One Model to Recognize Them All: Marginal Distillation from NER Models with Different Tag Sets

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Abstract

Named entity recognition (NER) is a fundamental component in the modern language understanding pipeline. Public NER resources such as annotated data and model services are available in many domains. However, given a particular downstream application, there is often no single NER resource that supports all the desired entity types, so users must leverage multiple resources with different tag sets. This paper presents a marginal distillation (MARDI) approach for training a unified NER model from resources with disjoint or heterogeneous tag sets. In contrast to recent works, MARDI merely requires access to pre-trained models rather than the original training datasets. This flexibility makes it easier to work with sensitive domains like healthcare and finance. Furthermore, our approach is general enough to integrate with different NER architectures, including local models (e.g., BiLSTM) and global models (e.g., CRF). Experiments on two benchmark datasets show that MARDI performs on par with a strong marginal CRF baseline, while being more flexible in the form of required NER resources. MARDI also sets a new state of the art on the progressive NER task.

1 Introduction

Named Entity Recognition (NER) is the task of locating and categorizing spans of text into a closed set of classes, such as people, organizations, and locations. As a core information extraction task, NER plays a critical role in many language processing pipelines, underlying a variety of downstream applications including relation extraction (Mintz et al., 2009) and question answering (Yih et al., 2015). Although many NER datasets have been created for various domains, a practical obstacle for applying NER to a specific downstream application is that there is often a mismatch between the application-desired entity types and those supported by a single tag set. The most common scenario is selective annotation that has been discussed by Beryozkin et al. (2019) and Greenberg et al. (2018). As annotating entities is expensive, collecting NER annotations for a particular domain usually focuses on domain-specific entity types and relies on existing datasets to identify entities of general types. Therefore, we have to consolidate NER corpora with multiple tag sets to build a joint named entity recognizer that covers the union of entity tags.

In addition, a substantial amount of NER resources exist in the form of models or services where the original data annotations are not available. This circumstance arises when the source domain is sensitive, such as medicine and finance, so only very limited access to data is allowed for privacy and security reasons. Another common case is when a production NER system has undergone multiple rounds of training and retraining on data sampled from different time periods, and it is impossible to infer the exact data set that contributed to the complicated system. A special case of the problem, progressive NER, has been studied by Chen and Moschitti (2019), in which they adapt a source model using the target data with new tag categories appear, without accessing to the source data. The setting poses additional challenges for training the unified NER model to recognize entities defined by all tag sets.

To overcome the aforementioned difficulties, we introduce a novel task of training a unified NER model using pre-trained models with different tag sets. In particular, the tag sets can be disjoint (Greenberg et al., 2018) or heterogeneous (Beryozkin et al., 2019) where we can induce a hierarchy from the tag sets (e.g., First Name and Last Name are children of Name). A naïve approach would infer the proper tag sequence using the predictions from multiple tag sets through a post-processing step. However, the post-processing requires heuristics — such as choosing the tag with
the highest probability score — to consolidate conflicted tag sequences, which often works poorly in practice. As the individual models are estimated on datasets whose scales may be remarkably unequal, probability scores of different models are generally not comparable.

To this end, we present marginal distillation (MARDI), a simple yet flexible framework inspired by the knowledge distillation technology (Hinton et al., 2015). MARDI distills the knowledges of pre-trained NER models with different tag sets into a unified model without accessing the training data. The setting diverges from the typical application of knowledge distillation, model compression, in which a small model (i.e., student) is trained to mimic a pre-trained, larger model (i.e., teacher). It resembles the specialist-generalist distillation setup presented in (Hinton et al., 2015), where a generalist model is trained to distill knowledge from an ensemble of specialist models. However, a specialist model concerns a subset of classes in the generalist label set, while the relationships between tags of different label sets are often beyond simple one-to-one mappings. Furthermore, as NER is a sequence tagging problem, it is unclear how to perform distillation for structured prediction models like conditional random fields (CRF). To address the challenges, we first construct a tag hierarchy (Beryozkin et al., 2019) to align tags of multiple label sets. The probabilities of the child nodes are summed together to match the probability of a parent node in the hierarchy. Then, we propose a simple but effective strategy to distill knowledge from a CRF model, where the distillation target is the token-level marginal distribution that can be computed using dynamic programming.

