Strategies to Improve Few-shot Learning for Intent Classification and Slot-Filling

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Abstract

Intent classification (IC) and slot filling (SF) are two fundamental tasks in modern Natural Language Understanding (NLU) systems. Collecting and annotating large amounts of data to train deep learning models for such systems are not scalable. This problem can be addressed by learning from few examples using fast supervised meta-learning techniques such as prototypical networks. In this work, we systematically investigate how contrastive learning and data augmentation methods can benefit these existing meta-learning pipelines for jointly modelled IC/SF tasks. Through extensive experiments across standard IC/SF benchmarks (SNIPS and ATIS), we show that our proposed approaches outperform standard meta-learning methods: contrastive losses as a regularizer in conjunction with prototypical networks consistently outperform the existing state-of-the-art for both IC and SF tasks, while data augmentation strategies primarily improve few-shot IC by a significant margin.

1 Introduction

NLU specific intent classification and slot-filling models often need to learn from only a few contextual examples given by the end user in industrial model deployment scenarios. Such models are often trained using meta-learning, a competitive few-shot learning strategy to learn from only a few examples. In this paper, we systematically dissect the existing meta-learning pipelines for jointly modelled few-shot Intent Classification (IC) and Slot Filling (SF) and identify practical training strategies to improve their performance by a significant margin. Precisely, we investigate how different data augmentation and contrastive learning strategies improve IC/SF performance, and show that our training approach outperforms state-of-the-art models for few-shot IC/SF. Given the user utterance: "*Book me a table for 6 at Lebanese Taverna*", an IC model identifies "*Restaurant Booking*" as the intent of interest, and an SF model identifies the slot types and values: *Party_Size:"6", Name: "Lebanese Taverna"*. These functionalities are typically driven by powerful deep learning models that rely on huge amounts of domain-specific training data. As such labeled data is rarely available, building models that can learn from only a few examples per class is inevitable.

Few-shot learning techniques (Krone et al., 2020; Ren and Xue, 2020; Geng et al., 2019, 2020; Liu et al., 2020b) have been recently proposed to address the problem of generalizing to unseen classes in IC/SF when only a few training examples per class are available. Krone et al. (2020) utilized meta-learning approaches such as prototypical networks (Snell et al., 2017) and MAML (Finn et al., 2017) to jointly model IC/SF. They showed that prototypical networks outperform other prevalent meta-learning techniques such as MAML as well as fine-tuning. Moreover, one primary benefit of prototypical networks is that it is computationally cheap during meta-testing, thus making it a good candidate for industrial few-shot learning systems. In this paper, we extend this powerful supervised meta-learning technique with unsupervised contrastive learning and data augmentation.

Rajendran et al. (2020) showed that meta-learners can be particular prone to overfitting which can be partially alleviated by data augmentation (Liu et al., 2020a). Data augmentation strategies in NLP have been shown to boost performance in general text classification settings (Wei and Zou, 2019b; Xie et al., 2019; Lee et al., 2021), however, there exists very little work on how data augmentation can be effectively used in the meta-learning pipeline specific to NLU tasks. To address this question, we first use a data augmentation strategy `slot-list values` for IC/SF tasks which generates synthetic utterances using dictionary-based slot-values. We note that similar dictionary based augmentation has been previously used in (Li et al.,

2021), but in the context of dialogue state tracking, orthogonal to our use-case. Additionally, we investigate how state-of-the-art augmentation strategies such as backtranslation (Xie et al., 2019) and perturbation-based augmentations such as EDA – Easy Data Augmentation (Wei and Zou, 2019b) – can be used alongside prototypical networks.

