Multilingual NER Transfer for Low-resource Languages

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Abstract

In massively multilingual transfer NLP models over many source languages are applied to a low-resource target language. In contrast to most prior work, which use a single model or a small handful, we consider many such models, which raises the critical problem of poor transfer, particularly from distant languages. We propose two techniques for modulating the transfer: one based on unsupervised truth inference, and another using limited supervision in the target language. Evaluating on named entity recognition over 41 languages, we show that our techniques are much more effective than strong baselines, including standard ensembling, and our unsupervised method rivals oracle selection of the single best individual model.²

1 Introduction

Supervised learning remains king in natural language processing, with most tasks requiring large quantities of annotated corpora. The majority of the world’s 6,000+ languages however have limited or no annotated text, and therefore much of the progress in NLP has not been realised for the majority. Cross-lingual transfer learning is a technique which can compensate in part for the dearth of data, by transferring knowledge from high- to low-resource languages, which has typically taken the form of projection of annotation over aligned parallel corpora or other multilingual resources Yarowsky et al. (2001); Hwa et al. (2005), or making use of transferable representations, such as phonetic transcriptions Bharadwaj et al. (2016), closely related languages Cotterell and Duh (2017) or bilingual dictionaries Mayhew et al. (2017); Xie et al. (2018).

Most proposed models for cross-lingual transfer rely on a single source language, which limits the transferable knowledge to only one source. The target language might be similar to many source languages, on the grounds of the script, word order, loan words etc, and transfer would benefit from these diverse sources of information. There are few exceptions, which use transfer from several languages, ranging from multitask learning Duong et al. (2015); Ammar et al. (2016); Fang and Cohn (2017), and annotation projection from several languages Täckström (2012); Fang and Cohn (2016); Plank and Agić (2018). However, to the best of our knowledge, none of these approaches adequately account for the quality of transfer, but rather “weight” the contribution each language uniformly.

* Both authors have equally contributed to this work.
² The code and the datasets will be made available at https://github.com/afshinrahimi/mmner.

Preprint. Work in progress.
In this paper, we propose a novel method for multilingual transfer, inspired by research in truth inference in crowd-sourcing, a related problem, in which the ‘ground truth’ must be inferred from the outputs of several unreliable annotators Dawid and Skene (1979). In this problem, the best approaches include means of individuals’ reliability, and their patterns of mistakes Kim and Ghahramani (2012). Our proposed model adapts these ideas to a multilingual transfer setting, whereby we learn the quality of transfer, and language-specific transfer errors, in order to infer the best labelling in the target language, as part of a Bayesian graphical model. The key insight that while the majority of poor models make lots of mistakes, these mistakes are diverse, while the few good models consistently provide reliable input. This allows the model to infer which are the reliable models in an unsupervised manner, i.e., without explicit supervision in the target language, and thereby make accurate inferences despite the substantial noise.

In the paper, we also consider a supervised setting, where a tiny annotated corpus is available in the target language. We present two methods to use this data: 1) estimate reliability parameters of the Bayesian model, and 2) explicit model selection and fine-tuning of a low-resource supervised model, thus allowing for more accurate modelling of language specific parameters, such as character embeddings. The latter method works by first training a model on unlabelled target data annotated by pretrained models from a diverse set of source languages, and then fine-tuning that model with the limited annotated data available in the target language. Contrasting to the multitask settings, our model doesn’t rely on annotated data in the source languages, which is very important if the source language corpora are proprietary, or retraining the source models is time-consuming.

We evaluate on named entity recognition (NER), over a collection of 41 language corpora, using a leave-one-language-out evaluation setting, i.e., in each case using 40 languages as input. We show that single model transfer has very variable performance, with F1 scores ranging from 0 to 80, and in many cases, the closest related language does not result in the best transfer. Additionally, we show that uniform ensembling is not very effective, substantially underperforming the single best model. In contrast, our unsupervised approaches do much better, exceeding the performance of the single best model, and our supervised models produces further gains.

The paper is structured as follows: in §2, we introduce the two unsupervised (BEA_uns) and supervised (RaRe) approaches for multilingual transfer, we describe the data and experiment details in §3, report the NER performance of the models in §4, review related work in §5, and conclude in §6.

