Combining Distant and Partial Supervision for Relation Extraction

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Abstract

Broad-coverage relation extraction either requires expensive supervised training data, or suffers from drawbacks inherent to distant supervision. We present an approach for providing partial supervision to a distantly supervised relation extractor using a small number of carefully selected examples. We compare against established active learning criteria and propose a novel criterion to sample examples which are both uncertain and representative. In this way, we combine the benefits of fine-grained supervision for difficult examples with the coverage of a large distantly supervised corpus. Our approach gives a substantial increase of 3.9% end-to-end F₁ on the 2013 KBP Slot Filling evaluation, yielding a net F₁ of 37.7%.

1 Introduction

Fully supervised relation extractors are limited to relatively small training sets. While able to make use of much more data, distantly supervised approaches either make dubious assumptions in order to simulate fully supervised data, or make use of latent-variable methods which get stuck in local optima easily. We hope to combine the benefits of supervised and distantly supervised methods by annotating a small subset of the available data using selection criteria inspired by active learning.

To illustrate, our training corpus contains 1208524 relation mentions; annotating all of these mentions for a fully supervised classifier, at an average of $0.13 per annotation, would cost approximately $160000. Distant supervision allows us to make use of this large corpus without requiring costly annotation. The traditional approach is based on the assumption that every mention of an entity pair (e.g., Obama and USA) participates in the known relation between the two (i.e., born in). However, this introduces noise, as not every mention expresses the relation we are assigning to it.

We show that by providing annotations for only 10000 informative examples, combined with a large corpus of distantly labeled data, we can yield notable improvements in performance over the distantly supervised data alone. We report results on three criteria for selecting examples to annotate: a baseline of sampling examples uniformly at random, an established active learning criterion, and a new metric incorporating both the uncertainty and the representativeness of an example. We show that the choice of metric is important – yielding as much as a 3% F₁ difference – and that our new proposed criterion outperforms the standard method in many cases. Lastly, we train a supervised classifier on these collected examples, and report performance comparable to distantly supervised methods. Furthermore, we notice that initializing the distantly supervised model using this supervised classifier is critical for obtaining performance improvements.

This work makes a number of concrete contributions. We propose a novel application of active learning techniques to distantly supervised relation extraction. To the best of the authors knowledge, we are the first to apply active learning to the class of latent-variable distantly supervised models presented in this paper. We show that annotating a proportionally small number of examples yields improvements in end-to-end accuracy. We compare various selection criteria, and show that this decision has a notable impact on the gain in performance. In many ways this reconciles our results with the negative results of Zhang et al. (2012), who show limited gains from naively annotating examples. Lastly, we make our annotations available to the research community.¹

¹http://nlp.stanford.edu/software/mimlre.shtml
2 Background

2.1 Relation Extraction

We are interested in extracting a set of relations $y_1 \ldots y_k$ from a fixed set of possible relations $R$, given two entities $e_1$ and $e_2$. For example, we would like to extract that Barack Obama was born in Hawaii. The task is decomposed into two steps: First, sentences containing mentions of both $e_1$ and $e_2$ are collected. The set of these sentences $x$, marked with the entity mentions for $e_1$ and $e_2$, becomes the input to the relation extractor, which then produces a set of relations which hold between the mentions. We are predominantly interested in the second step – classifying a set of pairs of entity mentions into the relations they express. Figure 1 gives the general setting for relation extraction, with entity pairs Barack Obama and Hawaii, and Barack Obama and president.

Traditionally, relation extraction has fallen into one of four broad approaches: supervised classification, as in the ACE task (Doddington et al., 2004; GuoDong et al., 2005; Surdeanu and Ciamarita, 2007), distant supervision (Craven and Kulp, 1999; Wu and Weld, 2007; Mintz et al., 2009; Sun et al., 2011; Roth and Klakow, 2013) deterministic rule-based systems (Soderland, 1997; Grishman and Min, 2010; Chen et al., 2010), and translation from open domain information extraction schema (Riedel et al., 2013). We focus on the first two of these approaches.

