sagawa, Henrik Marklund, Sang Michael Xie, Marvin Zhang, Akshay Balsubramani, Weihua Hu, Michihiro Yasunaga, Richard Lanas Phillips, Sara Beery, Jure Leskovec, Anshul Kundaje, Emma Pierson, Sergey Levine, Chelsea Finn, and Percy Liang. 2020. WILDS: A benchmark of in-the-wild distribution shifts. *CoRR*, abs/2012.07421.

Entony Lekhtman, Yftah Ziser, and Roi Reichart. 2021. DILBERT: customized pre-training for domain adaptation with category shift, with an application to aspect extraction. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Repub-*

lic, 7-11 November, 2021, pages 219–230. Association for Computational Linguistics.

Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. *CoRR*, abs/2104.08691.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, ACL 2020, Online, July 5-10, 2020*, pages 7871–7880. Association for Computational Linguistics.

Shoushan Li and Chengqing Zong. 2008. Multi-domain sentiment classification. In *ACL 2008, Proceedings of the 46th Annual Meeting of the Association for Computational Linguistics, June 15-20, 2008, Columbus, Ohio, USA, Short Papers*, pages 257–260. The Association for Computer Linguistics.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021*, pages 4582–4597. Association for Computational Linguistics.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In *Proceedings of Workshop on Text Summarization Branches Out, Post Conference Workshop of ACL 2004*.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021a. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *CoRR*, abs/2107.13586.

Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang. 2021b. GPT understands, too. *CoRR*, abs/2103.10385.

Ping Luo, Fuzhen Zhuang, Hui Xiong, Yuhong Xiong, and Qing He. 2008. Transfer learning from multiple source domains via consensus regularization. In *Proceedings of the 17th ACM Conference on Information and Knowledge Management, CIKM 2008, Napa Valley, California, USA, October 26-30, 2008*, pages 103–112. ACM.

David McClosky, Eugene Charniak, and Mark Johnson. 2010. Automatic domain adaptation for parsing. In *Human Language Technologies: Conference of the North American Chapter of the Association of Computational Linguistics, Proceedings, June 2-4, 2010, Los Angeles, California, USA*, pages 28–36. The Association for Computational Linguistics.

Krikamol Muandet, David Balduzzi, and Bernhard Schölkopf. 2013. Domain generalization via invariant feature representation. In *Proceedings of the 30th International Conference on Machine Learning, ICML 2013, Atlanta, GA, USA, 16-21 June 2013*, volume 28 of *JMLR Workshop and Conference Proceedings*, pages 10–18. JMLR.org.

Mathias Müller, Annette Rios, and Rico Sennrich. 2020. Domain robustness in neural machine translation. In *Proceedings of the 14th Conference of the Association for Machine Translation in the Americas, AMTA 2020, Virtual, October 6-9, 2020*, pages 151–164. Association for Machine Translation in the Americas.

Yonatan Oren, Shiori Sagawa, Tatsunori B. Hashimoto, and Percy Liang. 2019. Distributionally robust language modeling. 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 2019, Hong Kong, China, November 3-7, 2019*, pages 4226–4236. Association for Computational Linguistics.

Johannes von Oswald, Christian Henning, João Sacramento, and Benjamin F. Grewe. 2020. Continual learning with hypernetworks. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.

Mark Palatucci, Dean Pomerleau, Geoffrey E. Hinton, and Tom M. Mitchell. 2009. Zero-shot learning with semantic output codes. In *Advances in Neural Information Processing Systems 22: 23rd Annual Conference on Neural Information Processing Systems 2009. Proceedings of a meeting held 7-10 December 2009, Vancouver, British Columbia, Canada*, pages 1410–1418. Curran Associates, Inc.

Sinno Jialin Pan, Xiaochuan Ni, Jian-Tao Sun, Qiang Yang, and Zheng Chen. 2010. Cross-domain sentiment classification via spectral feature alignment. In *Proceedings of the 19th International Conference on World Wide Web, WWW 2010, Raleigh, North Carolina, USA, April 26-30, 2010*, pages 751–760. ACM.

Kuan-Chuan Peng, Ziyan Wu, and Jan Ernst. 2018. Zero-shot deep domain adaptation. In *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part XI*, volume 11215 of *Lecture Notes in Computer Science*, pages 793–810. Springer.

Jonas Pfeiffer, Ivan Vulic, Iryna Gurevych, and Sebastian Ruder. 2020. MAD-X: an adapter-based framework for multi-task cross-lingual transfer. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 7654–7673. Association for Computational Linguistics.

Maria Pontiki, Dimitris Galanis, John Pavlopoulos, Harris Papageorgiou, Ion Androutsopoulos, and Suresh Manandhar. 2014. Semeval-2014 task 4: Aspect based sentiment analysis. In *Proceedings of the 8th International Workshop on Semantic Evaluation, SemEval@COLING 2014, Dublin, Ireland, August 23-24, 2014*, pages 27–35. The Association for Computer Linguistics.

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. *Journal of Machine Learning Research*, 21:1–67.

Alan Ramponi and Barbara Plank. 2020. Neural unsupervised domain adaptation in NLP - A survey. In *Proceedings of the 28th International Conference on Computational Linguistics, COLING 2020, Barcelona, Spain (Online), December 8-13, 2020*, pages 6838–6855. International Committee on Computational Linguistics.