2 Approach

We frame the problem of multilingual transfer as follows. We assume a collection of $H$ models, all trained in a high resource setting, denoted $M^h = \{M^i_h, i \in (1, H)\}$. Each of these models are not well matched to our target data setting, for instance these may be trained on data from different domains, or on different languages, as we evaluate in our experiments, where we use cross-lingual embeddings for model transfer. This is a problem of transfer learning, namely, how best we can use the $H$ models for best results in the target language.\footnote{We limit our attention to transfer in a ‘black-box’ setting, that is, given predictive models, but not assuming access to their data, nor their implementation. This is the most flexible scenario, as it allows for application to settings with closed APIs, and private datasets. However, it preclude multitask learning, as the source models are assumed to be static.}

Simple approaches in this setting include a) choosing a single model $M \in M^h$, on the grounds of practicality, or the similarity between the model’s native data condition and the target, and this model is used to label the target data; or b) allowing all models to ‘vote’ in an classifier ensemble, such that the most frequent outcome is selected as the ensemble output. Unfortunately neither of these approaches are very accurate in a cross-lingual transfer setting, as Figure 1 illustrates, showing that using a single model (English: \texttt{en}) is often a terrible choice, and this is also often true for majority voting. The oracle best language does much better, however it is not always a closely related language (e.g., Italian: \texttt{it} does best for Indonesian: \texttt{id}, despite the target being closer to Malay: \texttt{ms}). Note the collection of Cyrillic languages (bg, mk, uk) where the oracle is substantially better than the majority vote, which is likely due to script differences. The transfer relationship is not symmetric e.g., Persian: \texttt{fa} does best for Arabic: \texttt{ar}, but German: \texttt{de} does best for Persian.

Figure 1 also shows that ensemble voting is well below the oracle best language, which is likely to be a result of error correlation: groups of models all make mistakes on the same instances, and
Motivated by these findings, we propose novel methods for learning. Where no labelled data is available in the target, we propose the BEA$_{uns}$ method inspired by work in truth inference from crowd-sourced datasets (§2.1). §2.2 presents a rival supervised technique, RaRe, based on using very limited annotations in the target language for model selection and classifier fine-tuning.

2.1 Model Transfer as Truth Inference

One way to improve the performance of the ensemble system is to select a subset of component models carefully, or more generally, learn a non-uniform weighting function. Clearly some models do much better than others, on their own, so it stands to reason that identifying these handful of models will give rise to better ensemble performance. How might we proceed to learn the relative quality of models in the setting where no annotations are available in the target language? This is a classic unsupervised inference problem, for which we propose a probabilistic graphical model, inspired by Kim and Ghahramani (2012).

We develop a generative model, illustrated in Figure 2, of the transfer models’ predictions, $y_{ij}$, where $i \in [1, N]$ is an instance (a token or an entity span), and $j \in [1, H]$ indexes a transfer model. The generative process assumes a ‘true’ label, $z_i \in [1, K]$, which is corrupted by each worker, in producing the observation, $y_{ij}$. The corruption process is described by

$$P(y_{ij} = l | z_i = k, V^{(j)}) = V^{(j)}_{kl}$$

where $V^{(j)} \in R^{K \times K}$ is a worker-specific confusion matrix.

For simplicity, hereinafter we refer to $y_{ij}$ as ‘annotations’ and the transfer models as ‘workers’. This reflects the inspiration of our approach from models of truth inference from crowd-sourcing Dawid and Skene (1979).
To complete the story, the confusion matrices are drawn from vague row-wise independent Dirichlet priors, with a parameter $\alpha = 1$\textsuperscript{5} and the true labels are governed by a Dirichlet prior, $\pi$, which is drawn from an uninformative Dirichlet distribution with a parameter $\beta = 1$.

Inference under this model involves explaining the observed $Y$ in the most efficient way. Where several workers have identical outputs, $k$, on an instance, this can be explained by letting $z_i = k$\textsuperscript{6} and the workers’ confusion matrices assigning high probability to $V_{kk}^{(j)}$. Other, less reliable, workers will have divergent labels, which are less likely to be in agreement, or else are heavily biased towards a particular class. Accordingly, the model can better explain these outputs through label confusion, using the off-diagonal elements of the confusion matrix. Aggregated over a corpus of instances, the model can learn to differentiate between those reliable workers, with high $V_{kk}^{(j)}$ and those less reliable ones, with high $V_{kl}^{(j)}$, $l \neq k$. This procedure applies per-label, and thus worker ‘reliability’ is with respect to a specific label, and may differ between classes. This helps in the NER setting where many poor classifiers have excellent accuracy for the outside label, but considerably worse performance for all entity labels.

