Semi-Supervised Few-Shot 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 is 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 unsupervised data augmentation methods can benefit these existing supervised 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 semi-supervised approaches outperform standard supervised meta-learning methods: contrastive losses 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
We study the problem of few-shot Intent Classification (IC) and Slot Filling (SF). In the few-shot learning setting, the learner has to learn given only a handful of training examples. We propose a semi-supervised approach for solving this problem based on augmenting supervised meta-learning with unsupervised data augmentation and contrastive learning. We systematically investigate how different data augmentation and contrastive learning strategies improve IC/SF performance, and show that our semi-supervised 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) 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. 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., 2020). 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 introduce a novel data augmentation strategy slot-list values for IC/SF tasks which generates synthetic utterances using dictionary-based slot-values. 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 an additional regularizer during the meta-training stage to cre-
ate 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 in conjunction with the general prototypical loss function improves IC/SF performance for unseen classes with few examples. Our contributions include:

- We demonstrate the effectiveness of contrastive losses as a regularizer in the meta-learning pipeline, by empirically showing how it improves few-shot IC/SF tasks across benchmark datasets such as SNIPS and ATIS.

- We illustrate the positive impact of data augmentation techniques such as backtranslation and EDA in improving few-shot IC tasks.

## 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 encoder, 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 \( x^i = \{x^i_1, x^i_2, ..., x^i_n\} \) with \( n \) tokens, we first use the RoBERTa model denoted by \( f_\phi \) to encode the utterance resulting in \( h^i = \{h^i_{<\text{cls}>}, h^i_1, ..., h^i_n\} \). We use the \(<\text{cls}>\) token embedding to denote the utterance level embedding which we use for intent classification. For slot filling, we use each of the token embeddings \( \{h^i_j\}_{j=1}^n \) of the \( i^{th} \) utterance. Given a support set \( S \), assuming \( S_i \) 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 (\( c_a \)):

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

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

Given a query example \( z \) 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:

\[
    L_{IC}(\phi, z) = -\log\left\{ \frac{\exp(-d(f_\phi(z), c_l))}{\sum_{c_l'} \exp(-d(f_\phi(z), c_l'))} \right\} \quad (3)
\]

We use euclidean distance as the standard distance function. Similarly, we define the slot specific loss as \( L_{Slots}(\phi, z) \). 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 \( L_{Total}(\phi) \):

\[
    L_{Total}(\phi) = \frac{1}{|Q|} \{ L_{IC}(\phi, z) + L_{Slots}(\phi, z) \} \quad (4)
\]

### 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 \(<\text{cls}>\) 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:

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

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., 2020; Ni et al., 2020) have shown that data augmentation 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.,
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 specified in a finite list. For example, given an utterance “Book a table at an indoor bar”, we synthesize another utterance “Book a table at a pool 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 work (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 this EDA technique achieves state-of-the-art results on various 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 standard benchmarks for IC/SF tasks: SNIPS (Coucke et al., 2018) and ATIS (Hemphill et al., 1990). In general, SNIPS is a more challenging dataset as it contains intents from diverse domains. The ATIS dataset, although imbalanced, contains intents only from 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. Triantafillou et al. (2020) showed that this dynamic sampling procedure helps in dealing with the intent class imbalances which is present in ATIS.

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 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 real-
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.

| 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 ± 0.036 | 0.737 ± 0.036 | 0.907 ± 0.033 | 0.80 ± 0.04 |
| DA (Slot-list) | Support(m-train) | 0.898 ± 0.064 | 0.735 ± 0.052 | 0.916 ± 0.055 | 0.810 ± 0.052 |
| | 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 | 0.923 ± 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 |
| | Support(m-train, m-test) | 0.881 ± 0.03 | 0.79 ± 0.05 | 0.931 ± 0.030 | 0.795 ± 0.036 |
| DA (Backtranslation) | Support(m-test) | 0.913 ± 0.036 | 0.711 ± 0.06 | 0.890 ± 0.036 | 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 |
| | 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 shows the results of adding data augmentation (DA) for prototypical networks. The table reports the IC accuracy for different levels of data augmentation. The results show that data augmentation generally improves IC accuracy, with significant gains observed for some settings.