We further investigate how contrastive learning (Chen et al., 2020) can be used as a regularizer during the meta-training stage to create better generalizable meta-learners. Contrastive learning is useful in creating improved prototypes as they pull similar representations together while pushing apart dissimilar ones. Through extensive experiments across SNIPS and ATIS, we show that meta-training with contrastive losses as a regularizer improves IC/SF performance for unseen classes with few examples. Our contributions include:

- We demonstrate the effectiveness of contrastive losses as a regularizer in meta-learning, by empirically showing how it improves few-shot IC/SF tasks across benchmark datasets.
- We illustrate the positive impact of data augmentation techniques such as `slot-list values`, backtranslation and EDA in the meta-learning pipeline.

2 Proposed Approaches

We follow the few-shot learning setup for IC/SF described in (Krone et al., 2020) with a few modifications. Instead of using a frozen backbone such as BERT or ELMo with a BiLSTM head, we use a more powerful pre-trained RoBERTa encoder. Additionally, in contrast to (Krone et al., 2020), we update our encoder during the meta-training stage. For a given utterance $x^i = \{x_1^i, x_2^i, ..., x_n^i\}$ with n tokens, we first use the RoBERTa model denoted by f_ϕ to encode the utterance resulting in $h^i = \{h^i_{<cls>}, h_1^i, ..., h_n^i\}$. We use the `<cls>` token embedding to denote the utterance level embedding which we use for intent classification. For slot filling, we use each of the token embeddings $\{h_j^i\}_{j=1}^n$ of the i^{th} utterance. Given a support set S, assuming S_l consists of utterances belonging to the intent class c_l and S_a consists of tokens from the slot class c_a, we first compute the class prototypes for intents (c_l) and slots (c_a):

$$c_l = \frac{1}{|S_l|} \sum_{x^i \in S_l} f_\phi(x^i) \quad (1)$$

$$c_a = \frac{1}{|S_a|} \sum_{x_j^i \in S_a} f_\phi(x_j^i) \quad \forall x^i \in S \quad (2)$$

Given a query example $\mathbf{z}$ and a distance function d, a distribution over the different classes is computed using the softmax of the distances to the different class prototypes. Specifically we denote the intent specific log likelihood loss as:

$$L_{IC}(\phi, \mathbf{z}) = -\log\{\frac{\exp(-d(f_\phi(\mathbf{z}), c_l))}{\sum_{l'} \exp(-d(f_\phi(\mathbf{z}), c_{l'}))}\} \quad (3)$$

We use euclidean distance as the standard distance function. Similarly, we define the slot specific loss as $L_{Slots}(\phi, \mathbf{z})$. For a given query set Q, the cumulative loss for intents and slots is the log likelihood averaged across all the query samples and is denoted by $L_{Total}(\phi)$:

$$L_{Total}(\phi) = \sum_{\mathbf{z} \in Q} \frac{1}{|Q|} \{L_{IC}(\phi, \mathbf{z}) + L_{Slots}(\phi, \mathbf{z})\} \quad (4)$$

2.1 Contrastive Learning

The general idea of contrastive learning (Chen et al., 2020) is to pull together the representations of similar samples while pushing apart the representations of dissimilar samples in an embedding space. In our work, we specifically incorporate the supervised contrastive loss as an added regularizer with the prototypical loss computation in Eq. (4). In particular we identify places in the meta-training pipeline where the incorporation of the contrastive loss is most beneficial for good generalization to few-shot classes. We devise two types of contrastive losses for the IC/SF tasks: (a) contrastive loss for intents $L_{contrastiveIC}(\phi)$ where the `<cls>` token embedding is used in the loss; (b) contrastive loss for slots $L_{contrastiveSF}(\phi)$ where the individual token embeddings are used in the loss. The regularized prototypical loss is the following:

$$L_{Total}(\phi) = \sum_{\mathbf{z} \in Q} \frac{1}{|Q|} \{L_{IC}(\phi, \mathbf{z}) + L_{Slots}(\phi, \mathbf{z})\} + \lambda_1 L_{contrastiveIC}(\phi) + \lambda_2 L_{contrastiveSF}(\phi) \quad (5)$$

We provide more details about the two contrastive losses in the Appendix section.