For inference, we use mean-field variational Bayes Jordan (1998), which learns a variational distribution, $q(Z, V, \pi)$ to optimise the evidence lower bound (ELBO),

$$\log P(Y | \alpha, \beta) \geq \mathbb{E}_q(Z, V, \pi) \log \frac{P(Y, Z, V, \pi | \alpha, \beta)}{q(Z, V, \pi)}$$

assuming a fully factorised variational distribution, $q(Z, V, \pi) = q(Z)q(V)q(\pi)$. This gives rise to an iterative learning algorithm with update rules:

$$\mathbb{E}_q \log \pi_k = \psi \left( \beta + \sum_i q(z_i = k) \right) - \psi (K \beta + N)$$

$$\mathbb{E}_q \log V_{kl}^{(j)} = \psi \left( \alpha + \sum_i q(z_i = k)1[y_{ij} = l] \right) - \psi \left( K\alpha + \sum_i q(z_i = k) \right)$$

$$q(z_i = k) \propto \exp \left\{ \mathbb{E}_q \log \pi_k + \sum_j \mathbb{E}_q \log V_{kj}^{(j)} \right\}$$

where $\psi$ is the digamma function, defined as the logarithmic derivative of the gamma function. The sets of rules (1) and (2) are applied alternately, to update the values of $\mathbb{E}_q \log \pi_k$, $\mathbb{E}_q \log V_{kl}^{(j)}$, and $q(z_{ij} = k)$ respectively. This repeats until convergence, when the difference in the ELBO between two iterations is smaller than a threshold.

The final prediction of the model is based on $q(Z)$, using the maximum a posteriori label $\hat{z}_i = \arg \max_z q(z_i = z)$. This method is referred to as $\text{BEA}_{\text{uns}}$.

### 2.1.1 Token versus Entity Granularity

Our proposed aggregation method in §2.1 is based on an assumption that the true annotations are independent from each other, which simplifies the model but may generate undesired results. That is, entities predicted by different models could be mixed, resulting in labels inconsistent with the BIO scheme. Table 1 shows an example, where a sentence with 4 is annotated by 5 models with 4 different predictions, among which at most one is correct as they overlap. However, the aggregated result in the token view is a mixture of two predictions, which is supported by no classifiers.

\textsuperscript{5}Using a non-uniform prior to encourage a dominant diagonal did not have a noticeable effect. We consider a supervised setting in §2.2 where this prior is modified to encode empirical confusion statistics.

\textsuperscript{6}Although there is no explicit breaking of the symmetry of the model, we initialise inference using the majority vote, which results in a bias towards this solution.
| $w_1$ | $w_2$ | $w_3$ | $w_4$ | $[1,4]$ | $[2,4]$ | $[3,4]$ |
|-------|-------|-------|-------|--------|--------|--------|
| $M^h_1$ | B-ORG | I-ORG | I-ORG | I-ORG | ORG | O | O |
| $M^h_2$ | O | B-ORG | I-ORG | I-ORG | O | ORG | O |
| $M^h_3$ | O | O | B-ORG | I-ORG | O | O | ORG |
| $M^h_4$ | O | B-PER | I-PER | I-PER | O | PER | O |
| $M^h_5$ | O | B-PER | I-PER | I-PER | O | PER | O |
| **Agg.** | O | B-PER | I-ORG | I-ORG | O | PER | O |

Table 1: An example sentence with its aggregated labels in both token view and entity view. Aggregation in token view may generate results inconsistent with the BIO scheme.

To deal with this problem, we consider aggregating the predictions in the entity view. As shown in Table 1, we convert the predictions for tokens to predictions for ranges, aggregate labels for every range, and then resolve remaining conflicts. A prediction is ignored if it conflicts with another one with higher probability. By using this greedy strategy, we can solve the conflicts raised in entity-level aggregation. We use superscripts $^{tok}$ and $^{ent}$ to denote token-level and entity-level aggregations, i.e. $BEA_{uns}^{tok}$ and $BEA_{uns}^{ent}$.