Roi Reichart and Ari Rappoport. 2007. Self-training for enhancement and domain adaptation of statistical parsers trained on small datasets. In *ACL 2007, Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics, June 23-30, 2007, Prague, Czech Republic*. The Association for Computational Linguistics.

Mark B. Ring. 1995. *Continual learning in reinforcement environments*. Ph.D. thesis, University of Texas at Austin, TX, USA.

Brian Roark and Michiel Bacchiani. 2003. Supervised and unsupervised PCFG adaptation to novel domains. In *Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics, HLT-NAACL 2003, Edmonton, Canada, May 27 - June 1, 2003*. The Association for Computational Linguistics.

Andreas Rücklé, Jonas Pfeiffer, and Iryna Gurevych. 2020. Multicqa: Zero-shot transfer of self-supervised text matching models on a massive scale. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 2471–2486. Association for Computational Linguistics.

Alexander M. Rush, Roi Reichart, Michael Collins, and Amir Globerson. 2012. Improved parsing and POS tagging using inter-sentence consistency constraints. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, EMNLP-CoNLL 2012, July 12-14, 2012, Jeju Island, Korea*, pages 1434–1444. ACL.

Shiori Sagawa, Pang Wei Koh, Tatsunori B. Hashimoto, and Percy Liang. 2020. Distributionally robust neural networks. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. Distilbert, a distilled version of BERT: smaller, faster, cheaper and lighter. *CoRR*, abs/1910.01108.

Teven Le Scao and Alexander M. Rush. 2021. How many data points is a prompt worth? In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2021, Online, June 6-11, 2021*, pages 2627–2636. Association for Computational Linguistics.

Timo Schick and Hinrich Schütze. 2021. Exploiting cloze-questions for few-shot text classification and natural language inference. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, EACL 2021, Online, April 19 - 23, 2021*, pages 255–269. Association for Computational Linguistics.

Tobias Schnabel and Hinrich Schütze. 2014. FLORS: fast and simple domain adaptation for part-of-speech tagging. *Transactions of the Association for Computational Linguistics*, 2:15–26.

Taylor Shin, Yasaman Razeghi, Robert L. Logan IV, Eric Wallace, and Sameer Singh. 2020. Autoprompt: Eliciting knowledge from language models with automatically generated prompts. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 4222–4235. Association for Computational Linguistics.

Fan-Keng Sun and Cheng-I Lai. 2020. Conditioned natural language generation using only unconditioned language model: An exploration. *CoRR*, abs/2011.07347.

Cigdem Toprak, Niklas Jakob, and Iryna Gurevych. 2010. Sentence and expression level annotation of opinions in user-generated discourse. In *ACL 2010, Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics, July 11-16, 2010, Uppsala, Sweden*, pages 575–584. The Association for Computer Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008.

Ashwin K. Vijayakumar, Michael Cogswell, Ramprasaath R. Selvaraju, Qing Sun, Stefan Lee, David J. Crandall, and Dhruv Batra. 2016. Diverse beam search: Decoding diverse solutions from neural sequence models. *CoRR*, abs/1610.02424.

Yoav Wald, Amir Feder, Daniel Greenfeld, and Uri Shalit. 2021. On calibration and out-of-domain generalization. In *Thirty-Fifth Conference on Neural Information Processing Systems*.

Adina Williams, Nikita Nangia, and Samuel Bowman. 2018. A broad-coverage challenge corpus for sentence understanding through inference. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Dustin Wright and Isabelle Augenstein. 2020. Transformer based multi-source domain adaptation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7963–7974.

Yi Yang and Jacob Eisenstein. 2014. Fast easy unsupervised domain adaptation with marginalized structured dropout. In *Proceedings of the 52nd Annual Meeting of the Association for*

Computational Linguistics, ACL 2014, June 22-27, 2014, Baltimore, MD, USA, Volume 2: Short Papers, pages 538–544. The Association for Computer Linguistics.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with BERT. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.

Han Zhao, Shanghang Zhang, Guanhang Wu, João Paulo Costeira, José M. F. Moura, and Geoffrey J. Gordon. 2018. Multiple source domain adaptation with adversarial learning. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Workshop Track Proceedings*. OpenReview.net.

Yftah Ziser and Roi Reichart. 2017. Neural structural correspondence learning for domain adaptation. In *Proceedings of the 21st Conference on Computational Natural Language Learning (CoNLL 2017), Vancouver, Canada, August 3-4, 2017*, pages 400–410. Association for Computational Linguistics.

Yftah Ziser and Roi Reichart. 2018. Pivot based language modeling for improved neural domain adaptation. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers)*, pages 1241–1251. Association for Computational Linguistics.

Yftah Ziser and Roi Reichart. 2019. Task refinement learning for improved accuracy and stability of unsupervised domain adaptation. In *Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers*, pages 5895–5906. Association for Computational Linguistics.

Arkaitz Zubiaga, Maria Liakata, and Rob Procter. 2017. Exploiting context for rumour detection in social media. In *Social Informatics - 9th International Conference, SocInfo 2017, Oxford, UK, September 13-15, 2017, Proceedings, Part I*, volume 10539 of *Lecture Notes in Computer Science*, pages 109–123. Springer.

Arkaitz Zubiaga, Maria Liakata, Rob Procter, Geraldine Wong Sak Hoi, and Peter Tolmie. 2016. Analysing how people orient to and spread rumours in social media by looking at conversational threads. *PloS one*, 11(3):e0150989.