Leaving No Valuable Knowledge Behind: Weak Supervision with Self-training and Domain-specific Rules

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Abstract

State-of-the-art deep neural networks require large-scale labeled training data that is often either expensive to obtain or not available for many tasks. Weak supervision in the form of domain-specific rules has been shown to be useful in such settings to automatically generate weakly labeled data for learning. However, learning with weak rules is challenging due to their inherent heuristic and noisy nature. An additional challenge is rule coverage and overlap, where prior work on weak supervision only considers instances to which domain-specific rules apply. In contrast, we develop a weak supervision framework (WST) that leverages all available data for a given task. To this end, we leverage task-specific unlabeled data that allows us to harness contextualized representations for instances where weak rules do not apply. In order to integrate this knowledge with domain-specific heuristic rules, we develop a rule attention network that learns how to aggregate them conditioned on their fidelity and the underlying context of an instance. Finally, we develop a semi-supervised learning objective for training this framework with small labeled data, domain-specific rules, and unlabeled data. Extensive experiments on six benchmark datasets demonstrate the effectiveness of our approach with significant improvements over state-of-the-art baselines.

1 Introduction

The success of state-of-the-art neural networks crucially hinges on the availability of large amounts of annotated training data. While recent advances on language model pre-training (Peters et al., 2018; Devlin et al., 2019; Radford et al., 2019) reduce the annotation bottleneck, they still require large amounts of labeled data for obtaining state-of-the-art performances on downstream tasks. However, it is prohibitively expensive to obtain large-scale labeled data for every new task, therefore posing a significant challenge for supervised learning.

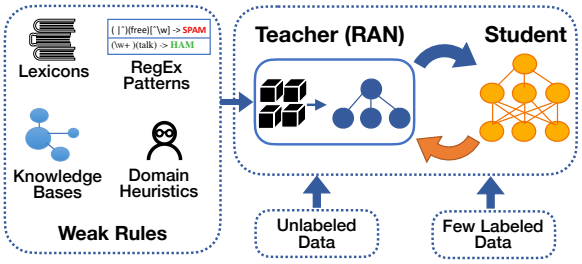

Figure 1: Our weak supervision framework WST leverages small labeled data and large amounts of task-specific unlabeled data with domain-specific heuristic rules via iterative self-training.

In order to mitigate labeled data scarcity, recent works have tapped into weak or noisy sources of supervision, such as regular expression patterns (Augenstein et al., 2016), class-indicative keywords (Ren et al., 2018b; Karamanolakis et al., 2019), alignment rules over existing knowledge bases (Mintz et al., 2009; Xu et al., 2013) or heuristic labeling functions (Ratner et al., 2017; Bach et al., 2019; Badene et al., 2019; Awasthi et al., 2020). These different types of sources can be used to generate weak rules for heuristically annotating large amounts of unlabeled data. For instance, consider the question type classification task from TREC with regular expression patterns such as: *label all questions containing the token "when" as* `numeric` (e.g., "When was Shakespeare born?"). Such approaches relying on weak rules typically suffer from the following challenges. (i) *Noise.* Rules by their heuristic nature rely on shallow patterns and may predict wrong labels for many instances. For example, the question "When would such a rule be justified?" refers to circumstances rather than numeric expressions. (ii) *Coverage.* Rules generally have a low coverage as they apply to only specific subsets of instances. (iii) *Conflicts.* Different rules may generate conflicting predictions for the same instance, making it challenging to train

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a robust classifier.

To address the challenges with conflicting and noisy rules, existing approaches learn weights indicating how much to trust individual rules. In the absence of large-scale manual annotations, the rule weights are generally learned via mutual agreement and disagreement of rules over unlabeled data (Ratner et al., 2017; Sachan et al., 2018; Bach et al., 2019; Ratner et al., 2019; Awasthi et al., 2020). For instance, such techniques would upweight rules that agree with the majority, and downweight them otherwise. A typical drawback of these approaches is coverage since rules apply to only a subset of the data leading to low rule overlap to compute agreement. For instance, in our experiments on six real-world datasets, we observe that 66% of the instances are covered by fewer than 2 rules, out of which 60% are not covered by any rule at all. Rule sparsity limits the effectiveness of previous approaches, thus leading to strong assumptions, such as, each rule has the same weight across all instances (Ratner et al., 2017; Bach et al., 2019; Ratner et al., 2019), or additional supervision in the form of labeled "exemplars" used to create such rules in the first place (Awasthi et al., 2020). Most importantly, all these works ignore unlabeled instances that are not covered by any of the rules.