2.2 Supervised Relation Extraction

Relation extraction can be naturally cast as a supervised classification problem. A corpus of relation mentions is collected, and each mention $x$ is annotated with the relation $y$, if any, it expresses. The classifier’s output is then aggregated to decide the relations between the two entities.

However, annotating supervised training data is generally expensive to perform at large scale. Although resources such as Freebase or the TAC KBP knowledge base have on the order of millions of training tuples over entities it is not feasible to manually annotate the corresponding mentions in the text. This has led to the rise of distantly supervised methods, which make use of this indirect supervision, but do not necessitate mention-level supervision.

2.3 Distant Supervision

Traditional distant supervision makes the assumption that for every triple $(e_1, y, e_2)$ in a knowledge base, every sentence containing mentions for $e_1$ and $e_2$ express the relation $y$. For instance, taking Figure 1, we would create a datum for each of the three sentences containing Barack Obama and Hawaii labeled with state of birth, and likewise with state of residence, creating 6 training examples overall. Similarly, both sentences involving Barack Obama and president would be marked as expressing the title relation.

While this allows us to leverage a large database effectively, it nonetheless makes a number of naïve assumptions. First – explicit in the formulation of the approach – it assumes that every mention expresses some relation, and furthermore expresses the known relation(s). For instance, the sentence Obama visited Hawaii would be erroneously treated as a positive example of the born in relation. Second, it implicitly assumes that our knowledge base is complete: entity mentions with no known relation are treated as negative examples.

The first of these assumptions is addressed by multi-instance multi-label (MIML) learning, described in Section 2.4. Min et al. (2013) address the second assumption by extending the MIML model with additional latent variables, while Xu et al. (2013) allow feedback from a coarse relation extractor to augment labels from the knowledge base. These latter two approaches are compatible with but are not implemented in this work.

2.4 Multi-Instance Multi-Label Learning

The multi-instance multi-label (MIML-RE) model of Surdeanu et al. (2012), which builds upon work
by Hoffmann et al. (2011) and Riedel et al. (2010), addresses the assumptions of distantly supervised relations extractors in a principled way by positing a latent mention-level annotation.

The model groups mentions according to their entity pair – for instance, every mention pair with Obama and Hawaii would be grouped together. A latent variable $z_i$ is created for every mention $i$, where $z_i \in R \cup \{\text{None}\}$ takes a single relation label, or a no relation marker. We create $|R|$ binary variables $y$ representing the known positive and negative relations for the entity pair. A set of binary classifiers (log-linear factors in the graphical model) links the latent predictions $z_1 \ldots z_{|M_i|}$ and each $y_j$. These classifiers include two classes of features: first, a binary feature which fires if at least one of the mentions expresses a known relation between the entity pair, and second, a feature for each co-occurrence of relations for a given entity pair. Figure 2 describes the model.

2.5 Background on Active Learning

We describe preliminaries and prior work on active learning; we use this framework to propose two sampling schemes in Section 3 which we use to annotate mention-level labels for MIML-RE. One way of expressing the generalization error of a hypothesis $h$ is through its mean-squared error with the true hypothesis $\hat{h}$:

$$E[(h(x) - \hat{h}(x))^2]$$

$$= E[E[(h(x) - \hat{h}(x))^2|x]]$$

$$= \int_x E[(h(x) - \hat{h}(x))^2|x]p(x)dx.$$

The integrand can be further broken into bias and variance terms:

$$E[(h(x) - \hat{h}(x))^2] = (E[\hat{h}(x)] - h(x))^2$$

$$+ E[(\hat{h}(x) - E[\hat{h}(x)])^2]$$

where for simplicity we’ve dropped the conditioning on $x$.