2.1.2 Spammer Removal

Raykar and Yu (2012) show that iteratively removing spammers and re-estimating the true labels based on remaining workers can improve the accuracy of estimation. Here spammers are defined as workers whose confusion matrix can be well approximated by an outer product of two vectors, i.e. a rank-1 matrix. Such matrices have identical rows, i.e. $p(y_{ij} = l | z_i = k) = p(y_{ij} = l | z_i = k')$, thus their labels are independent from the true labels and not informative for estimating the truth. Even worse, due to the goal of maximizing the likelihood of all observed labels, the fact that labels from spammers can’t be well explained by the truth can make the model alter the truth to better explain spammers’ labels. This effect degrades the quality of truth inference.

In our NER transfer task, classifiers are diverse in their F1 scores ranging from almost 0 to around 80, so spammer removal is necessary. We adopt a simple strategy that first estimates the confusion matrices for all classifiers on all labels, then ranks classifiers based on their mean recall on different entity categories (elements on the diagonals of their confusion matrices), and then runs the model again on labels from the top $k$ classifiers only. We call this method $BEA_{uns} \times 2$ and its results are reported in §4.

2.2 Using Target Supervision

Until now, we have assumed no access to annotations in the target language. However, when some labelled text is available, how might this best be used? In our experimental setting, we assume a modest set of 100 labelled sentences, in keeping with a low-resource setting Garrette and Baldridge (2013). We propose two models $BEA_{sup}$ and RaRe in this setting.

**Supervising BEA ($BEA_{sup}$)** One possibility is to use the labelled data to find the posterior for the parameters $V^{(j)}$ and $\pi$ of the Bayesian model described in §2.1. Let $n_k$ be the number of instances in the labelled data whose true label is $k$, and $n_{jkl}$ the number of instances whose true label is $k$ and classifier $j$ labels them as $l$. Then the quantities in Equation (1) can be calculated as

$$E \log \pi_k = \psi(n_k) - \psi(N)$$

$$E \log v_{jkl} = \psi(n_{jkl}) - \psi\left(\sum_l n_{jkl}\right).$$

These are used in Equation (2) for inference on the test set. We refer to this setting as $BEA_{sup}$.

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7Garrette and Baldridge (2013) showed that about 100 sentences can be annotated with POS tags in two hours by non-native annotators.
**Ranking and Retraining (RaRe)** We also propose an alternative way of exploiting the limited annotations, RaRe, which first ranks the systems, and then uses the top ranked models’ outputs alongside the gold data to retrain a model on the target language. The motivation is that the above technique is agnostic to the input text, and therefore is unable to exploit situations where regularities occur, such as common words or character patterns that are indicative of specific class labels, including names, titles, etc. These signals are unlikely to be consistently captured by cross-lingual transfer. Training a model on the target language with a character encoder component, can distil the signal that are captured by the transfer models, while relating this towards generalisable lexical and structural evidence in the target language. This on its own will not be enough, as many tokens will be consistently misclassified by most or all of the transfer models, and for this reason we also perform model fine-tuning using the supervised data.

The ranking step in RaRe proceeds by evaluating each of the $H$ transfer models on the target gold set, to produce scores $s_h$ (using the F1 score). The scores are then truncated to the top $k \leq H$ values, such that $s_h = 0$ for those systems not ranked in the top $k$, and the results normalised

$$\omega_h = \frac{s_h}{\sum_{j=1}^k s_j}.$$  

(3)

The range of scores are quite wide, covering $0.00 - 0.81$ (see Figure 1), and accordingly this simple normalisation conveys a strong bias towards the top scoring transfer systems.

The next step is a distillation step, where a model is trained on a large unannotated dataset in the target language, such that the model predictions match those of a weighted mixture of transfer models, using $\vec{\omega} = (\omega_1, \ldots, \omega_H)$ as the mixing weights. This process is implemented as mini-batch scheduling, where the labels for each mini-batch are randomly sampled from transfer model $h$ with probability $\omega_h$. This is repeated over the course of several epochs of training.