Overview of our method. In this work, we propose a weak supervision framework, namely WST, that considers all task-specific unlabeled instances and domain-specific rules without any assumptions about the nature or source of the rules. WST makes effective use of a small amount of labeled data, lots of task-specific unlabeled data, and domain-specific rules through iterative teacher-student co-training. A student model provides pseudo-labeled annotations for all instances, thereby, allowing us to leverage unlabeled data where weak rules do not apply. To deal with the noisy nature of heuristic rules and pseudo-labels from the student, we develop a rule attention (teacher) network that learns the fidelity of these rules and pseudo-labels conditioned on the context of the instances to which they apply. We develop a semi-supervised learning objective based on minimum entropy regularization and learn all of the above tasks jointly.

Overall, we make the following contributions:

- We propose an iterative self-training mechanism for training deep neural networks with weak supervision by making effective use of task-specific unlabeled data and domain-specific heuristic rules. The self-trained student model predictions augment the weak supervision framework with instances where rules do not apply.

- We propose a rule attention teacher network (RAN) for combining multiple rules and student model predictions with instance-specific weights conditioned on the corresponding contexts. Furthermore, we construct a semi-supervised learning objective for training our framework without any assumptions about the structure or nature of the weak rules.

- We demonstrate the effectiveness of our approach on several benchmark text classification datasets where our method significantly outperforms state-of-the-art weak supervision methods.

2 Self-Training with Weak Rules and Unlabeled Data

We now present our approach, WST, that leverages small labeled data, unlabeled data and domain-specific heuristic rules. Our architecture consists of two main components: the base student model (Section 2.1) and the rule attention teacher network (Section 2.2), which are iteratively co-trained in a self-training framework.

Formally, let $\mathcal{X}$ denote the set of all instances and $\mathcal{Y} = \{1, \ldots, K\}$ denote the set of labels for a K-class classification task. We consider a small set of manually-labeled examples $D_L = \{(x_l, y_l)\}$, where $x_l \in \mathcal{X}$ and $y_l \in \mathcal{Y}$ and a large set of unlabeled examples $D_U = \{x_i\}$. We also consider a set of pre-defined heuristic rules $R = \{r^j\}$, where each rule r^j is a labeling function that considers as input an instance $x_i \in \mathcal{X}$, and either assigns a *weak* label q_i^j or does not apply, i.e., does not predict any label for x_i. Our goal is to leverage D_L, D_U, and R to train a classifier that, given an unseen test instance $x' \in \mathcal{X}$, predicts a label $y' \in \mathcal{Y}$.

2.1 Base Student Model

Our self-training framework starts with a base model trained on the available small labeled set D_L. The model is then applied to unlabeled data D_U to obtain pseudo-labeled instances. In classic self-training (Riloff, 1996; Nigam and Ghani, 2000), the student model's pseudo-labeled instances are directly used to augment the training dataset and iteratively re-train the student. In our setting, we

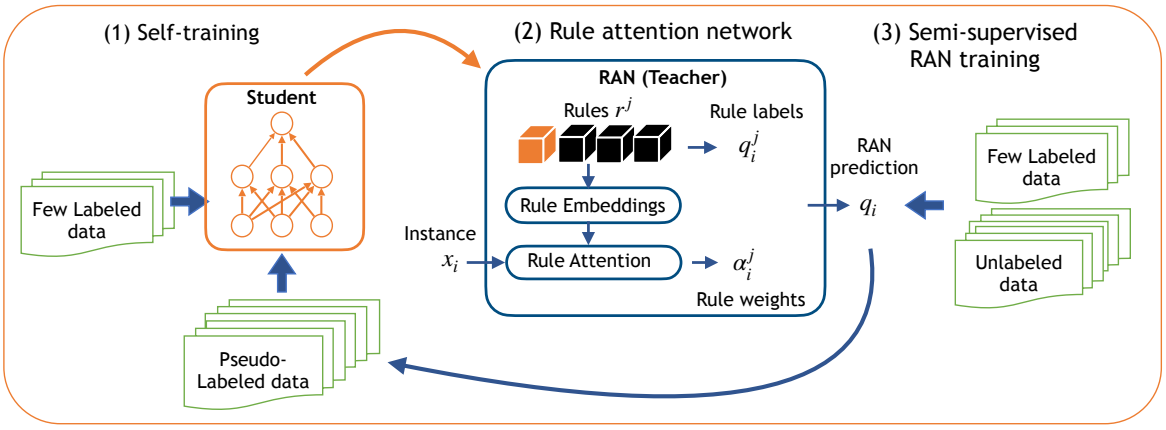


Figure 2: Our WST framework for self-training with weak supervision.