Many traditional sampling strategies, such as query-by-committee (QBC) (Freund et al., 1992; Freund et al., 1997) and uncertainty sampling (Lewis and Gale, 1994), work by decreasing the variance of the learned model. In QBC, we first create a ‘committee’ of classifiers by randomly sampling their parameters from a distribution based on the training data. These classifiers then make predictions on the unlabeled examples, and the examples on which there is the most disagreement are selected for labeling. This strategy can be seen as an attempt to decrease the version space – the set of classifiers that are consistent with the labeled data. Decreasing the version space should lower variance, since variance is inversely related to the size of the hypothesis space.

In most scenarios, active learning does not concern itself with the bias term. If a model is fundamentally misspecified, then no amount of additional training data can lower its bias. However, our paradigm differs from the traditional setting, in that we are annotating latent variables in a model with a non-convex objective. These annotations may help increase the convexity of our objective, leading us to a more accurate optimum and thereby lowering bias.

The other component to consider is $\int_x \ldots p(x)dx$. This suggests that it is important to choose examples that are representative of the underlying distribution $p(x)$, as we want to label points that will improve the classifier’s predictions on as many and as high-probability examples as possible. Incorporating a representativeness metric has been shown to provide a significant improvement over plain QBC or
uncertainty sampling (McCallum and Nigam, 1998; Settles, 2010).

2.6 Active Learning for Relation Extraction

Several papers have explored active learning for relation extraction. Fu and Grishman (2013) employ active learning to create a classifier quickly for new relations, simulated from the ACE corpus. Finn and Kushmerick (2003) compare a number of selection criteria – including QBC – for a supervised classifier. To the best of our knowledge, we are the first to apply active learning to distantly supervised relation extraction. Furthermore, we evaluate our selection criteria live in a real-world setting, collecting new sentences and evaluating on an end-to-end task.

For latent variable models, McCallum and Nigam (1998) apply active learning to semi-supervised document classification. We take inspiration from their use of QBC and the choice of metric for classifier disagreement. However their model assumes a fully Bayesian set-up, whereas ours does not require strong assumptions about the parameter distributions.

Settles et al. (2008) use active learning to improve a multiple-instance classifier. Their model is simpler in that it does not allow for unobserved variables or multiple labels, and the authors only evaluate on image retrieval and synthetic text classification datasets.

3 Example Selection

We describe three criteria for selection examples to annotate. The first – sampling uniformly – is a baseline for our hypothesis that intelligently selecting examples is important. For this criterion, we select mentions uniformly at random from the training set to annotate. This is the approach used in Zhang et al. (2012). The other two criteria rely on a metric for disagreement provided by QBC; we describe our adaptation of QBC for MIML-RE as a preliminary to introducing these criteria.

3.1 QBC For MIML-RE

We use a version of QBC based on bootstrapping (Saar-Tsechansky and Provost, 2004). To create the committee of classifiers, we re-sample the training set with replacement 7 times and train a model over each sampled dataset. We measure disagreement on z-labels among the classifiers using a generalized Jensen-Shannon divergence (McCallum and Nigam, 1998), taking the average KL divergence of all classifier judgments.

We first calculate the mention-level confidences. Note that \( z_i^{(m)} \in M_i \) denotes the latent variable in entity pair \( i \) with index \( m \); \( z_i^{(-m)} \) denotes the set of all latent variables except \( z_i^{(m)} \):

\[
p(z_i^{(m)} | y_1, x_1) = \frac{p(y_1, z_i^{(m)} | x_1)}{\sum_{z_i^{(-m)}} p(y_1, z_i | x_1)}
\]

Notice that the denominator just serves to normalize the probability within a sentence group.