Finally, the model is fine-tuned using the small supervised dataset, in order to correct for phenomena that are not captured from model transfer, particularly character level information which is not likely to transfer well for all but the most closely related languages. Fine-tuning proceeds for a fixed number of epochs on the supervised dataset, to limit overtraining of richly parameterise models on a tiny dataset. Note that in all stages, the same supervised dataset is used, both in ranking and fine-tuning, and moreover, we do not use a development set. This is not ideal, and generalisation performance would likely improve were we to use additional annotated data, however our meagre use of data is designed for a low resource setting where labelled data is at a premium.

### 3 Experiments

#### 3.1 Data

We evaluate using the Wiki-NER dataset Pan et al. (2017), which comprises 282 languages automatically extracted from Wikipedia, based on using the cross-lingual link structure of wikipedia to identify entity spans, alongside grounding in an English knowledge base, and several other techniques such as self-training. Although the annotations in these datasets are automatically generated, and of varying quality, throughout this paper we treat them as gold labels.

We chose 41 of those languages based on the overlap between the NER datasets and accessible bilingual dictionaries from Conneau et al. (2017). We omitted Chinese, Japanese, and Thai, because of difficulties with tokenisation. The distribution of entity annotations was often highly skewed so we created a balanced subset for each language, and split these into training, test, and development sets. We set the development and test set sizes to be either 1k or 10k (depending on how much data was available for the language), and used the remained sentences for training with sizes between 5k to 20k.

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*With ISO 639-1 codes: af, ar, bg, bn, bs, ca, cs, da, de, el, en, es, et, fa, fi, fr, he, hi, hr, hu, id, it, lt, lv, mk, ms, nl, no, pl, pt, ro, ru, sk, sl, sq, sv, ta, tl, tr, uk and vi.*

*The dataset details omitted for space reasons, but the datasets, splits etc. will be made available upon publication.*
Table 2: Data requirements for each of the models, in terms of the number of annotated and unannotated sentences in each target language. Entries with “+” denote variable sizes, depending on the availability of data in each language (see §3.1).

| Annotated train | Unannotated | Models |
|-----------------|-------------|--------|
| 5k+ 1k+         | -           | HSup   |
| 100 100         | -           | LSup   |
| 100 - 5k+       | -           | RaRe   |
| 100 -           | -           | BEA_{sup} |
| - - -           | BEA_{uns x 2} |
|                 | BEA_{uns x MV} |

We use fastText 300 dimensional monolingual embeddings trained on Wikipedia Bojanowski et al. (2017). The monolingual embeddings are in different vector spaces, to create cross-lingual word embeddings we use the bilingual dictionaries and supervised cross-lingual Procrustes rotation method from project MUSE Conneau et al. (2017), such that all language embeddings are mapped to the English vector space. We included embeddings for words in fastText, using a special UNK tag for others. Note that accurate unsupervised methods exist for creating cross-lingual word embeddings (Conneau et al., 2017; Artetxe et al., 2018), which would allow our technique to be applied without the need for bilingual dictionaries.

We experiment in five different data requirement scenarios, relating to the amount of annotated target language data, and the use of unannotated target data, as shown in Table 2. The bottom rows simulate low resource settings, while HSup provides an empirical comparison against a high resource setting. LSup, shows a naive low resource setting without using transfer learning.

Other models compared include:

- **MV** uniform ensemble, a.k.a. “majority vote”;
- **BEA_{uns x 2}, BEA_{uns}** unsupervised aggregation models, applied to entities or tokens (see §2.1);
- **BEA_{sup}** supervised estimation of BEA prior (§2.2);
- **RaRe** supervised ranking and retraining model (§2.2); and
- **Oracle** selecting the best performing single transfer model, based on test performance.

As the sequential tagger, we use a BiLSTM-CRF Lample et al. (2016), which has been shown to result in state-of-the-art results in high resource settings. This model includes both word embeddings (for which we used fixed cross-lingual embeddings) and character embeddings, to form a parameterised potential function in a linear chain conditional random field. We trained models on all 41 languages, which were then used for transfer in a leave-one-out setting, i.e., taking the predictions of 40 models into a single target language. The same BiLSTM-CRF is also used for RaRe and the pre/re-training steps in RaRe.