augment the self-training process with weak labels drawn from our teacher model (described in the next section). The overall self-training process can be formulated as:

$$\min_{\theta} \mathbb{E}_{x_l,y_l \in D_L}[-\log\ p_\theta(y_l \mid x_l)] + \lambda \mathbb{E}_{x \in S_U} \mathbb{E}_{y \sim q_{\phi^*}(y|x)}[-\log\ p_\theta(y \mid x)] \quad (1)$$

where, $p_\theta(y|x)$ is the conditional distribution under student model parameters θ; $\lambda \in \mathbb{R}$ is a hyper-parameter controlling the relative importance of the two terms; and $q_{\phi^*}(y \mid x)$ is the conditional distribution under the teacher model's parameters ϕ^* from the last iteration and fixed in the current iteration. The unlabeled subset $S_U \subset D_U$ is selected based on confidence scores of the teacher (e.g., top K examples based on the least incurred model loss).

2.2 Rule Attention Teacher Network (RAN)

Our Rule Attention Teacher Network (RAN) aggregates multiple weak sources of supervision with trainable weights and computes a soft weak label q_i for an unlabeled instance x_i. One of the potential drawbacks on relying only on heuristic rules is that a lot of data get left behind. Heuristic rules by nature (e.g., regular expression patterns, keywords) apply to only a subset of the data. Therefore, a substantial number of instances are not covered by any rules and thus are not considered in prior weakly supervised learning approaches (Ratner et al., 2017; Awasthi et al., 2020). To address this challenge and leverage contextual information from all available task-specific unlabeled data, we leverage corresponding pseudo-labels from the base student model (from Section 2.1). To this end, we apply the base model to the unlabeled data $x \in D_U$ and obtain pseudo-label predictions as $p_\theta(y|x)$. These predictions are used to augment the set of already available weak rule labels to increase rule coverage.

Consider $q_i^j \in \{0,1\}^K$ to be the one-hot encoding of the weak label assigned by a heuristic rule $r^j \in R$ to an instance $x_i \in D_U$ from the unlabeled set, where K is the number of classes. The objective of RAN is to aggregate all of these weak labels (including pesudo-labels) to compute a soft label q_i for every instance x_i to augment the base model. Let $R_i \subset R$ be the set of all heuristic rules that *apply* to instance x_i.

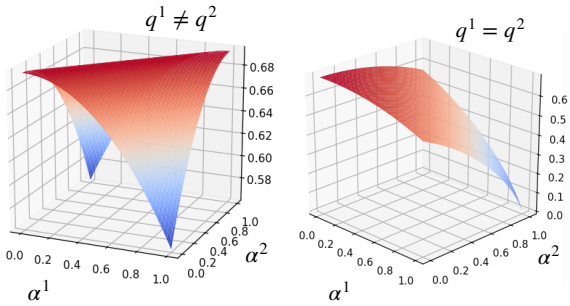
Simple majority voting (e.g predicting the label assigned by the majority of rules) may not be effective as it treats all rules equally, while in practice, certain rules are more accurate than others.

RAN predicts pseudo-labels q_i by aggregating rules r^j with trainable weights $a_i^j \in [0,1]$ that capture their fidelity towards an instance x_i as:

$$q_i = \frac{1}{Z_i}\left(\sum_{j \in R_i} a_i^j q_i^j + a_i^{R+1} p_\theta(y|x_i) + a_i^u u\right), \quad (2)$$

where u is a uniform rule distribution that assigns equal probabilities for each of the K classes as $u = [\frac{1}{K}, \ldots, \frac{1}{K}]$; $a_i^{R+1} \in [0,1]$; $a_i^u = (|R_i| + 1 - \sum_{j \in R_i} a_i^j - a_i^{R+1})$; and Z_i is a normalization coefficient to ensure that q_i is a valid probability distribution. u acts as a uniform smoothing factor that prevents overfitting for sparse settings, for instance, when a single weak rule applies to an instance.

According to Eq. (2), a rule r^j with higher fidelity weight a_i^j contributes more to the computation of q_i. If $a_i^j = 1\ \forall r^j \in \{R_i \cup p_\theta\}$, then RAN reduces to majority voting. If $a_i^j = 0\ \forall r^j \in \{R_i \cup p_\theta\}$, then RAN ignores all rules and predicts



(a) Rule predictions disagree. (b) Rule predictions agree.