2.2 Data Augmentation for Few-shot IC/SF

Prior works in computer vision (Liu et al., 2020a; Ni et al., 2020) have shown that data augmentation

	Level	SNIPS (Kmax=20)		ATIS (Kmax=20)		SNIPS (Kmax=100)		ATIS (Kmax=100)	
		IC Acc	Slot F1	IC Acc	Slot F1	IC Acc	Slot F1	IC Acc	Slot F1
Krone et al. (2020)	-	0.877 ± 0.01	0.597 ± 0.017	0.660 ± 0.02	0.340 ± 0.004	0.877 ± 0.01	0.621 ± 0.007	0.719 ± 0.01	0.412 ± 0.02
Baseline (Ours)	-	0.887 ± 0.06	0.597 ± 0.04	0.737 ± 0.06	0.74 ± 0.01	0.907 ± 0.05	0.593 ± 0.04	0.80 ± 0.04	0.70± 0.02
CL (IC)	Support(m-train)	0.905 ± 0.05	0.594 ± 0.04	0.75 ± 0.07	0.748 ± 0.02	0.912 ± 0.03	0.594 ± 0.04	0.802 ± 0.06	0.70 ± 0.02
CL (IC)	Support,Query(m-train)	0.908 ± 0.06	0.596 ± 0.04	**0.76 ± 0.04**	0.748 ± 0.02	0.93 ± 0.05	0.60 ± 0.03	0.829 ± 0.06	0.703 ± 0.03
CL (IC + SF)	Support(m-train)	0.903 ± 0.06	0.60± 0.04	0.757 ± 0.04	0.755 ± 0.02	0.92 ± 0.01	0.60 ± 0.04	0.826 ± 0.05	0.70 ± 0.03
CL (IC + SF)	Support,Query(m-train)	**0.91 ± 0.04**	**0.60 ± 0.03**	0.75 ± 0.07	**0.756 ± 0.02**	**0.93 ± 0.03**	**0.60 ± 0.04**	**0.833 ± 0.05**	**0.71 ± 0.02**
CL (IC + SF), DA (Slot list)	Support,Query(m-train)	**0.921± 0.037**	**0.619± 0.037**	**0.803 ± 0.069**	0.748 ± 0.019	0.923± 0.055	**0.619± 0.035**	0.821± 0.08	**0.73± 0.02**

Table 1: Few-shot classification accuracy with contrastive learning (CL) for prototypical networks. For CL (IC) only $L_{contrastiveIC}$ is used, whereas for CL (IC + SF), both $L_{contrastiveIC}$ and $L_{contrastiveSF}$ are used.

is very effective in meta-learning. In this section, we use various data augmentation strategies to improve the meta-learning pipeline for IC/SF tasks. Data augmentation for joint IC/SF tasks in NLU is particularly challenging as the augmentation is primarily possible at the level of intents. For intent level data augmentation, we use state-of-the-art techniques such as backtranslation (Xie et al., 2019) and EDA (Wei and Zou, 2019b) along with prototypical networks. We also introduce a novel data augmentation technique called `slot-list values` which effectively leverages the structure of joint IC/SF tasks. In particular, we investigate the effectiveness of these data augmentation techniques in the meta-learning pipeline at different levels such as: (a) support at meta-training; (b) support + query at meta-training; (c) support at meta-testing; (d) combination of those. We provide details about these augmentation methods below.

2.2.1 `Slot-List Values` Augmentation

In IC/SF datasets, certain slot types often can take on values specified in a finite list. For example, in the SNIPS dataset the slot type *facility* can take on values from the list *["smoking room", "spa", "indoor", "outdoor", "pool", "internet", "parking", "wifi"]* . Specific to the discrete slot filling task, (Shah et al., 2019) used such values to learn an additional attention module for improving SF. Such lists can be created from the training dataset and be used for data augmentation. We leverage such lists to create synthetic utterances by replacing the values of slot types in a given utterance with other values from the list: e.g. given an utterance "*Book a table at a pool bar*", we synthesize another utterance "*Book a table at a indoor bar*".