We can rewrite the numerator as follows:

\[
\sum_{z_i^{(-m)}} p(y_1, z_i | x_1) = \sum_{z_i^{(-m)}} p(y_1 | z_i) p(z_i | x_1)
\]

\[
= p(z_i^{(m)} | x_1) \sum_{z_i^{(-m)}} p(y_1 | z_i) p(z_i^{(-m)} | x_1).
\]

For computational efficiency, we approximate \( p(z_i^{(-m)} | x_1) \) with a point mass at its maximum. Next, we calculate the Jensen-Shannon (JS) divergence from the \( k \) bootstrapped classifiers:

\[
\frac{1}{k} \sum_{c=1}^k \text{KL}(p_c(z_i^{(m)} | y_1, x_1)||p_{\text{mean}}(z_i^{(m)} | y_1, x_1)) \tag{1}
\]

where \( p_c \) is the probability assigned by each of the \( k \) classifiers to the latent \( z_i^{(m)} \), and \( p_{\text{mean}} \) is the average of these probabilities. We use this metric to capture the disagreement of our model with respect to a particular latent variable. This is then used to inform our selection criteria.

We note that QBC may be especially useful in our situation as our objective is highly nonconvex. If two committee members disagree on a latent variable, it is likely because they converged to different local optima; annotating that example could help bring the classifiers into agreement.

The second selection criterion we consider is the most straightforward application of QBC – selecting the examples with the highest JS disagreement. This allows us to compare our criterion, described next, against an established criterion from the active learning literature.
3.2 Sample by JS Disagreement

We propose a novel active learning sampling criterion that incorporates not only disagreement but also representativeness in selecting examples to annotate. Prior work has taken a weighted combination of an example’s disagreement and a score corresponding to whether the example is drawn from a dense portion of the feature space (e.g., McCallum and Nigam (1998)). However, this requires both selecting a criterion for defining density (e.g., distance metric in feature space), and tuning a parameter for the relative weight of disagreement versus representativeness.

Instead, we account for choosing representative examples by sampling without replacement proportional to the example’s disagreement. Formally, we define the probability of selecting an example \( z_i^{(m)} \) to be proportional to the Jensen-Shannon divergence in (1). Since the training set is an approximation to the prior distribution over examples, sampling uniformly over the training set is an approximation to sampling from the prior probability of seeing an input \( x \). We can view our criterion as an approximation to sampling proportional to the product of two densities: a prior over examples \( x \), and the JS divergence mentioned above.

4 Incorporating Sentence-Level Annotations

Following Surdeanu et al. (2012), MIML-RE is trained through hard discriminative Expectation Maximization, inferring the latent \( z \) values in the E-step and updating the weights for both the \( z \) and \( y \) classifiers in the M-step. During the E-step, we constrain the latent \( z \) to match our sentence-level annotations when available.

It is worth noting that even in the hard-EM regime, we can in principle incorporate annotator uncertainty elegantly into the model. At each E step, each \( z_i \) is set according to

\[
\hat{z}_i^{(m)*} \approx \arg \max_{z \in \mathcal{R}} \left[ p(z \mid x_i^{(m)}, w_z) \times \prod_r p(y_i^{(r)} \mid z_i^{(m)}, w_y^{(r)}) \right]
\]

where \( z_i^{(m)} \) contains the inferred labels from the previous iteration, but with its \( m \)th component replaced by \( z_i^{(m)} \).

By setting the distribution \( p(z \mid x_i^{(m)}, w_z) \) to reflect uncertainty among annotators, we can leave open the possibility for the model to choose a relation which annotators deemed unlikely, but the model nonetheless prefers. For simplicity, however, we treat our annotations as a hard assignment.

In addition to incorporating annotations during training, we can also use this data to intelligently initialize the model. Since the MIML-RE objective is non-convex, the initialization of the classifier weights \( w_y \) and \( w_z \) is important. The \( y \) classifiers are initialized with the “at-least-once” assumption of Hoffmann et al. (2011); \( w_z \) can be initialized either using traditional distant supervision or from a supervised classifier trained on the annotated sentences. If initialized with a supervised classifier, the model can be viewed as augmenting this supervised model with a large distantly labeled corpus, providing both additional entity pairs to train from, and additional mentions for an annotated entity pair.