Figure 3: Variation in unsupervised entropy loss with instance-specific rule predictions and attention weights encouraging rule agreement. Consider this illustration with two rules for a given instance. When rule predictions disagree ($q^1 \neq q^2$), minimum loss is achieved for attention weights a^1=0, a^2=1 or a^1=1, a^2=0. When rule predictions agree ($q^1 = q^2$), minimum loss is achieved for attention weights a^1=a^2=1. For instances covered by three rules, if q^1=$q^2 \neq q^3$, then minimum loss is achieved for a^1=a^2=1 and a^3=0.

a uniform label distribution for x_i. Note the distinction of our setting to recent works like Snorkel (Ratner et al., 2017), that learns global rule-weights $a_i^j = a^j \; \forall x_i$ by ignoring the instance-specific rule fidelity.

In order to effectively compute rule fidelities, RAN considers instance embeddings that capture the context of instances beyond the shallow patterns considered by rules. In particular, we model the weight a_i^j of rule r_j as a function of the context of the instance x_i and r_j through an attention-based mechanism. Consider $h_i \in \mathbb{R}^{d'}$ to be the hidden state representation of x_i from the base model. Also, consider the embedding of each rule r_j as $e_j = g(r_j) \in \mathbb{R}^d$. Rule embedding allows us to exploit the similarity between different rules in terms of instances to which they apply, and further leverage their semantics for modeling agreement. We use e_j as a query vector with *sigmoid attention* to compute instance-specific rule attention weights as:

$$a_i^j = \sigma(f(h_i)^T \cdot e_j) \in [0, 1], \tag{3}$$

where f is a multi-layer perceptron that projects h_i to $\mathbb{R}^d$ and $\sigma(\cdot)$ is the sigmoid function.

Note that the rule predictions q_i^j are considered fixed, while we estimate their attention weights. The above coupling between rules and instances via their corresponding embeddings e_j and h_i allows us to obtain representations where similar rules apply to similar contexts, and model their agreements via the attention weights a_i^j. To this end, the trainable parameters of RAN (f and g) are shared across all rules and instances. Next, we describe how to train RAN.

Algorithm 1 Self-training with Weak Supervision

Input: Small amount of labeled data D_L; task-specific unlabeled data D_U; weak rules R
Outputs: Student p_θ^*, RAN Teacher q_ϕ^*

1: Train $p_\theta(y \mid x)$ using D_L
2: **Repeat until convergence:**
  2.1: Train $q_\phi(y \mid R, p_\theta, x)$ using D_L, D_U through Eq. (2) and (4)
  2.2: Apply $q_\phi(\cdot)$ to D_U to obtain pseudo-labeled data: $D_{RAN} = \{(x_i, q_i)\}_{x_i \in D_U}$ through Eq. (2)
  2.3: Train $p_\theta(y|x)$ using D_L, D_{RAN} through Eq. (1)

2.3 Semi-Supervised Learning of WST

Learning of instance-specific weights $a_i^{(\cdot)}$ for the weak sources (including rules and pseudo-labels) is challenging due to the absence of any explicit knowledge about the source quality and limited amount of labeled training data. We thus treat the weights $a_i^{(\cdot)}$ as latent variables and propose a semi-supervised objective for training RAN with supervision on the coarser level of q_i:

$$\mathcal{L}^{RAN} = - \sum_{(x_i, y_i) \in D_L} y_i \log q_i - \sum_{x_i \in D_U} q_i \log q_i. \tag{4}$$

Given task-specific labeled data D_L, the first term in Eq. (4) minimizes the cross-entropy loss between the teacher assigned label q_i for the instance x_i and the corresponding clean label y_i. This term penalizes weak sources that assign instance-specific labels $q_i^{(\cdot)}$ that contradict with the ground-truth label y_i by assigning a low instance-specific fidelity weight $a_i^{(\cdot)}$.

The second term in Eq. (4) considers unlabeled data D_U to minimize the entropy of the aggregated pseudo-label q_i and therefore learns source weights that maximize their agreement. To this end, we leverage minimum entropy regularization objective from Grandvalet and Bengio (2005) to integrate unlabeled data into the teacher model. This is highly beneficial in our setting given the small amount of labeled data. Since the teacher label q_i is obtained by aggregating weak labels $q_i^{(\cdot)}$, entropy minimization encourages RAN to assign higher instance-specific weights $a_i^{(\cdot)}$ to sources that agree in their

	TREC	SMS	Youtube	CENSUS	MIT-R	Spouse
$\|D_L\|$	68	69	100	83	1842	100
$\|D_U\|$	5K	5K	2K	10K	65K	22K
Test Size	500	500	250	16K	14K	3K
#Classes	6	2	2	2	9	2
#Rules	68	73	10	83	15	9
Rule Accuracy (Majority Voting)	60.9%	48.4%	82.2%	80.1%	40.9%	44.2%
Rule Coverage (instances in D_U covered by ≥ 1 rule)	95%	40%	87%	100%	14%	25%
Rule Overlap (instances in D_U covered by ≥ 2 rules)	46%	9%	48%	94%	1%	8%

Table 1: Dataset statistics.

labels over the given instance x_i, and lower weights when there are disagreements between them – aggregated across all the unlabeled instances.