Our contributions are:

- We introduce a novel task to integrate heterogeneous NER resources.
- We present MARDI to tackle the novel task, which transfers knowledge from pre-trained NER models to a unified NER model.
- We propose an effective method for CRF knowledge distillation using node marginals.
- Experiments on standard datasets show that MARDI achieves state-of-the-art results on consolidating NER systems with multiple tag sets without accessing raw annotations.

2 Background

In this section, we first introduce a standard neural architecture for NER that this work builds upon and then summarize previous work on joint training a NER model on datasets with multiple tag sets. Finally, we briefly describe knowledge distillation and its application to model compression.

2.1 Neural networks for NER

In recent years, neural network architectures such as convolutional neural networks (CNN) and recurrent neural networks (RNN) have revolutionized the field of natural language processing. Lample et al. (2016) introduce the bi-directional long short-term memory networks with conditional random fields (BiLSTM-CRF) that has become the standard architecture for NER.

As depicted in Fig. 1, given a sequence of tokens \( \{x_t\}_T \), BiLSTM-CRF first encodes each token into a vector representation using a character-level LSTM model. We adopt a uni-directional character-level LSTM model, as we found it performs slightly better than the BiLSTM model. The vector is then concatenated with a word embedding vector\(^1\) and the new vector is fed into a word-level BiLSTM model to produce a contextual representation for each token. This feature vector is then projected to the label dimension \( L \) using a linear layer, representing the emission scores for predict-

\(^1\)We employ the publicly available 100-dimensional GloVe vectors (Pennington et al., 2014) to initialize the word embeddings for all the models.
Figure 2: Illustration of the marginal CRF method (Greenberg et al., 2018). Two tag sets that one contains GPE and the other contains DATE are shown in the example. Here the annotations for the first tag set are given. Tokens labeled as O could potentially be either O or DATE of the second tag set. Marginal CRF marginalizes over all potential sequences.

2.2 Marginal CRF

In order to jointly train a NER model with multiple tag sets, Greenberg et al. (2018) propose marginal CRF that is a variant of the BiLSTM-CRF model described above. Consider each dataset is partially annotated in which the annotations for the labels of other tag sets are unobserved. Specifically, a token that is labeled as O (i.e., not an entity) in a dataset can possibly be an entity token of another tag set. Marginal CRF marginalizes over all potential sequences.

To train a CRF model for the unified tag set, marginal CRF learns to score a partially observed tag sequence by marginalizing over unobserved paths. As shown in Fig. 2, a token labeled as O potentially takes any entity type label from any of the other datasets. Thus, the probability of the partially observed tag sequence is actually the marginal probability of observed entities according to the unified tag set. The marginal can be calculated efficiently using the forward algorithm.

The method was further extended by Beryozkin et al. (2019) to tackle label sets whose tags constitute relationships beyond simple one-to-one mappings. For example, the GPE label in the OntoNotes 5.0 (Weischedel et al., 2013) tag set corresponds to three entity labels (CITY, STATE, and COUNTRY) defined in the I2B2 2014 (Stubbs and Uzuner, 2015) tag set. To capture the semantic relationships between tags, a tag hierarchy in which GPE is the parent node of CITY, STATE, and COUNTRY is manually constructed. Given the tag hierarchy, the training procedure for the marginal CRF model is similar. The source probability of a sequence containing entities of a parent label type equals the target marginal probability over the child entity types.

2.3 Knowledge distillation

Knowledge distillation is first proposed by Bucilu et al. (2006) as a model compression method in which a small model is trained to mimic a pre-trained, larger model (or ensemble of models). It was generalized by Hinton et al. (2015) and now widely adopted in compressing deep neural networks with millions to billions of parameters into shallower networks with significantly smaller numbers of parameters. The pre-trained source model is typically referred to as the “teacher” and the target model is called the “student”.