2.2.2 Augmentation by Backtranslation

Backtranslation is a technique of translating an utterance into an intermediate language and back to its original language using a neural machine translation model. Previous works (Edunov et al., 2018; Yu et al., 2018; Sennrich et al., 2015) showed that backtranslation is extremely effective as a data augmentation technique for NLP applications. In our paper in particular, we use a pre-trained `en-es` NMT model (Junczys-Dowmunt et al., 2018) for generating the augmented utterances. To ensure that the generated utterances are diverse, we follow the procedure in (Xie et al., 2019) in which we employ restricted sampling from the model output probability distribution instead of beam-search.

2.2.3 EDA Data Augmentation

Adding small perturbations to the training data via random insertion, deletion, swapping and synonym replacement is one simple technique to generate synthetic data for data augmentation. Previous work by (Wei and Zou, 2019a) showed that EDA achieves state-of-the-art results on text-classification tasks. In our work, we use EDA to generate synthetic data to perform data augmentation at different stages of meta-learning.

3 Experiments

Datasets: We use two well-known IC/SF benchmarks: SNIPS (Coucke et al., 2018) and ATIS (Hemphill et al., 1990). SNIPS is a more challenging dataset as it contains intents from diverse domains whereas the ATIS dataset contains intents from only the *Airline* domain.

Episode Construction: We follow the standard episode construction technique described in (Krone et al., 2020; Triantafillou et al., 2020) where the number of classes and the shots per class in each episode are sampled dynamically.

Few-shot Splits: For the SNIPS dataset, we use 4 intent classes for meta-training and 3 intent classes for meta-testing. Similar to (Krone et al., 2020), we do not form a development split for SNIPS as there are only 7 intent classes and the episode construction process requires at least 3 classes in each split. For the ATIS dataset, we first select intent classes with more than 15 examples, then use 5 intent classes for meta-training and 7 intent classes for meta-testing. The rest of the

	Level	SNIPS(Kmax=20)	ATIS (Kmax=20)	SNIPS (Kmax=100)	ATIS(Kmax=100)
		IC Acc	IC Acc	IC Acc	IC Acc
(Krone et al., 2020)	-	0.877 ± 0.01	0.660 ± 0.02	0.877 ± 0.01	0.719 ± 0.01
Baseline (Ours)	-	0.887 ± 0.06	0.737 ± 0.06	0.907 ± 0.05	0.80 ± 0.04
DA (Slot-list)	Support(m-train)	0.898 ± 0.061	0.735 ± 0.052	0.916 ± 0.055	0.810 ± 0.052
DA (Slot-list)	Support,Query(m-train)	0.919 ± 0.062	**0.800 ± 0.054**	0.917 ± 0.051	0.806 ± 0.066
DA (Slot-list)	Support(m-train, m-test)	0.905± 0.062	0.772 ± 0.044	0.922± 0.051	0.818± 0.056
DA (Slot-list)	Support(m-test)	**0.926 ± 0.038**	0.764 ± 0.073	**0.931 ± 0.037**	**0.840± 0.047**
DA (Backtranslation)	Support(m-train)	0.885 ± 0.03	0.77 ± 0.06	0.928 ± 0.029	0.79 ± 0.06
DA (Backtranslation)	Support(m-train, m-test)	0.881 ± 0.03	0.79 ± 0.05	**0.931 ± 0.030**	0.795 ± 0.06
DA (Backtranslation)	Support(m-test)	0.895 ± 0.036	0.71 ± 0.06	0.899 ± 0.06	0.77 ± 0.14
DA (EDA)	Support(m-train)	0.893 ± 0.062	0.787 ± 0.07	0.911 ± 0.04	0.805 ± 0.08
DA (EDA)	Support(m-train,m-test)	0.893 ± 0.047	0.761 ± 0.08	0.915 ± 0.04	0.808 ± 0.10
DA (EDA)	Support(m-test)	0.892 ± 0.047	0.731 ± 0.06	0.915 ± 0.05	0.78 ± 0.059