Figure 3 plots the minimum entropy loss over unlabeled data over two scenarios where two rules agree or disagree with each other for a given instance. The optimal instance-specific fidelity weights $a_i^{(\cdot)}$ are 1 when rules agree with each other, thereby, assigning credits to both rules, and only one of them when they disagree. We use this unsupervised entropy loss in conjunction with cross-entropy loss over labeled data to ensure grounding.

End-to-end Learning: Algorithm 1 presents an overview of our learning mechanism. We first use the small amount of labeled data to train a base student model that generates pseudo-labels and augments heuristic rules over unlabeled data. Our RAN network computes fidelity weights to combine these different weak labels via minimum entropy regularization to obtain an aggregated pseudo-label for every unlabeled instance. This is used to re-train the student model with the above student-teacher training repeated till convergence.

3 Experiments

Datasets. We evaluate our framework on the following six benchmark datasets for weak supervision from Ratner et al. (2017) and Awasthi et al. (2020). (1) Question classification from TREC-6 into 6 categories (Abbreviation, Entity, Description, Human, Location, Numeric-value); (2) Spam classification of SMS messages; (3) Spam classification of Youtube comments; (4) Income classification on the CENSUS dataset on whether a person earns more than $50K or not; (5) Slot-filling in sentences on restaurant search queries in the MIT-R dataset: each token is classified into 9 classes (Location, Hours, Amenity, Price, Cuisine, Dish, Restaurant Name, Rating, Other); (6) Relation classification in the Spouse dataset, whether pairs of people mentioned in a sentence are/were married or not.

Method	Learning to Weight Rules	Learning to Weight Instances	Unlabeled (no rules)
Majority	-	-	-
Snorkel (Ratner et al., 2017)	✓	-	-
PosteriorReg (Hu et al., 2016)	✓	-	-
L2R (Ren et al., 2018a)	-	✓	-
ImplyLoss (Awasthi et al., 2020)	✓	✓	-
Self-train	-	-	✓
WST	✓	✓	✓

Table 2: WST learns rule-specific and instance-specific attention weights and leverages task-specific unlabeled data where no rules apply.

Table 1 shows the dataset statistics along with the amount of labeled, unlabeled data and domain-specific rules for each dataset. Rules have various types, including regular expression patterns, lexicons, and knowledge bases for weak supervision.

On average across all the datasets, 66% of the instances are covered by fewer than 2 rules, whereas 40% are not covered by any rule at all – demonstrating the sparsity in our setting. We also report the accuracy of the rules in terms of majority voting on the task-specific unlabeled datasets. Additional details on the dataset are presented in Appendix.

Evaluation. We train WST five times for five different random splits of the labeled training data and evaluate on held-out test data. We report the average performance as well as the standard deviation across multiple runs. We report the same evaluation metrics as used in prior works (Ratner et al., 2017; Awasthi et al., 2020) for a fair comparison.

Model configuration. Our student model consists of embeddings from pre-trained language models like ELMO (Peters et al., 2018) or BERT (Devlin et al., 2019) for generating contextualized representations for an instance, followed by a softmax classification layer. The RAN teacher model considers a rule embedding layer and a multilayer perceptron for mapping the contextualized representation for an instance to the rule embedding space. Refer to Appendix for more details on the configurations and hyper-parameters.

	TREC (Acc)	SMS (F1)	Youtube (Acc)	CENSUS (Acc)	MIT-R (F1)	Spouse (F1)
Majority	60.9 (0.7)	48.4 (1.2)	82.2 (0.9)	80.1 (0.1)	40.9 (0.1)	44.2 (0.6)
LabeledOnly	66.5 (3.7)	93.3 (2.9)	91.0 (0.7)	75.8 (1.7)	74.7 (1.1)	47.9 (0.9)
Snorkel+Labeled	65.3 (4.1)	94.7 (1.2)	93.5 (0.2)	79.1 (1.3)	75.6 (1.3)	49.2 (0.6)
PosteriorReg	67.3 (2.9)	94.1 (2.1)	86.4 (3.4)	79.4 (1.5)	74.7 (1.2)	49.4 (1.1)
L2R	71.7 (1.3)	93.4 (1.1)	92.6 (0.5)	82.4 (0.1)	58.6 (0.4)	49.5 (0.7)
ImplyLoss	75.5 (4.5)	92.2 (2.1)	93.6 (0.5)	80.5 (0.9)	75.7 (1.5)	49.8 (1.7)
Self-train	71.1 (3.9)	95.1 (0.8)	92.5 (3.0)	78.6 (1.0)	72.3 (0.6)	51.4 (0.4)
WST (ours)	**80.3** (2.4)	**95.3** (0.5)	**95.3** (0.8)	**83.1** (0.4)	**76.9** (0.6)	**62.3** (1.1)