Concretely, we can transfer the knowledge in the teacher model to the student model by forcing them to have a similar prediction for any input instance. This can be achieved by training the student model to minimize a loss function where the target is the distribution of class probabilities predicted by the teacher model. The typical choice of the loss function is the Kullback-Leibler (KL) divergence between the distributions, \( D_{KL}(\mathbf{q} \parallel \mathbf{p}) \), where \( \mathbf{p} \) and \( \mathbf{q} \) are the source and target output label distributions respectively. The distribution can be attained with a softmax function:

\[
p_i = \frac{\exp\left(\frac{z_i}{\tau}\right)}{\sum_j \exp\left(\frac{z_j}{\tau}\right)},
\]

where \( z_i \) is the model logit for class \( i \) and \( \tau \) is a temperature parameter that controls the shape of the distribution for distilling richer knowledge from the teacher. We found \( \tau = 1 \) works well for our application in practice, which is consistent with findings in some recent works (Kim and Rush, 2016). The KL loss is also referred to as the “distillation loss” in literature.

In addition to the distillation loss, it is also beneficial to train the student model to predict the ground truth labels using the standard cross-entropy loss, dubbed as the “student loss”. The overall objective is a linear combination of the distillation loss and the student loss. Note that the student loss is optional for knowledge distillation, which demonstrates the flexibility of the framework that makes it a perfect fit for the task of training a unified NER model.
Figure 3: A tag hierarchy constructed for two tag sets, whose tags are represented by filled nodes and bordered nodes respectively. The \texttt{PERSON-OTHER} tag is introduced to fill the remaining semantic space of the \texttt{PERSON} tag.

3 Marginal Distillation (\textsc{MARDI})

We formally present marginal distillation (\textsc{MARDI}) in this section. Specifically, \textsc{MARDI} is a general NER model unification framework that works with both disjoint tag sets and heterogeneous tag sets. We start with building a tag hierarchy to align tags of different label sets, and then show how to transfer knowledges from models pre-trained on different tag sets to a unified NER model with \textsc{MARDI}. Finally, we present a simple strategy to distill knowledge from a pre-trained CRF model to a student CRF model.

3.1 Building a tag hierarchy

Different tag sets often contain semantically inequivalent but related entity types. Downstream NER applications could be interested in types of entities of different granularity. For example, \texttt{GPE} in the OntoNotes 5.0 tag set corresponds to three fine-grained tags, \texttt{CITY}, \texttt{STATE}, and \texttt{COUNTRY}, in the I2B2 2014 tag set. To address this phenomenon, Beryozkin et al. (2019) propose to build a tag hierarchy to unify multiple tag sets.

As displayed in Fig. 3, a tag hierarchy is a directed acyclic graph (DAG), in which each node represents a semantic tag of a label set (e.g., \texttt{GPE} and \texttt{CITY}). A directed edge between the parent node $p$ and the child node $c$, $p \rightarrow c$, indicates that $c$ is a hyponym or finer-grained tag of $p$ and $c$ captures a subset of the semantics of $p$. As shown, we include three directed edges each of which is between \texttt{GPE} and one of \texttt{CITY}, \texttt{STATE}, and \texttt{COUNTRY} to capture their semantic relationships. In many cases, we need to introduce an additional edge between the parent node and a placeholder child node (e.g., \texttt{PERSON-OTHER}), as the present child nodes fail to cover the full semantic space corresponding to the parent node.

One caveat about the tag hierarchy that Beryozkin et al. (2019) do not mention is that the hierarchy is not capable to align complicated tags whose semantics intersect but no specific hypernym-hyponym relationship exists. Such example tag pairs including (\texttt{CARDINAL}, \texttt{AGE}) and (\texttt{CARDINAL}, \texttt{STREET}) when aligning the tag sets of OntoNotes 5.0 and I2B2 2014. We leave the resolution of this issue for future work.