The parameters of the model and optimiser were taken from Lample et al. (2016), with the exception of batch size and learning rate. We tuned the batch size and the learning rate using development sets in four languages, and then fixed these hyperparameters for all other languages in each model. The batch size was 1 sentence in low-resource scenarios (in baseline LSup and fine-tuning of RaRe), and to 100 sentences, in high-resource settings (HSup and the pretraining phase of RaRe). The learning rate was set to 0.001 and 0.01 for the high-resource and low-resource baseline models, respectively.

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10. https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md
11. https://github.com/facebookresearch/MUSE
12. One might expect better results using embeddings from subwords for words not covered in fastText, however, our preliminary results for LSup on English showed a reduction in performance when doing so, versus using UNK token. This might be due to OOVs being a good indicator of named entities captured by UNK.
13. Afrikaans, Arabic, Bulgarian and Bengali.
Table 3: The top features that appeared the most on top important features in predicting the $F_1$ performance of source-target NER transfer task.

and to 0.0005, 0.005 for the pretraining and fine-tuning phase of RaRe based on development results for the four languages.

To avoid overfitting, we use early stopping based on a validation set for the HSup, and LSup baselines. For RaRe, given that the model is already trained on noisy data, we stop fine-tuning after only 5 iterations, chosen based on the performance for the four languages.

### 3.2 Predicting Transfer Quality

When transferring models from a high-resource source languages to a target language, a natural question is how much to trust each source language. We now take a brief detour to assess how well this can be characterised by assumption, or using explicit modelling.

Previous work has indirectly measured the expertise of a source language using intuition about language similarities. For example, when a Russian source model is used to transfer to Ukrainian target data, it is implicitly accepted that the expertise of a Russian model on Ukrainian data is probably more than an English model. Where gold labels are available for the target language, it is possible to measure the expertise of several source languages using their $F_1$ over the available annotated data as formulated in Equation 3, as we did for the 41 languages. The best performing source language for direct transfer on a subset of the languages is shown in Figure 1, and is compared with using English as the source language, with unsurprising results such as ru is best for bg, but also unexpected results such as de performing best for fa.

In contrast to the models proposed in the paper, here we consider measuring prediction quality based on language typology features. For example, if the target language is SOV, it is less likely to have a named entity at the end of the sentence. A target language that’s SOV might capture this feature better than a VSO language. We use the language script id\textsuperscript{14}, language family features Hammarström et al. (2015) and the syntactic typological features Dryer et al. (2005); Collins and Kayne (2009); Lewis and Gary (2015), collected in Littell et al. (2017), to analyise their effect on source-target NER transfer. Given the typological features of a language, the goal is to predict which languages would best perform as a source language for transfer. We frame this as random forest regression to predict the $F_1$ score, based on the shared binary features between pairs of languages and the target language id\textsuperscript{15}, applied to our combinations of $41 \times 40 = 1,640$ language pairs. Given an unseen target language, the model learns to predict the expected $F_1$ performance of other source languages.

The performance in terms of mean MSE $F_1$ over training and test languages was 5 and 206, respectively. The performance varies depending on presence of related languages in terms of syntax and language family ranging from maximum of 1099 (±33 in $F_1$) for bn, to 437 and 405 for ar and el, to 120 and 46 for id and et, which have similar languages ms and fi, respectively, in the training set. The most compelling finding, though, is that Latin and Cyrillic script, and syntactic features related to word order appeared as the most important, as shown in Table 3. These relate to presence of articles, word ordering within phrases and the canonical sentence ordering, confirming our hypothesis about language similarity giving rise to better transfer, which we leave for future work.

\textsuperscript{14}The 41 languages are written with 8 scripts: Latin, Cyrillic, Arabic, Bengali, Greek, Hebrew, Hindi, and Tamil.

\textsuperscript{15}This feature adds a bias term for each language, and breaks symmetry.
Figure 3: The mean and standard deviation for the $F_1$ score of the proposed unsupervised models (BEA$_{tok}$ and BEA$_{ent}$), supervised models (RaRe and BEA$_{ent}$ t10) compared with high- and low-resource models HSup and LSup, and majority voting (MV$_{tok}$) in terms of entity level $F_1$ over the 41 languages summarised from Table 4. The $x$ axis shows the annotation requirement of each model in the target language where “200” means 100 sentences each for training and development, and “5K+” means using all the available annotation for training and development sets. Points with the same colour have equal data requirement.