5 Crowdsourced Example Annotation

Most prior work on active learning is done by simulation on a fully labeled dataset; such a dataset doesn’t exist for our case. Furthermore, a key aim of this paper is to practically improve state-of-the-art performance in relation extraction in addition to evaluating active learning criteria. Therefore, we develop and execute an annotation task for collecting labels for our selected examples.

We utilize Amazon Mechanical Turk to crowdsource annotations. For each task, the annotator (Turker) is presented with the task description, followed by 15 questions, 2 of which are randomly placed controls. For each question, we present Turkers with a relation mention and the top 5 relation predictions from our classifier. The Turker also has an option to freely specify a relation not presented in the first five options, or mark that there is no relation. We attempt to heuristically match common free-form answers to official relations.

To maintain the quality of the results, we discard all submissions in which both controls were answered incorrectly, and additionally discard all submissions from Turkers who failed the controls on more than \( \frac{1}{3} \) of their submissions. Rejected tasks were republished for other workers to complete. We collect 5 annotations for each example, and use the most commonly agreed answer as the ground truth. Ties are broken arbitrarily, except in
In 1993, GD Searle withdrew from India and sold its holdings to RPG Group.

Which option below describes the relationship between India and RPG Group?

- RPG Group is a subsidiary of India
- RPG Group is a member of India
- RPG Group is headquartered in the country India
- RPG Group was founded by India
- RPG Group's top employees includes India
- RPG Group is India (please specify).

Figure 3: The task shown to Amazon Mechanical Turk workers. A sentence along with the top 5 relation predictions from our classifier are shown to Turkers, as well as an option to specify a custom relation or manually enter “no relation.” The correct response for this example should be either no relation or a custom relation.

The case of deciding between a relation and no relation, in which case the relation was always chosen.

A total of 23725 examples were annotated, covering 10000 examples for each of the three selection criteria. Note that there is overlap between the examples selected for the three criteria. In addition, 10023 examples were annotated during development; these are included in the set of all annotated examples, but excluded from any of the three criteria. The compensation per task was 23 cents; the total cost of annotating examples was $3156, in addition to $204 spent on developing the task. Informally, Turkers achieved an accuracy of around 75%, as evaluated by a paper author, performing disproportionately well on identifying the no relation label.

6 Experiments

We evaluate the three high-level research contributions of this work: we show that we improve the accuracy of MIML-RE, we validate the effectiveness of our selection criteria, and we provide a corpus of annotated examples, evaluating a supervised classifier trained on this corpus. The training and testing methodology for evaluating these contributions is given in Sections 6.1 and 6.2; experiments are given in Section 6.3.

6.1 Training Setup

We adopt the setup of Surdeanu et al. (2012) for training the MIML-RE model, with minor modifications. We use both the 2010 and 2013 KBP official document collections, as well as a July 2013 dump of Wikipedia as our text corpus. We subsample negatives such that \( \frac{1}{3} \) of our dataset consists of entity pairs with no known relations. In all experiments, MIML-RE is trained for 7 iterations of EM; for efficiency, the \( z \) classifier is optimized using stochastic gradient descent;\(^2\) the \( y \) classifiers are optimized using L-BFGS.

Similarly to Surdeanu et al. (2011), we assign negative relations which are either incompatible with the known positive relations (e.g., relations whose co-occurrence would violate type constraints); or, are actually functional relations in which another entity already participates. For example, if we know that Obama was born in the United States, we could add born in as a negative relation to the pair Obama and Kenya.

Our dataset consists of 325891 entity pairs with at least one positive relation, and 158091 entity pairs with no positive relations. Pairs with at least one known relation have an average of 4.56 mentions per group; groups with no known relations have an average of 1.55 mentions per group. In total, 1208524 distinct mentions are considered; the annotated examples are selected from this pool.

6.2 Testing Methodology

We compare against the original MIML-RE model using the same dataset and evaluation methodology as Surdeanu et al. (2012). This allows for an evaluation where the only free variable between this and prior work is the predictions of the relation extractor.