3.2 Marginal distillation over the hierarchy

Given the hierarchy, our goal is to build an NER system that can extract any type of entities corresponding to a tag hierarchy node. To achieve this, we aim at training a NER model that predicts the most fine-grained tags in the hierarchy. The entity extraction results for an ancestor tag can be inferred by aggregating the extracted entities corresponding to its fine-grained descendants.

As shown in Fig. 4, \textsc{MARDI} transfers knowledge from multiple teacher models to a student NER model, where the student is trained to make predictions on the unified tag set that consists of all the fine-grained tags in the hierarchy. The entity extraction results for an ancestor tag can be inferred by aggregating the extracted entities corresponding to its fine-grained descendants.

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in the hierarchy,
\[ p_{t,i} = \sum_{j \in \text{DescendantLeaf}(i)} p_{t,j}, \]  
(2)

where \( p_{t,j} \) is the predicted probability from the student for the \( j \)-th class in the unified tag set.

In addition to the distillation loss, to establish a fair comparison with prior work, we also consider the student loss for some of our experiments. The student loss replaces the soft target label \( q_{t,i} \) with the ground truth hard label in Eq. 1. The overall loss is then the linear combination of the distillation loss and the student loss.

3.3 CRF distillation with node marginals

Despite its popularity, knowledge distillation is generally only applicable to classification problems, as it is often intractable to calculate a distillation loss with respect to a structured learning model that involves exponentially large output label space. Kim and Rush (2016) conduct sequence-level knowledge distillation by training the student using the sequence-level predictions of the teacher. We argue that the approximation that only considers the best sequence-level predictions fails to transfer expressive information encoded in the teacher to the student.

To address the limitation, we instead propose an alternative strategy for knowledge distillation of a structured learning model, such as the CRF. Specifically, we train the student CRF by enforcing the token-level marginals produced by the teacher CRF. The marginal probability of a token \( t \) being tagged as class \( i \) is
\[ p_{t,i} = p(y_t = i | x), \]  
(3)

which can be efficiently computed by the forward-backward algorithm (Rabiner, 1989). The CRF distillation loss can be obtained by replacing the softmax probabilities in Eq. 1 with the CRF node marginals.

We incorporate the proposed technique into MARDI to distill knowledges of the pre-trained BiLSTM-CRF based NER models into a unified BiLSTM-CRF model. During training, we back-propagate the gradients of the CRF distillation loss with respect to not only the BiLSTM parameters but also the CRF transition parameters to optimize the student CRF model.

4 Experiments

In this section, we compare MARDI against competitive methods on three tasks related to NER with different tag sets: tag set extension, full tag set integration, and progressive NER. We derive datasets for the tasks based on two standard benchmark corpora on named entity recognition.

| Dataset     | Domain | # of tokens | # of entities |
|-------------|--------|-------------|---------------|
| OntoNotes-train | NW     | 387,082     | 35,771        |
|             | BN     | 180,300     | 17,573        |
|             | BC     | 144,590     | 8,654         |
|             | MZ     | 164,223     | 10,921        |
|             | TC     | 81,144      | 2,233         |
|             | WB     | 131,164     | 6,676         |
| Total       |        | 1,088,503   | 81,828        |

| Dataset     | Domain | # of tokens | # of entities |
|-------------|--------|-------------|---------------|
| OntoNotes-dev | NW     | 52,618      | 4,883         |
|             | BN     | 22,148      | 2,172         |
|             | BC     | 26,550      | 1,459         |
|             | MZ     | 15,422      | 1,232         |
|             | TC     | 11,467      | 311           |
|             | WB     | 19,519      | 1,009         |
| Total       |        | 147,724     | 11,066        |

| Dataset     | Domain | # of tokens | # of entities |
|-------------|--------|-------------|---------------|
| OntoNotes-test | NW     | 49,235      | 4,696         |
|              | BN     | 23,209      | 2,184         |
|              | BC     | 32,488      | 1,697         |
|              | MZ     | 17,875      | 1,163         |
|              | TC     | 10,976      | 380           |
|              | WB     | 18,945      | 1,137         |
| Total       |        | 152,728     | 11,257        |

| Dataset     | Domain | # of tokens | # of entities |
|-------------|--------|-------------|---------------|
| I2B2-2014-train | Medical | 444,191     | 12,033        |
| I2B2-2014-dev  | Medical | 198,870     | 5,609         |
| I2B2-2014-test | Medical | 414,661     | 11,591        |

Table 1: Dataset statistics. OntoNotes datasets are further divided based on the source domains of the documents: newswire (NW), broadcast news (BN) , broadcast conversation (BC), magazine (MZ), telephone conversation (TC), and web data (WB).