Table 2: Few-shot IC accuracy with Data Augmentation (DA) for prototypical networks; m-train refers to meta-training and m-test refers to meta-testing

classes are used as a development split. In (Krone et al., 2020), the intent classes for each split are *manually chosen*. This is not representative of realistic situations where the types of few-shot classes can vary considerably. To address this issue, we report our experiment results averaged over 5 seeds where in each run the intent classes for each split are randomly sampled. In each experiment run, we evaluate our results for 100 episodes sampled from the test-split. We refer to our re-implementation of (Krone et al., 2020) with this strategy as *Baseline*.

Contrastive Learning Helps IC/SF tasks: Table 1 shows the results of experiments adding contrastive losses as a regularizer to our baseline. Overall, we observe that across both SNIPS and ATIS datasets, using contrastive losses as a regularizer predominantly improves IC accuracy, while marginally improving SF F1 score. In particular, we notice that using contrastive losses as a regularizer with both the support and query during meta-training leads to the best performances.

Impact of Data Augmentation is Dependent on Stage of Application: Table 2 shows the results of adding data augmentation to the few-shot IC tasks. We find that the data augmentation techniques in general improve the performance of few-shot IC, depending on the stage in the meta-learning pipeline at which the data is augmented. More specifically, for SNIPS we notice up to 4% and 2% gain in IC accuracy for $Kmax = 20$ and $Kmax = 100$ respectively. With EDA, we find that augmentation during meta-training and meta-testing together leads to a noteworthy gain in few-shot IC performances across both SNIPS and ATIS. In comparison, backtranslation is effective in improving the few-shot IC performance for SNIPS, when the shots per class is higher such as in $Kmax = 100$. However for ATIS, we observe a significant gain in IC only for $Kmax = 20$.

Slot-list Values Augmentation at Meta-Testing Helps: We find that dictionary based augmentation techniques such as `slot-list values` generally show consistent gain in IC at all stages during meta-training and shots per class.

Combination of Contrastive Learning and Data Augmentation Helps IC/SF tasks: We find that the combination of contrastive losses and data augmentation via `slot-list values` outperforms models trained independently with only contrastive losses or data augmentation. We hypothesize that this is due to two independent effects working together in conjunction: (a) contrastive learning helps to create improved prototypes whereas (b) data augmentation helps mitigate meta-overfitting.

For SF, we find that data augmentation leads to only limited improvements when compared to IC (see Appendix C). We attribute this to the low shots per slot class, an artifact of the episodic sampling procedure (Krone et al., 2020), done per intent class in the joint IC/SF setting.

4 Conclusion

In this work, we systematically dissect meta-learning pipelines for few-shot IC/SF tasks and identify stages during meta-learning where contrastive learning and data augmentation can be effective. Empirically, we found that contrastive losses are effective regularizers during meta-training and outperform the current state-of-the-art few-shot joint IC/SF benchmarks across both SNIPS and ATIS. Impact of data augmentation in general is highly dependent on the stage at which it is applied during meta-learning. Notably, a combination of contrastive losses and data augmentation via `slot-list values` during meta-training leads to the best performances across both SNIPS and ATIS. These strategies for improving few-shot IC/SF tasks create a strong benchmark and open up possibilities on more stronger modes of meta-specific augmentation and contrastive learning.

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A Hyperparameters

For the ATIS dataset, we use the development set to tune for λ_1 and λ_2 in Eq. (5). For the SNIPS dataset, we empirically set both λ_1 and λ_2 to be 0.06 due to the lack of a development set. In our experiments with the three data augmentation strategies, we generate synthetic utterances to exactly double the training data size for fair comparison throughout. Across all the experiments, we meta-train the models for 50 episodes and use a learning rate of $5e-5$.