Additionally, we evaluate the relation extractors in the context of Stanford’s end-to-end KBP system (Angeli et al., 2014) using the NIST TAC-KBP 2013 English Slotfilling evaluation. In the end-to-end framework, the input to the system is a query entity and a set of articles, and the output is a set of slot fills – each slot fill is a candidate triple in the knowledge base, the first element of which is the query entity. This amounts to roughly populating a data structure like Wikipedia infoboxes automatically from a large corpus of text.

Importantly, an end-to-end evaluation in a top-performing full system gives a more accurate idea of the expected real-world gain from each model. Both the information retrieval component providing candidates to the relation extractor, as well as

\(^2\)For the sake of consistency, the supervised classifiers and those in Mintz++ are trained identically to the \( z \) classifiers in MIML-RE.
the consistency and inference performed on the classifier output introduce bias in this evaluation’s sensitivity to particular types of errors. Mistakes which are easy to filter, or are difficult to retrieve using IR are less important in this evaluation; in contrast, factors such as providing good confidence scores for consistency become more important.

For the end-to-end evaluation, we use the official evaluation script with two changes: First, all systems are evaluated with provenance ignored, so as not to penalize any system for finding a new provenance not validated in the official evaluation key. Second, each system reports its optimal F1 along its P/R curve, yielding results which are optimistic when compared against other systems entered into the competition. However, this also yields results which are invariant to threshold tuning, and is therefore more appropriate for comparing between systems in this paper.

Development was done on the KBP 2010–2012 queries, and results are reported using the 2013 queries as a simulated test set. Our best system achieves an F1 of 37.7; the top two teams at KBP 2013 (of 18 entered) achieved F1 scores of 40.2 and 37.1 respectively, ignoring provenance.

### 6.3 Results

Table 1 summarizes all results for the end-to-end task; relevant features of the table are copied in subsequent sections to illustrate key trends. Models which perform worse than the original MIML-RE model (MIML-RE, initialized with “Dist,” under “Not Used”) are denoted in gray. The best performing model improves on the base model by 3.9 F1 points on the end-to-end task.

We evaluate each of the individual contributions of the paper: improving the accuracy of the MIML-RE relation extractor, evaluating our example selection criteria, and demonstrating the annotated examples’ effectiveness for a fully-supervised relation extractor.

### Improve MIML-RE Accuracy

A key goal of this work is to improve the accuracy of the MIML-RE model; we show that we improve the model both on the end-to-end slotfilling task (Table 2) as well as on a standard evaluation (Figure 5). Similar to our work, recent work by Pershina et al. 1562
Table 3: A summary of the performance of each example selection criterion. In each case, the model was initialized with a supervised classifier. The first row corresponds to the MIML-RE model initialized with a supervised classifier. The middle three rows show performance for the three selection criteria, used both for initialization and during training. The last row shows results if all available annotations are used, independent of their source.

| System                  | P     | R     | F1  |
|-------------------------|-------|-------|-----|
| MIML + Sup              | 35.1  | 35.6  | 35.4|
| MIML + Sup + Uniform    | 34.4  | 35.0  | 34.7|
| MIML + Sup + HighJS     | 46.2  | 30.8  | 37.0|
| MIML + Sup + SampleJS   | 39.4  | 36.2  | 37.7|
| MIML + Sup + All        | 36.0  | 37.1  | 36.5|

Table 4: A comparison of the best performing supervised classifier with other systems. The top section compares the supervised classifier with prior work. The lower section highlights the improvements gained from initializing MIML-RE with a supervised classifier.

| System     | P     | R     | F1  |
|------------|-------|-------|-----|
| Mintz++    | 41.3  | 28.2  | 33.5|
| MIML + Dist| 38.0  | 30.5  | 33.8|
| Supervised + SampleJS | 33.5 | 35.0 | 34.2 |
| MIML + Sup | 35.1  | 35.6  | 35.5|
| MIML + Sup + SampleJS | 39.4 | 36.2 | 37.7 |

Figure 4: MIML-RE and Mintz++ evaluated according to Surdeanu et al. (2012). The original model from the paper is plotted for comparison, as our training methodology is somewhat different.