4.1 Data

In our experiments, we consider two standard NER datasets: OntoNotes 5.0 (Weischedel et al., 2013) and I2B2 2014 (Stubbs and Uzuner, 2015). To our knowledge, they are by far the two largest annotated NER corpora for the general and medical domains respectively. The datasets are labeled with popular and diverse named entity types for their corresponding domains. In particular, OntoNotes contains 18 entity types and I2B2’14 annotates 23 entity types, among which only the DATE entity type aligns perfectly between the two tag sets. Table 1 presents detailed statistics of the datasets. We use the OntoNotes train/development/test splits re-
Adapter (Chen and Moschitti, 2019) is a trans-

We train the models on the training datasets, tune
which are not resolvable with the tag hierarchy. A
marginal) tag probability. Marginal CRF

Progressive learns to transfer knowledge from a
variety of sources, including newswire, broadcast
conversation, magazine, telephone
conversation, and web data.

Tag hierarchy We filter out I2B2’14 tags whose
overall frequencies are less than 20, as well as tags that
conflict with the OntoNotes CARDINAL tag, which are not resolvable with the tag hierarchy. A
total of 16 I2B2’14 tags remained after the filtering.

We build the hierarchy similar to Fig. 3. In par-
cular, the following hypernym-hyponym relationships between OntoNotes and I2B2’14 tag sets are
included:
- PERSON: {DOCTOR, PATIENT, PERSON-OTHER}
- GPE: {CITY, STATE, COUNTRY}
- ORG: {HOSPITAL, ORGANIZATION, ORG-OTHER}

The rest of the tags are either OntoNotes-spec or
I2B2’14-spec entity types, except for DATA that is
shared by both tag sets.

4.2 Experimental settings

We train the models on the training datasets, tune
the hyper-parameters on the development datasets, and evaluate the competitive systems on the test
datasets. We report the standard evaluation metrics
for NER: micro averaged precision, recall, and F1
score.

Competitive systems We consider four compet-
tive NER methods that can work with multiple
tag sets. Post Processing is a simple heuristic that
resolves the conflicted tag predictions from differ-
et models by choosing the one with the highest
(marginal) tag probability. Marginal CRF (Green-
berg et al., 2018; Beryozkin et al., 2019) is the
state-of-the-art (SOTA) approach for training a uni-
fied NER model with different tag sets. Neural
Adapter (Chen and Moschitti, 2019) is a transfer
learning technique for sequence labeling that
only uses source model and target data. It is the
SOTA method for the progressive NER task. Fi-

ally, we compare the three variants of MARDI that
differ in the availability of the raw annotations.
MARDI solely uses the pre-trained models to per-
form knowledge distillation. MARDI-Data also
utilizes the labeled training data to produce the stu-
dent loss when training the unified model. MARDI-
Progressive learns to transfer knowledge from a

| System       | BN | BC | WB | MZ | TC | AVG |
|--------------|----|----|----|----|----|-----|
| BiLSTM systems | Post Processing | 80.0 | 50.8 | 65.3 | 69.7 | 62.3 | 65.6 |
|              | MARDI | 83.9 | 73.7 | 70.7 | 72.9 | 65.6 | 73.4 |
|              | MARDI-Data | 85.1 | 74.3 | 72.7 | 74.7 | 67.8 | 74.6 |
| BiLSTM-CRF systems | Post Processing | 82.6 | 67.2 | 67.3 | 70.1 | 66.3 | 70.7 |
|              | Marginal CRF | 87.2 | 78.2 | 73.8 | 76.7 | 69.2 | 77.0 |
|              | MARDI | 86.6 | 76.5 | 73.3 | 75.7 | 69.5 | 76.3 |
|              | MARDI-Data | 86.9 | 77.7 | 75.1 | 76.8 | 70.2 | 77.3 |

Table 2: F1 score results for tag set extension experiments. The best results are in bold.