4 Results

We report the results for the proposed low-resource supervised models (RaRe and BEA$_{sup}$), and unsupervised models (BEA$_{uns}$ and BEA$_{uns}$×2) for each of the 41 languages in Table 4, and compare them with high- and low-resource supervised baselines (HSup and LSup, respectively). Figure 3 shows summary statistics for these models, alongside their annotation requirement. The best achievable performance of $F_1 = 89.4$ is achieved with a high supervision (HSup), while very limited supervision (LSup) results in a considerably lower $F_1$ of 63.6. The results for MV$_{tok}$ show that uniform ensembling of multiple source models is even worse, by about 3 points.

Unsupervised truth inference improves dramatically over MV$_{tok}$, and BEA$_{ent}$ outperforms BEA$_{tok}$, and also showing the effectiveness of inference over entities (BEA$_{ent}$) rather than tokens in BEA$_{tok}$.

It is clear that having access to limited annotation in the target language makes a substantial difference in BEA$_{sup}$ and RaRe with $F_1$ of 77.0 and 78.5, respectively. Moreover, Figure 4 shows that adding more source languages to RaRe generally improves the transfer, especially when we have no prior knowledge of transfer quality, which will often be the case for many low-resource language scenarios.

The detailed results in Table 4 show that majority voting works reasonably well for Roman and Germanic languages, which are well represented in the dataset, but fails miserably compared to single best for Slavic languages (e.g. ru, uk, bg) where there are only a few related languages. For most of the isolated languages (ar, fa, he, vi, ta), explicitly training a model in RaRe outperforms BEA$_{ent}$, showing that relying only on aggregation of annotated data has limitations, in that it cannot exploit character and structural features.

An important question is how the other models, particularly the unsupervised variants, are affected by the number and choice of sources languages. Figure 5 charts the performance of MV and BEA against the number of source language classifiers, comparing the use of ideal or realistic selection methods to attempt to find the best input classifiers. Even when coupled with supervised data for ordering the source classifiers, MV does poorly, and does not show any benefit from using more than 3 classifiers.\footnote{The sawtooth pattern arises from the increased numbers of ties (broken randomly) with even numbers of inputs.} In contrast, BEA continues to improve with substantially more inputs: in a “cheating” setting where the oracle ranking is used, but with BEA$_{ent}$, performance peaks at 7 inputs. However, BEA$_{sup}$ outperforms further, by about 1 $F_1$ point, showing that the model is highly effective at discriminating between good and bad input models, and accordingly filtering out the bad inputs gives
Table 4: $F_1$ scores on the test set, comparing baseline supervised models (HSup, LSup (5 runs)), multilingual transfer from top $k$ source languages (RaRe, 5 runs, $k = 1, 10$) and aggregation methods: majority voting (MVtok), BEAtok and BEAents (Bayesian aggregation in token- and entity-level), and the oracle single best annotation (Oracle). The mean and standard deviation over all 41 languages, $\mu, \sigma$, are also reported.
Figure 4: The mean and standard deviation $F_1$ performance of RaRe over the 41 languages categorised by the number of source languages used for transfer. The top $k$ languages are chosen either based on $F_1$ performance of the source model on the target language (●), or randomly (■).

Figure 5: The mean $F_1$ performance of MVent, BEAent sup, BEAent uns, BEAent uns × 2, BEAent sup, cheat (cheating selection) over the 41 languages categorised by the number of source languages used for transfer.

the best results. The BEAent uns × 2 curve shows the effect of filtering using purely unsupervised signal, which has a positive, albeit more mild, effect on performance. Note also that neither of the curves for the two realistic BEA scenarios (unsupervised: BEAent uns × 2, and supervised: BEAent sup) show evidence of the sawtooth pattern, i.e., they largely benefit from more inputs, irrespective of their parity.

5 Related Work

Cross-lingual transfer approaches can broadly be classed into annotation or representation projection, based on the manner in which information from high resource languages are transferring into the target language.