Figure 5: Our best active learning criterion evaluated against our version of MIML-RE, alongside the best system of Pershina et al. (2014).

Also interesting is the relatively small gain MIML-RE provides over traditional distant supervision (Mintz++) in this setting. We conjecture that the mistakes made by Mintz++ are often relatively easily filtered by the downstream consistency component. This is supported by Figure 4; we evaluate our trained MIML-RE model against Mintz++ and the results reported in Surdeanu et al. (2012). We show that our model performs as well or better than the original implementation, and consistently outperforms Mintz++.

Evaluate Selection Criteria A key objective of this work is to evaluate how much of an impact careful selection of annotated examples has on the overall performance of the system. We evaluate the three selection criteria from Section 3.2, showing the results for MIML-RE in Table 3; results for the supervised classifier are given in Table 1. In both cases, we show that the sampled JS cri-
At least two interesting trends can be noted from these results: First, the uniformly sampled criterion performed worse than MIML-RE initialized with a supervised classifier. This may be due to noise in the annotation: a small number of annotation errors on entity pairs with only a single corresponding mention could introduce dangerous noise into training. These singleton mentions will rarely have disagreement between the committee of classifiers, and therefore will generally only be selected in the uniform criterion.

Second, adding in the full set of examples did not improve performance – in fact, performance generally dropped in this scenario. We conjecture that this is due to the inclusion of the uniformly sampled examples, with performance dropping for the same reasons as above.

Both of these results can be reconciled with the results of Zhang et al. (2012); like this work, they annotated examples to analyze the trade-off between adding more data to a distantly supervised system, and adding more direct supervision. They conclude that annotations provide only a relatively small improvement in performance. However, their examples were uniformly selected from the training corpus, and did not make use of the structure provided by MIML-RE. Our results agree in that neither the uniform selection criterion nor the supervised classifier significantly outperformed the unmodified MIML-RE model; nonetheless, we show that if care is taken in selecting these labeled examples we can achieve noticeable improvements in accuracy.

We also evaluate our selection criteria on the evaluation of Surdeanu et al. (2012), both initialized with Mintz++ (Figure 7) and with the supervised classifier (Figure 6). These results mirror those in the end-to-end evaluation; when initialized with the supervised classifier the high disagreement (High JS) and sampling proportional to disagreement (Sample JS) criteria clearly outperform both the base MIML-RE model as well as the uniformly sampling criterion. Using the annotated examples only during training yielded no perceivable benefit over the base model (Figure 7).

**Supervised Relation Extractor** The examples collected can be used to directly train a supervised classifier, with results summarized in Table 4. The most salient insight is that the performance of the best supervised classifier is similar to that of the MIML-RE model, despite being trained on nearly two orders of magnitude less training data.

More interestingly, however, the supervised classifier provides a noticeably better initialization for MIML-RE than Mintz++, yielding better results even without enforcing the labels during EM. These results suggest that the power gained from the more sophisticated MIML-RE model is best used in conjunction with a small amount of training data. That is, using MIML-RE as a principled model for combining a large distantly labeled corpus and a small number of careful annotations yields significant improvement over using either of the two data sources alone.
### 6.4 Analysis By Relation

In this section, we explore which of the KBP relations were shown to Turkers, and whether the improvements in accuracy correspond to these relations. We compare only the unmodified MIML-RE model, and our best model (MIML-RE initialized with the supervised classifier, under the SampleJS criterion). Results are shown in Table 5.

A few interesting trends emerge from this analysis. We note that annotating even 80+ examples for a relation seems to provide a consistent boost in accuracy, whereas relations with fewer annotated examples tended to show little or no change. However, the gains of our model are not universal across relation types, even dropping noticeably on some – for instance, $F_1$ drops on both *state of residence* and *country of birth*. This could suggest systematic noise from Turker judgments; e.g., for foreign geography (*state of residence*) or ambiguous relations (*top members*).