Our first set of experiments are motivated by the
real world scenario related to selective annotation
discussed in § 1. When building a NER dataset for
a special domain, to avoid expensive annotations,
we can selectively annotate entities that are specifi-
cally for that domain, and rely on general NER
datasets to handle the rest of named entities. We
treat OntoNotes 5.0 as the testbed for the tag set
extension experiments, as it contains documents.

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2Available at: http://conll.cemantix.org/2012/data.html
from multiple source domains.

To mimic the scenario, we treat the newswire (NW) domain as the general domain and each of the other OntoNotes domains as specific target domains. The source tag set covers the five most frequent entity types in the newswire domain that are \textsc{org}, \textsc{date}, \textsc{gpe}, \textsc{person}, and \textsc{cardinal}, and the target tag set consists of the rest of OntoNotes entity types. The source annotations corresponding to the target tag set and the target annotations corresponding to the source tag set are wiped out — we simply retag the relevant tokens to \textsc{o}.

For each extension setting, we train on the training sets with the corresponding source and target tag sets, and tune hyper-parameters and evaluate on the development and test sets of the target domain with the original full tag set. The results are shown in Table 2, indicating that \textsc{mardi} performs generally on par with Marginal CRF when the training datasets are given. When \textsc{mardi} has access only to the pre-trained NER models, Marginal CRF slightly outperforms it. However, \textsc{mardi} provides dramatic flexibility on the required form of NER resources. Both Marginal CRF and \textsc{mardi}-based systems considerably outperform the Post Processing baseline, showing the power of joint training a NER model over multiple tag sets. Finally, knowledge distillation of CRF models yields much more superior results than distillation of classification models on the NER task, which suggests that \textsc{mardi} is indeed able to properly distill knowledge from a CRF teacher into a CRF student.

4.4 Full tag set integration

![Table](https://example.com/table.png)

Table 3: Precision, Recall, and F1 score results for full tag set integration experiments. The best results are in \textbf{bold}.

Following Beryozkin et al. (2019), we also experiment with the full tag set integration evaluation setting. We need to consolidate the heterogeneous tag sets of OntoNotes and I2B2’14 to have the best of both worlds. In particular, we train a named entity tagger on the training sets of the OntoNotes and I2B2’14 corpora with the unified tag set. Compared to the setting used by Beryozkin et al. (2019), where they integrate the tag sets of I2B2’06 and I2B2’14, we argue that our setting is more realistic and also more challenging. The I2B2’06 tag set is basically a subset of the I2B2’14 tag set that generally regard similar entity types. As we have shown before, the tag sets of OntoNotes and I2B2’14 focus on very different entity types, which provide a better platform to evaluate the systems on consolidating heterogeneous tag sets.

The full tag set integration results are presented in Table 3. As shown, both \textsc{mardi} and \textsc{mardi-data} achieve similar results as Marginal CRF in the full tag set integration setting. Again, joint-training-based methods significantly outperform the Post Processing baseline for both BiLSTM-based and BiLSTM-CRF-based systems. The results show that \textsc{mardi} can principally integrate NER models trained with heterogeneous tag sets using an easy-to-build tag hierarchy.

4.5 Progressive NER

![Table](https://example.com/table.png)

Table 4: F1 score results for progressive NER experiments. The best results are in \textbf{bold}.