Annotation Projection: In annotation projection, the annotations of tokens in a source sentence are projected to their aligned tokens in the target language through a parallel corpus. Annotation projection has been applied to POS tagging Yarowsky et al. (2001); Das and Petrov (2011); Duong et al. (2014); Fang and Cohn (2016), NER Zitouni and Florian (2008); Ehrmann et al. (2011), and parsing Hwa et al. (2005); Rasooli and Collins (2015). The Bible, Europarl, and recently the Watchtower has been used as parallel corpora, which are limited in genre, size, and language coverage, motivating the use of Wikipedia to create weak annotation for multilingual tasks such as NER Nothman et al. (2013).
Annotations can also be projected through cheap translation models from gold bilingual dictionaries Mayhew et al. (2017). Recent advances in (un)supervised bilingual dictionary induction Gouws and Søgaard (2015); Duong et al. (2016); Conneau et al. (2017); Artetxe et al. (2018) has enabled cross-lingual lexical alignment without parallel corpora, which can be used to project annotations Xie et al. (2018). Most annotation projection methods with few exceptions Täckström (2012); Plank and Agić (2018) use only one language (often English) as the source language. In multi-source language setting, majority voting is often used to aggregate noisy annotations (e.g. Plank and Agić (2018)). Fang and Cohn (2016) show the importance of modelling the annotation biases that the source language(s) might project to the target language.

**Representation Projection:** Representation projection learns a model in a high-resource source language using representations that are cross-linguistically transferable, and then directly applies the model to data in the target language. This can include the use of cross-lingual word clusters Täckström et al. (2012) and word embeddings Ammar et al. (2016); Ni et al. (2017), multitask learning with a closely related high-resource language (e.g. Spanish for Galician) Cotterell and Duh (2017), or bridging the source and target languages through phonemic transcription Bharadwaj et al. (2016) or Wikification Tsai et al. (2016).

**Transfer from multiple source languages:** Previous work has shown the improvements of multi-source transfer in NER Täckström (2012); Fang et al. (2017), POS tagging Snyder et al. (2009); Plank and Agić (2018), and parsing Ammar et al. (2016) compared to single source transfer, however, multi-source transfer might be noisy as a result of divergence in script, phonology, morphology, syntax, and semantics between the source languages, and the target language. To capture such differences, various methods have been proposed: latent variable models Snyder et al. (2009), majority voting Plank and Agić (2018), utilising typological features Ammar et al. (2016), or explicitly learning annotation bias Fang and Cohn (2017). In this work, we use truth inference to model the transfer annotation bias from diverse source models.

**Truth Inference in Crowd-sourcing:** Since Dawid and Skene (1979) proposed a model to aggregate the clinical diagnoses of doctors, various methods have been proposed to aggregate information from diverse and sometimes conflicting sources, including predictions from different classifiers (Kim and Ghahramani, 2012), annotations from crowd-sourcing workers (Whitehill et al., 2009; Welinder et al., 2010), and entity descriptions from web pages or databases (Zhao et al., 2012; Li et al., 2014). Most of them adopt an iterative approach that alternatively estimates the latent truth and the source reliability, where the source reliability is commonly captured by a confusion matrix. Among existing works, the most related one to ours is Kim and Ghahramani (2012), which are both Bayesian models for classifier combination, but differ in terms of model structure, such as the use of hyper-priors, as well as inference algorithm (Gibbs sampling vs. variational inference).

6 Conclusion

Cross-lingual transfer does not work out of the box, especially when using large numbers of source languages, and distantly related target languages. In an NER setting using a collection of 41 languages, we showed that simple methods such as uniform ensembling do not work well, which we show can be explained, in part, by linguistic typology. We proposed two new multilingual transfer models (RaRe and BEA), based on unsupervised transfer, or a supervised transfer setting with a small 100 sentence labelled dataset in the target language. Our unsupervised method, BEA_{uns}, provides a fast and simple way of annotating data in the target language, which is capable of reasoning under noisy annotations, and outperforms several competitive baselines, including the majority voting ensemble, a low-resource supervised baseline, and the oracle single best transfer model. We show that light supervision improve performance further, and that our second approach, RaRe, based on ranking transfer models, and then retraining on the target language, results in further performance improvements, and is more consistent across target languages.

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