Table 3: Overall result comparison across multiple datasets. Results are aggregated over five runs with random training splits and standard deviation across the runs in parentheses.

Baselines. We compare our method with the following methods: *(a) Majority* predicts the majority vote of the rules with ties resolved by predicting a random class. *(b) LabeledOnly* trains classifiers using only labeled data (fully supervised baseline). *(c) Self-train* (Nigam and Ghani, 2000; Lee, 2013) leverages both labeled and unlabeled data for iterative self-training on pseudo-labeled predictions over task-specific unlabeled data. This baseline ignores domain-specific rules. *(e) Snorkel+Labeled* (Ratner et al., 2017) trains classifiers using weakly-labeled data with a generative model. The model is trained on unlabeled data for computing rule weights in an unsupervised fashion, and learns a single weight per rule across all instances. It is further fine-tuned on labeled data. *(f) L2R* (Ren et al., 2018b) learns to re-weight noisy or weak labels from domain-specific rules via meta-learning. It learns instance-specific but not rule-specific weights. *(g) PosteriorReg* (Hu et al., 2016) trains classifiers using rules as soft constraints via posterior regularization (Ganchev et al., 2010). *(h) ImplyLoss* (Awasthi et al., 2020) leverages *exemplar*-based supervision as additional knowledge for learning instance-specific and rule-specific weights by minimizing an implication loss over unlabeled data. This requires maintaining a record of all instances used to create the weak rules in the first place. Table 2 shows a summary of the different methods contrasting them on how they learn the weights (rule-specific or instance-specific) and if they leverage task-specific unlabeled data not covered by any rules.

3.1 Experimental Results

Overall results. Table 3 summarizes the main results across all datasets. Among all the semi-supervised methods that leverage weak supervision from domain-specific rules, WST outperforms Snorkel by 6.1% in average accuracy across all datasets by learning instance-specific rule weights in conjunction with self-training over unlabeled instances where weak rules do not apply. Similarly, WST also improves over a recent work and the best performing baseline ImplyLoss by 3.1% on average. Notably, our method does not require additional supervision at the level of exemplars used to create rules in contrast to ImplyLoss.

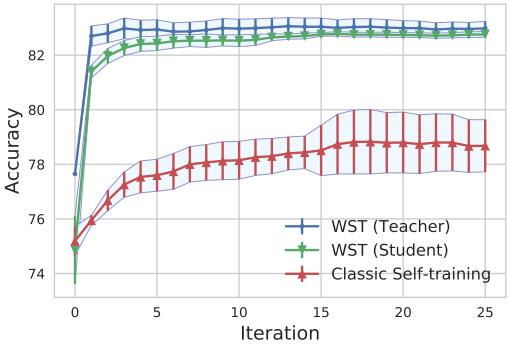


Figure 4: Gradual accuracy improvement over self-training iterations in the CENSUS dataset. WST (Student) performs better than Classic Self-training (Student) being guided by a better teacher.

Self-training over unlabeled data. Recent works for tasks like image classification (Li et al., 2019; Xie et al., 2020; Zoph et al., 2020) and neural sequence generation (Zhang and Zong, 2016; He et al., 2019) show the effectiveness of self-training methods in exploiting task-specific unlabeled data with stochastic regularization techniques like dropouts and data augmentation. We also make similar observations for our tasks, where classic self-train methods ("Self-train") leveraging only a few task-specific labeled examples and lots of unlabeled data outperform weakly supervised methods like Snorkel and PosteriorReg that have additional access to domain-specific rules.

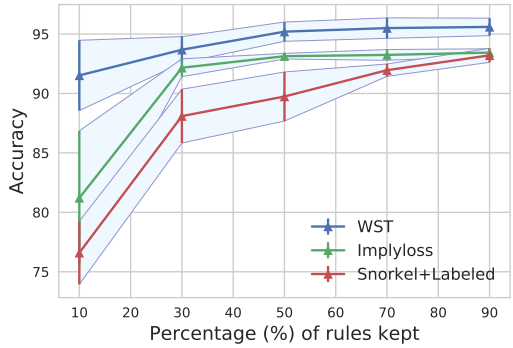


Figure 5: Performance improvement on increasing the proportion of weak rules in the Youtube datsaset. For each setting, we randomly sample a subset of rules, aggregate and report results across multiple runs. WST is effective across all settings with biggest improvements under high rule sparsity (left region of the x-axis).