To demonstrate \textsc{mardi}’s flexibility on the existence of source data, we consider the progressive NER setting proposed by Chen and Moschitti (2019). Specifically, we conduct another set of experiments that are similar to the tag set extension experiments described in § 4.3. The key distinction is that we assume that only the source model and the target training data are available in the progressive NER setting. As \textsc{mardi} needs to access unlabeled data to perform knowledge distillation, we further experiment with two variants of \textsc{mardi}. In the first variant, we employ unlabeled data from both the source and target domains to train the distiller. In the second variant, we assume that the source unlabeled data is not available and distill
both the source and target models using the unlabeled data from the target domain. The variant erects a fairer comparison with Neural Adapter.

As shown in Table 4, MARDI leads to a significant boost in performance compared to the SOTA method Neural Adapter. Neural Adapter (Chen and Moschitti, 2019) initializes the parameters of the unified NER model with the source model parameters and then fine-tune the model on the target data. Collisions rooted from different tag sets still occur during the fine-tuning, resulting in less optimal transfer performance. Among the two MARDI variants, the one with access to unlabeled source data performs better, suggesting in-domain unlabeled data is crucial for effective knowledge distillation.

5 Related Work

**Neural NER** Early works on NER focused on engineering useful linguistic features for the task (Tjong Kim Sang and De Meulder, 2003; Nadeau and Sekine, 2007). With the resurgence of neural networks, recent works have been focused on adopting neural models for the task of NER. Lample et al. (2016) proposed a BiLSTM-CRF model that consists of a BiLSTM layer to learn feature representations from the input and a CRF layer to model the interdependencies between adjacent labels. A similar neural architecture for NER was introduced by Ma and Hovy (2016), where the subword unit information was modeled with character-level CNNs instead of the BiLSTM networks used in BiLSTM-CRF. In this work, we use BiLSTM-CRF as our base model, as it is widely used in literature. However, MARDI works with any probabilistic model in principle.

**NER with multiple tag sets** Early research efforts made on NER with multiple tag sets are mostly related to NER with partially annotated data. Bellare and McCallum (2007) proposed a missing label linear-chain CRF that was essentially a latent variable CRF (Quattoni et al., 2005) for a set of NLP tasks with partially annotated data. Greenberg et al. (2018) presented a marginal CRF model that was a variant of the latent variable CRF method. Marginal CRF achieved promising performance in joint training a biomedical NER model with multiple tag sets. The method was extended by (Beryozkin et al., 2019) to handle datasets with heterogeneous label sets. Marginal CRF needs to be trained on the data annotations, while MARDI can be learned from pre-trained models with different tag sets.

**Progressive learning** Standard machine learning methods assume the data for training and testing has the same feature space and distribution (i.e., the independent, identically distributed assumption). In recent years, the technique of transfer learning has emerged to relax this assumption that makes machine learning models more applicable to real world applications. Progressive learning falls in a more specific transfer learning category, in which we need to transfer knowledge from a source model using a target dataset that involves additional labels. Venkatesan and Er (2016) adopted progressive learning techniques to a set of multiclass classification problems. In particular, they remodeled a single layer feed-forward network by increasing the number of new neurons and interconnections while encountering unseen class labels in the dataset. The technique was then further extended to NER by Chen and Moschitti (2019), where they copied parameters of the source model to a new model with enlarged label space and then fine tuned the model on the target data. Progressive NER is a special case of the NER model unification problem discussed in the work. We show that MARDI can successfully solve a set of related tasks including progressive NER.

6 Conclusion

In this paper, we present MARDI, a knowledge distillation based approach to unify NER models pre-trained on different tag sets into a centralized model. It is capable of effectively distilling knowledge from CRF teachers into a CRF student. MARDI can work with heterogeneous NER resources in the form of either a dataset or a model, making it a flexible framework to consolidate NER systems across different domains. We conduct extensive experiments on three related tasks. Despite the unavailability of annotations, MARDI performs on par with the state-of-the-art (SOAT) method on joint training of NER models with either disjoint tag sets or heterogeneous tag sets. It significantly outperforms the SOAT model on the progressive NER task. In the future, we would like to extend MARDI to handle tag sets that involve partially overlapping tags. We are also interested in applying the CRF distillation technique to other NLP problems such as part-of-speech tagging and chunking.
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