In this work, we systematically dissect the existing meta-learning pipeline for few-shot IC/SF tasks and identify places 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 datasets. Our novel data augmentation technique, slot-list values, along with other techniques such as backtranslation and EDA, improve upon a strong few-shot baseline by a significant margin for few-shot IC. Notably, a combination of contrastive losses and data augmentation with the support and query examples during meta-training leads to the best performances across both SNIPS and ATIS datasets. These semi-supervised strategies for improving few-shot IC/SF tasks create a strong benchmark and open up possibilities for stronger modes of meta-specific data augmentation and contrastive learning.
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A Hyperparameters

For the ATIS dataset, we use the development set to tune for $\lambda_1$ and $\lambda_2$ in Eq. (5). For the SNIPS dataset, we empirically set both $\lambda_1$ and $\lambda_2$ 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 $L_{\text{contrastiveIC}}(\phi)$ where the $<\text{cls}>$ token embedding is used in the loss; (b) contrastive loss for slots $L_{\text{contrastiveSF}}(\phi)$ 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 the intents $L_{\text{contrastiveIC}}(\phi)$: given a set of utterances with their corresponding intent labels $S_{\text{intents}} = \{(x_i, y_i)_{i=1}^m\}$, assume $P(i)$ to be a set consisting of examples from $S_{\text{intents}}$ 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 $L_{\text{contrastiveIC}}(\phi)$ is defined as the following:

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

(6)

Here $f_\phi(x_i)$ denotes the $<\text{cls}>$ 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 $S_{\text{slots}} = \{(h_j, y'_j) \ \forall j \in N\}$, 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 $L_{\text{slots}}(\phi)$ as:

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

(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 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
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) |
|------|------------------|--------------------|-----------------|------------------|
|      |     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) | 0.803 ± 0.043 | 0.738 ± 0.020 | 0.609 ± 0.047 | 0.713 ± 0.025 |
| DA (Slot-list) | Support(m-test) | 0.569 ± 0.043 | 0.74 ± 0.02 | 0.609 ± 0.03 | 0.715 ± 0.02 |
| DA (Slot-list) | Support(m-test) | 0.572 ± 0.036 | 0.697 ± 0.028 | 0.589 ± 0.042 | 0.684 ± 0.02 |
| DA (Backtransl.) | Support(m-test) | 0.595 ± 0.04 | 0.742 ± 0.01 | 0.611 ± 0.036 | 0.716 ± 0.02 |
| DA (Backtransl.) | Support(m-test) | 0.595 ± 0.04 | 0.742 ± 0.01 | 0.611 ± 0.03 | 0.716 ± 0.02 |
| DA (Backtransl.) | Support(m-test) | 0.598 ± 0.03 | 0.74 ± 0.01 | 0.60 ± 0.03 | 0.72 ± 0.01 |
| DA(EDA) | Support(m-train,m-test) | 0.585 ± 0.032 | 0.742 ± 0.02 | 0.596 ± 0.03 | 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 |
| Table 4: Effect of adding syntactic information into the joint IC/SF model.

|      | SNIPS (Kmax = 20) | SNIPS (Kmax = 100) | ATIS (Kmax = 20) | ATIS (Kmax = 100) |
|------|------------------|--------------------|-----------------|------------------|
|      |     Slot F1      |       Slot F1      |       Slot F1    |       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 | 0.73 ± 0.01 | 0.807 ± 0.01 | 0.711 ± 0.02 |
| With POS-tag features | 0.906 ± 0.04 | 0.602 ± 0.04 | 0.926 ± 0.03 | 0.590 ± 0.04 | 0.764 ± 0.06 | 0.747 ± 0.01 | 0.793 ± 0.09 | 0.711 ± 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 |

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 $\eta_j^i$ respectively, with the token embeddings $f_\phi(x_j^i)$. Formally, in our meta-learning pipeline, we revise Eq. (2) for our slot prototype:

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

D.2 Multi-task POS Loss

Although training language models distills implicitly the structural knowledge of the underlying languages (Jawahar et al., 2019; Sundaramanan 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 $q$ and slot class prototypes $c_a$, we define an additional class prototype $c_{pos}$ for the POS tags:

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

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

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

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

$$L_{Total}(\phi) = \frac{1}{|Q|} \{ L_{IC}(\phi, z) + L_{Slot}(\phi, z) + \beta L_{pos}(\phi, z) \}$$ (11)

where $\beta$ is a hyperparameter. For the ATIS dataset, we select $\beta$ by using a validation set. In case of the SNIPS dataset, we empirically set $\beta$ 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 auxiliary loss.
However, similar to feature-based addition, we notice only a marginal and small improvement for SF. To understand further this issue, we examined 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 $\approx 5$ and $\approx 10$ for $K_{max} = 20$ and $K_{max} = 100$ respectively. However for slots, we find that the average shots per class are $\approx 1.3$ and $\approx 3$ for $K_{max} = 20$ and $K_{max} = 100$ 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 $K_{max} = 100$ with data augmentation, we use V100-32GB GPU due to increased memory requirements.