% Overlap	TREC	YTube	SMS	MITR	CEN.	Spouse
Only Rules	46	48	9	1	94	8
WST	**95**	**87**	**40**	**14**	**100**	**25**
Increase	+49	+39	+31	+13	+6	+17

Table 4: WST substantially increases rule overlap (%) determined by the proportion of unlabeled instances that are covered by at least 2 weak sources (from multiple rules and pseudo-labels, as applicable).

Self-training with weak supervision. Our framework WST provides an efficient method to incorporate weak supervision from domain-specific rules to augment the self-training framework and improves by 6% over classic self-training.

To better understand the benefits of our approach compared to classic self-training, consider Figure 4 which depicts the gradual performance improvement over iterations. The student models in classic self-training and WST have the same architecture and the same number of parameters. However, the latter is guided by a better teacher (RAN) that learns to aggregate noisy rules and pseudo-labels over unlabeled data.

Impact of rule sparsity and coverage for weak supervision. In this experiment, we compare the performance of various methods by varying the proportion of available domain-specific rules. To this end, we randomly choose a subset of the rules (varying the proportion from 10% to 100%) and train various weak supervision methods. For each setting, we repeat experiments with multiple rule splits and report aggregated results in Figure 5. We observe that our method WST is effective across all settings with the most impact at high levels of rule sparsity. For instance, with 10% of domain-specific rules available, WST outperforms ImplyLoss by 12% and Snorkel+Labeled by 19%.

Configuration	Acc
WST (Teacher)	**88.1**
WST (Student)	87.7 (↓ 0.4%)
No minm. entropy regularization in Eq. (4)	86.9 (↓ 1.4%)
No student fine-tuning on D_L (step 2.3)	86.7 (↓ 1.6%)
No student pseudo-labels in RAN in Eq. (2)	85.3 (↓ 3.2%)

Table 5: Summary of ablation experiments aggregated across multiple datasets. Refer to Appendix for corresponding results in each dataset.

This performance improvement is made possible by incorporating self-training in our framework to obtain pseudo-labels for task-specific unlabeled instances, and further re-weighting them with other domain-specific rules via the rule attention network. Correspondingly, Table 4 shows the increase in data coverage for every task given by the proportion of unlabeled instances that are now covered by at least two weak sources (from multiple rules and pseudo-labels) in contrast to just considering the rules.

3.2 Ablation Study

Table 5 reports several ablation experiments to evaluate the impact of various components in WST.

WST teacher marginally outperforms the student model on an aggregate having access to domain-specific rules. WST student that is self-trained over task-specific unlabeled data and guided by an efficient teacher model significantly outperforms other state-of-the-art baselines.

Minimum entropy regularization in the semi-supervised learning objective (Eq. (4)) allows WST to leverage agreement between various weak supervision sources (including rules and pseudo-labels) over task-specific unlabeled data. Removing this component results in an accuracy drop of 1.4% on an aggregate demonstrating its usefulness.

Fine-tuning the student on labeled data is important for effective self-training: ignoring D_L in the step 2.3 in Algorithm 1, leads to 1.6% lower accuracy than WST.

We observe significant performance drop on removing the student's pseudo-labels ($p_\theta(\cdot)$) from the rule attention network in Eq. (2). This significantly limits the coverage of the teacher ignoring unlabeled instances where rules do not apply, thereby, degrading the overall performance by 3.2%.

3.3 Case Study: TREC-6 Dataset

Refer to Table 6 for some illustrative examples on how our WST framework aggregates various weak

Instances	Teacher	Student	Set of Heuristic Rule Labels
1. Which president was unmarried ?	HUM	HUM(1)	{}
2. What is a baby turkey called?	ENTY	DESC(1)	{ENTY(1), DESC(0), HUM(0)}
3. What currency do they use in Brazil?	ENTY	ENTY(1)	{DESC(0), DESC(0)}
4. What was President Johnson's reform program called?	ENTY	ENTY(1)	{HUM(1), ENTY(1), DESC(0), HUM(0)}
5. What is the percentage of water content in the human body?	NUM	DESC(0)	{HUM(0), NUM(0.2), DESC(0)}