B On Contrastive Learning

In our work, we use two types of contrastive losses for IC/SF tasks: (a) contrastive loss for intents $L_{contrastiveIC}(\phi)$ where the <cls> token embedding is used in the loss; (b) contrastive loss for slots $L_{contrastiveSF}(\phi)$ where the individual token embeddings from the encoder are used in the loss. In particular, we use the supervised contrastive loss (Khosla et al., 2020) and leverage the label information present in the support or support + query set during meta-training. First we define the contrastive loss for intents $L_{contrastiveIC}(\phi)$: given a set of utterances with their corresponding intent labels $S_{intents} = \{(x_i, y_i)_{i=1}^m\}$, assume $P(i)$ to be a set consisting of examples from $S_{intents}$ with same labels as the i^{th} example. Formally $P(i) : \{x_j : y_j = y_i \ \forall j \in [1, m] \ \& \ j \neq i\}$. The contrastive loss for the intents $L_{contrastiveIC}(\phi)$ is defined as the following:

$$\sum_{i=1}^{m} -\log \Big\{ \frac{1}{|P(i)|} \sum_{z \in P(i)} \frac{\exp(f_\phi(x_i)^T f_\phi(z))/\tau}{\sum_{j=1, j\neq i}^{m} \exp(f_\phi(x_i)^T f_\phi(x_j))/\tau} \Big\} \tag{6}$$

Here $f_\phi(x_i)$ denotes the <cls> embedding for the i^{th} utterance. In case of slots, we first obtain the individual token embeddings in each utterance $x_i \ \forall i \in [1, m]$. Consider the total number of tokens to be N in an episode and their associated embeddings' set to be $S_{slots} = \{(h_j, y_j^{'}), \ \forall j \in N\}$, where $y_j^{'}$ is the slot label for the j^{th} token. Similar to the intents, we define the set $Q(i) : \{h_j : y_j^{'} = y_i^{'} \ \forall j \in [1, N] \ \& \ j \neq i\}$. Next we define the contrastive loss for the slots $L_{slots}(\phi)$ as:

$$\sum_{i=1}^{N} -\log \Big\{ \frac{1}{|Q(i)|} \sum_{z \in Q(i)} \frac{\exp(h_i^T z)/\tau}{\sum_{j=1, j\neq i}^{N} \exp(h_i^T h_j)/\tau} \Big\} \tag{7}$$

C Impact of Data Augmentation for Slot Filling

Data augmentation for joint IC/SF tasks is challenging as augmentation is only possible at the level of intents. Although data augmentation leads to large improvements in few-shot IC performances, its impact on SF tasks is limited. From Table 3, across the different data augmentation methods such as backtranslation, EDA and `slot-list values`, we observe that there is no consistent improvements in SF performances across our different experiment settings. We hypothesize that as data augmentation does not provide any direct signal to the SF task, the improvements are insubstantial. To address this issue and provide a more direct signal to the SF task, we incorporate part-of-speech (POS) and noun-phrase information of the different slot values into the joint IC/SF model. In the next section, we discuss ways to incorporate these additional syntactic information into the meta-learning pipeline.

D Beyond Semantic Information

Part-of-speech (POS) and noun-parser information can provide additional syntactic information about of an utterance, thus augmenting the semantic information from the encoded tokens. In particular, POS tags can help resolve decisions for ambiguous tokens or words. Previous work (Wang et al., 2020) has shown that prior information from POS tags helps in improving IC and SF tasks in the general supervised many shot setting. In our work, we use POS tags as an additional source of information particularly for the few-shot setting. We propose two primary ways to incorporate POS tags in the general meta-learning setting: (a) POS tag as an additional input feature; (b) Explicitly training the model to predict POS tags via a multi-task loss.