An additional insight from the table is the mismatch between examples chosen to be annotated, and the most popular relations in the KBP evaluation. For instance, by far the most popular KBP relation (*title*) had only 121 examples annotated.

### 7 Conclusion

We have shown that providing a relatively small number of mention-level annotations can improve the accuracy of MIML-RE, yielding an end-to-end improvement of 3.9 $F_1$ on the KBP task. Furthermore, we have introduced a new active learning criterion, and shown both that the choice of criterion is important, and that our new criterion performs well. Lastly, we make available a dataset of mention-level annotations for constructing a traditional supervised relation extractor.

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Table 5: A summary of relations annotated, and end-to-end slotfilling performance by relation. The first column gives the relation; the second shows the number of examples annotated. The subsequent columns show the performance of the unmodified MIML-RE model and our best performing model (SampleJS). Changes in values are bolded; positive changes are shown in green and negative changes in red. The most frequent 10 relations in the evaluation are likewise bolded.

| Relation                  | #   | P  | R  | F1 |
|---------------------------|-----|----|----|----|
| no_relation                | 3073| 29 | 33 | 31 |
| employee_of               | 1978| 32 | 46 | 38 |
| countries_of_res.         | 1061| 42 | 40 | 41 |
| states_of_residence       | 427 | 33 | 14 | 23 |
| cities_of_residence       | 356 | 52 | 30 | 34 |
| (org):member_of           | 290 | 0  | 0  | 0  |
| country_of_hq             | 280 | 62 | 62 | 62 |
| top_members               | 221 | 26 | 50 | 42 |
| country_of_birth          | 205 | 0  | 0  | 0  |
| parents                   | 196 | 26 | 54 | 15 |
| city_of_hq                | 194 | 52 | 61 | 51 |
| (org):alt_names           | 184 | 48 | 39 | 43 |
| founded_by                | 180 | 89 | 38 | 44 |
| city_of_birth             | 145 | 75 | 17 | 25 |
| state_of_hq               | 132 | 64 | 30 | 48 |
| title                     | 121 | 20 | 35 | 30 |
| subsidiaries              | 105 | 25 | 6  | 10 |
| founded                   | 102 | 26 | 59 | 62 |
| spouse                    | 88  | 54 | 85 | 51 |
| origin                    | 86  | 43 | 70 | 53 |
| state_of_birth            | 83  | 50 | 10 | 17 |
| charges                   | 69  | 54 | 16 | 24 |
| cause_of_death            | 69  | 93 | 39 | 55 |
| (per:alt_names)           | 69  | 20 | 2  | 3  |
| country_of_death          | 65  | 100| 10 | 18 |
| members                   | 54  | 0  | 0  | 0  |
| children                  | 52  | 62 | 18 | 22 |
| parents                   | 50  | 64 | 28 | 39 |
| city_of_death             | 38  | 75 | 19 | 23 |
| dissolved                 | 38  | 50 | 0  | 0  |
| date_of_death             | 33  | 64 | 44 | 39 |
| political_affiliation      | 23  | 7  | 25 | 40 |
| state_of_death            | 19  | 0  | 0  | 0  |
| shareholders              | 19  | 0  | 0  | 0  |
| siblings                  | 16  | 50 | 33 | 40 |
| schools_attended          | 14  | 80 | 41 | 54 |
| date_of_birth             | 11  | 100| 85 | 92 |
| other_family              | 9   | 0  | 0  | 0  |
| age                       | 4   | 97 | 94 | 94 |
| #_of_employees            | 3   | 0  | 0  | 0  |
| religion                  | 2   | 100| 29 | 44 |
| website                   | 0   | 25 | 0  | 6  |

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The table shows the number of examples annotated and the performance metrics for each relation. The metrics include precision (P), recall (R), and F1 score (F1) for the end-to-end slotfilling performance. Positive changes are shown in green, negative changes in red.
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