Table 6: Snapshot of answer-type predictions for questions in TREC-6 from WST teacher and student along with a set of labels assigned by various weak rules (DESC: description, ENTY: entity, NUM: number, HUM: human) with corresponding attention weights (in parentheses). Correct and incorrect predictions are colored in green and red respectively. Detailed analysis and rule semantics reported in Appendix.

supervision sources with corresponding attention weights shown in parantheses. In Example 1 where no rules apply, the student leverages the context of the sentence (e.g., semantics of "president") to predict the HUM label. While in Example 2, the teacher downweights the incorrect student (as well as conflicting rules) and upweights the appropriate rule to predict the correct ENTY label. In example 3, WST predicts the correct label ENTY relying only on the student as both rules report noisy labels.

4 Related Work

Self-Training Self-training (Yarowsky, 1995; Nigam and Ghani, 2000; Lee, 2013) as one of the earliest semi-supervised learning approaches (Chapelle et al., 2009) trains a base model (student) on a small amount of labeled data and applies it to pseudo-label (task-specific) unlabeled data. This is used to augment the labeled data and re-train the student in an iterative manner. Self-training has recently been shown to obtain state-of-the-art performance for tasks like image classification (Li et al., 2019; Xie et al., 2020; Zoph et al., 2020), text classification (Mukherjee and Awadallah, 2020), and neural machine translation (Zhang and Zong, 2016; He et al., 2019) and has shown complementary advantages to unsupervised pre-training (Zoph et al., 2020). A typical issue in self-training is error propagation from noisy pseudo-labels. This is addressed in WST via rule attention network to compute fidelity of the pseudo-labels.

Learning with Noisy Labels Classification under label noise from a single source has been an active research topic (Frénay and Verleysen, 2013). One major line of research focus on correcting the labels by learning label corruption matrices (Patrini et al., 2017; Hendrycks et al., 2018; Zheng et al., 2019). More related to our work are the instance reweighting approaches (Ren et al., 2018b; Shu et al., 2019), which learn to up-weight and down-weight instances with cleaner and noisy labels respectively. However these operate on only instance-level and do not consider rule-specific importance. Our approach learns both instance- and rule-specific fidelity weights and substantially outperforms Ren et al. (2018b) across all datasets.

Learning with Multiple Rules To address the challenges with multiple noisy rules, existing approaches learn rule weights based on mutual rule agreements with some strong assumptions. For instance, Meng et al. (2018); Karamanolakis et al. (2019); Mekala and Shang (2020) denoise seed words using vector representations of their semantics. However it is difficult to generalize these approaches from seed words to more general labeling functions that only predict heuristic labels (as in our datasets). Ratner et al. (2017); Sachan et al. (2018); Ratner et al. (2019) assume each rule to be equally accurate across all the instances that it applies to. Awasthi et al. (2020) learn rule-specific and instance-specific weights but assume access to *labeled exemplars* that were used to create the rule in the first place. Most importantly, all these works ignore unlabeled instances that are not covered by any of the rules, while our approach leverages all unlabeled instances via self-training.

5 Conclusions and Future Work

We developed a weak supervision framework (WST) to integrate task-specific unlabeled data, few labeled data, and domain-specific knowledge as rules for training efficient models. To this end, we leverage self-training for harnessing contextualized representations for unlabeled instances where weak rules do not apply. This significantly improves the model coverage in contrast to prior works. Additionally, we developed a rule attention network to aggregate various noisy sources of weak supervision (including rules and pseudo-labels) with instance-specific weights – that are trained without any assumptions about the source or nature of the sources. Extensive experiments on

several benchmark datasets demonstrate WST outperforming state-of-the-art models with particular effectiveness at high levels of rule sparsity.

Ethical Considerations

In this work, we introduce a framework for training of neural network models with few labeled examples and domain-specific knowledge. This work is likely to increase the progress of NLP applications for domains with limited annotated resources but access to domain-specific knowledge. While it is not only expensive to acquire large amounts of labeled data for every task and language, in many cases, we cannot perform large-scale labeling due to access constraints from privacy and compliance concerns. To this end, our framework can be used for applications in finance, legal, healthcare, retail and other domains where adoption of deep neural network may have been hindered due to lack of large-scale manual annotations on sensitive data.

While our framework accelerates the progress of NLP, it also suffers from associated societal implications of automation ranging from job losses for workers who provide annotations as a service. Additionally, it involves deep neural models that are compute intensive and has a negative impact on the environment in terms of carbon footprint. The latter concern is partly alleviated in our work by leveraging pre-trained language models and not training from scratch, thereby, leading to efficient and faster compute.

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