In addition to POS tags, we also augment information about noun-phrases as an additional input feature. Noun chunks or phrases have the potential to provide strong signals about possible spans of different slots to the underlying model, thus improving SF performance. For example, in the utterance "*book me a table for one at blue ribbon barbecue*"(with intent *BookRestaurant*, and slots: *party_size_number:"one", restaurant_name: "blue ribbon barbecue"*), *"blue ribbon barbecue"* is identified as a noun-chunk and the span information

	Level	SNIPS(Kmax=20)	ATIS (Kmax=20)	SNIPS (Kmax=100)	ATIS(Kmax=100)
		Slot F1	Slot F1	Slot F1	Slot F1
Baseline (Ours)	-	0.599 ± 0.04	0.748 ± 0.01	0.593 ± 0.04	0.703 ± 0.02
DA (Slot-list)	Support(m-train)	0.603 ± 0.043	0.738 ± 0.020	0.609 ± 0.047	0.713 ± 0.025
DA (Slot-list)	Support,Query(m-train)	**0.609 ± 0.043**	0.74 ± 0.02	0.609 ± 0.03	0.715 ± 0.02
DA (Slot-list)	Support(m-train, m-test)	0.587± 0.045	0.712 ± 0.026	0.595 ± 0.042	0.686± 0.029
DA (Slot-list)	Support(m-test)	0.572 ± 0.036	0.697 ± 0.028	0.589 ± 0.042	0.684± 0.02
DA (Backtranslation)	Support(m-train)	0.595 ± 0.04	0.742 ± 0.01	**0.611 ± 0.036**	**0.716 ± 0.02**
DA (Backtranslation)	Support(m-train, m-test)	0.595 ± 0.04	0.742 ± 0.01	**0.611 ± 0.03**	0.716 ± 0.02
DA(Backtranslation)	Support(m-test)	0.598 ± 0.03	0.74 ± 0.01	0.60 ± 0.03	0.72 ± 0.01
DA(EDA)	Support(m-train)	0.585 ± 0.032	0.742 ± 0.02	0.596 ± 0.05	0.701 ± 0.03
DA(EDA)	Support(m-train,m-test)	0.593 ± 0.033	0.742 ± 0.02	0.594 ± 0.04	0.711 ± 0.005
DA(EDA)	Support(m-test)	0.586 ± 0.036	0.74 ± 0.01	0.593 ± 0.037	**0.714 ± 0.02**

Table 3: Few-shot Slot F1 with Data Augmentation (DA) for prototypical networks; m-train refers to meta-training and m-test refers to meta-testing

	SNIPS (Kmax = 20)		SNIPS(Kmax=100)		ATIS(Kmax=20)		ATIS(Kmax=100)	
	IC Acc	Slot F1	IC Acc	Slot F1	IC Acc	Slot F1	IC Acc	Slot F1
Baseline (Ours)	0.887 ± 0.06	0.597 ± 0.04	0.907 ± 0.05	0.593 ± 0.04	0.737 ± 0.06	0.748 ± 0.02	0.801 ± 0.05	0.703 ± 0.02
Multi-task POS loss	0.905 ± 0.04	**0.603 ± 0.03**	**0.929 ± 0.03**	0.595 ± 0.03	**0.769 ± 0.06**	0.75 ± 0.01	0.807 ± 0.05	0.711 ± 0.02
With POS-tag features	0.896 ± 0.06	0.592 ± 0.04	0.926 ± 0.03	0.590 ± 0.04	0.745 ± 0.06	0.747 ± 0.01	0.793 ± 0.09	0.713 ± 0.02
With noun-parser features	**0.912 ± 0.05**	0.599 ± 0.04	0.897 ± 0.05	**0.597 ± 0.03**	0.764 ± 0.04	**0.755 ± 0.02**	0.805 ± 0.07	**0.715 ± 0.02**

Table 4: Effect of adding syntactic information into the joint IC/SF model

can potentially help with the SF task for the *restaurant_name* slot. Conversely, the POS tag for "*one*" is *NUM* and can help classify numeric words to the numeric slot *party_size_number*.

D.1 Feature-Based Addition

Previous works have shown that adding POS tags as features improves IC (Zhang et al., 2016; Xie et al., 2018) as well SF performances (Firdaus et al., 2018) in many-shot settings. In this work we look into incorporating syntactic features in our meta-learning pipeline. A simple idea to incorporate POS or noun-chunk tags of an utterance is to concatenate a vector representation of them, p_j^i and η_j^i respectively, with the token embeddings $f_\phi(x_j^i)$. Formally, in our meta-learning pipeline, we revise Eq. (2) for our slot prototype:

$$c_a = \frac{1}{|S_a|} \sum_{x_j^i \in S_a} f_\phi(x_j^i) \oplus p_j^i \oplus \eta_j^i \quad \forall x^i \in S \quad (8)$$

D.2 Multi-task POS Loss

Although training language models distills implicitly the structural knowledge of the underlying languages (Jawahar et al., 2019; Sundararaman et al., 2019) into the model, such knowledge can be imperfect. Explicitly training to learn structural knowledge such as POS tags (Wang et al., 2020), however, can help the model to improve on downstream tasks such as IC/SF. We treat POS tagging as a token level classification problem, similar to SF. Given a support set S, assume S_l to consist of utterances belonging to the intent class c_l, S_a to consist of tokens from the slot class c_a and S_{pos} to consist of POS tag tokens from the class c_{pos}. In addition to the intent class prototypes c_l and slot class prototypes c_a, we define an additional class prototype c_{pos} for the POS tags:

$$c_{pos} = \frac{1}{|S_{pos}|} \sum_{x_j^i \in S_{pos}} f_\phi(x_j^i) \quad \forall x^i \in S \quad (9)$$

Given a query example $\mathbf{z}$, we define the corresponding loss with the POS tag prototypes as:

$$L_{pos}(\phi, \mathbf{z}) = -\log\{\frac{\exp(-d(f_\phi(\mathbf{z}), c_{pos}))}{\sum_{pos'} \exp(-d(f_\phi(\mathbf{z}), c_{pos'}))}\} \quad (10)$$

For the query set Q, the composite loss function is the following:

$$L_{Total}(\phi) = \sum_{\mathbf{z} \in Q} \frac{1}{|Q|} \{L_{IC}(\phi, \mathbf{z}) + L_{Slots}(\phi, \mathbf{z}) + \beta L_{pos}(\phi, \mathbf{z})\} \quad (11)$$

where β is a hyperparameter. For the ATIS dataset, we select β by using a validation set. In case of the SNIPS dataset, we empirically set β as 0.01 due to unavailability of a development set.

In Table 4, we observe an improvement in both IC and SF over the baseline with the addition of information from the POS tags as an auxilliary loss.

However, similar to feature-based addition, we notice only a marginal and small improvement for SF. To understand further this issue, we exmined the episodic sampling procedure used in (Krone et al., 2020). Across both the SNIPS and ATIS datasets, the average shots per class for intents are ≈ 5 and ≈ 10 for $Kmax = 20$ and $Kmax = 100$ respectively. However for slots, we find that the average shots per class are ≈ 1.3 and ≈ 3 for $Kmax = 20$ and $Kmax = 100$ respectively. We conjecture that as the shots per class for slots are much lesser in comparison to that of intents, it results in smaller improvements when compared to intents in the joint IC/SF setting.

E Compute

For all our experiments we primarily use a V100-16GB GPU. For meta-training on ATIS for $Kmax = 100$ with data augmentation, we use V100-32GB GPU due to increased memory requirements.

F Note on Data Augmentation Techniques

In our paper, we investigate only a limited number of data augmentation techniques specific to natural language processing. We note that in the recent years, a wide variety of augmentation techniques for NLP has been developed (See (Feng et al., 2021) for a good overview). However, we choose EDA, backtranslation and use a dictionary based `slot-list values` in our experiments due to it's inherent simplicity which can enable easy integration with existing meta-learning methods. Designing and adapting existing augmentation techniques to meta-learning is a future direction of research.