Bayesian Ensembles of Crowds and Deep Learners for Sequence Tagging

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Abstract

Current methods for sequence tagging, a core task in NLP, are data hungry. Crowdsourcing is a relatively cheap way to obtain labeled data, but the annotators are unreliable, so redundant labeling and aggregation techniques are required. We evaluate multiple models of annotator reliability and develop a Bayesian method for aggregating sequence labels from multiple annotators. Typically, the process of data collection, aggregation and training a sequence tagger is a pipeline of discrete steps. We integrate these steps by training black-box sequence taggers as components in the aggregation model and accounting for their unreliability. We evaluate our model on named entity recognition and information extraction tasks, showing that our method outperforms previous methods, particularly in small data scenarios that are encountered at the beginning of a crowdsourcing process. Our code is published to encourage adaptation and reuse.

1 Introduction

The high demand for labeled training data in current NLP methods, particularly deep learning, is widely recognized (Zoph et al., 2016; Rastogi et al., 2016; Gormley et al., 2014). A common NLP task that has benefited from deep learning is *sequence tagging*, which involves classifying sequences of tokens for tasks such as named entity recognition (NER), part-of-speech tagging (POS), or information extraction (IE). Neural network sequence taggers are typically trained on tens of thousands of documents (Ma and Hovy, 2016; Lample et al., 2016). This requirement for large labeled datasets presents a challenge when facing new domains or tasks, where obtaining labels is often time-consuming or costly.

One way to obtain labeled data relatively cheaply is crowdsourcing, in which large numbers of untrained workers annotate documents instead of more expensive experts. However, this requires aggregating multiple unreliable labels for each document. We could also obtain noisy labels from models trained on different domains, multiple experts, or users of applications who click on and interact with text. Probabilistic methods for aggregating unreliable classifications have been shown to be more accurate than simple heuristics such as majority voting (Raykar et al., 2010; Sheshadri and Lease, 2013; Rodrigues et al., 2013; Hovy et al., 2013). However, work on sequence tagging is less extensive and existing methods cannot model some common annotator error patterns or the effects of the order of annotators' labels (Rodrigues et al., 2014; Nguyen et al., 2017).

The sequence labeling tasks we consider in this paper follow a *beginning, inside, outside* (*BIO*) scheme, in which the first token in a span of type 'x' is labeled 'B-x', subsequent tokens in the same span are labeled 'I-x', and tokens outside spans are labeled 'O'. We propose an aggregation method that takes advantage of the sequential dependencies between BIO tags to learn the reliability of individual annotators and predict the true sequence.

When learning from noisy or small datasets, commonly-used methods based on maximum likelihood estimation may produce over-confident predictions (Xiong et al., 2011; Srivastava et al., 2014). We therefore apply a Bayesian treatment to our method to account for model uncertainty in our predictions. The resulting posterior probabilities facilitate active learning (Settles, 2010), which aims to reduce the number of labels required to train a model by iteratively selecting the most informative data points to label.

When aggregating crowdsourced data, we can improve performance and make predictions for unlabeled documents by modeling the text features as well as the annotators (Simpson et al., 2015; Felt et al., 2016) For complex tasks such as sequence tagging, we may wish to exploit existing state-of-the-art models, such as neural networks that do not account for model uncertainty. In this paper, we show how to integrate existing black box methods into the aggregation model to construct ensembles of deep learners and human annotators. Our method learns the reliability of each black box method, since they may not always perform well, particularly given small training datasets, and avoids the need to aggregate crowdsourced data using a separate pre-processing step before training a sequence tagger.

This paper provides the following contributions:

- A taxonomy of annotator reliability models and evaluation on sequence tagging tasks
- *Bayesian sequence combination (BSC)*, a method for aggregating sequence labels from multiple annotators that can model sequential dependencies between tags
- A technique for wrapping existing black-box sequence taggers into the aggregation model to improve the quality of aggregated labels

The following sections discuss related work, then detail annotator models for sequence tagging, and present our variational approach that enables us to integrate existing classifiers. We then describe the modular implementation of our proposed method, which is made public with all of our experimental code[1] and can easily be extended to new aggregation problems. The next sections compare different aggregation methods with simulated annotators and two crowdsourced NLP datasets, showing that our Bayesian aggregation method consistently outperforms the previous state-of-the-art. Our experiments evaluate both active and passive learning scenarios with varying dataset sizes, analyze types of errors, and visualize the annotator models learned by our method. Finally, we give conclusions and ideas for future work.

1.1 Related Work

A number of works have investigated methods for aggregating non-sequential classifications from crowds, including Sheshadri and Lease (2013), who benchmarked several aggregation methods. They found the most consistent performance from the method of Raykar et al. (2010), which employs probabilistic confusion matrices to model the reliability of individual annotators, as proposed by Dawid and Skene (Dawid and Skene, 1979). In this paper, we develop and compare variations of this model for sequence tagging, including a variant based on MACE (Hovy et al., 2013). We focus on the core annotator representation, rather than extensions for clustering annotators (Venanzi et al., 2014; Moreno et al., 2015), modeling their dynamics (Simpson et al., 2013), adapting to task difficulty (Whitehill et al., 2009; Bachrach et al., 2012), or time spent (Venanzi et al., 2016).

For aggregating sequence tags, Rodrigues et al. (2014) proposed a CRF-based model, *CRF-MA*, that assumes only one annotator is correct for any given label. Recently, Nguyen et al. (2017) proposed an approach that outperformed CRF-MA, based on hidden Markov models (HMMs), called *HMM-crowd*. Both CRF-MA and HMM-crowd use simpler annotator models than Dawid and Skene (1979) that do not capture the effect of sequential dependencies on annotator reliability. Neither CRF-MA nor HMM-crowd use a fully Bayesian approach, which has been shown to be effective for handling uncertainty due to noise in crowdsourced data for non-sequential classification (Kim and Ghahramani, 2012; Simpson et al., 2013; Venanzi et al., 2014; Moreno et al., 2015). In this paper, we develop a sequential annotator model and a fully Bayesian method for aggregating sequence labels that improves performance over previous approaches.

The HMM adapted by Nguyen et al (2017) uses only a simple model conditional independence model of text features. The authors also show how to train neural network sequence taggers directly on crowdsourced data using an additional network layer to handle worker reliability, similar to Rodrigues and Pereira (2018). However, the proposed approaches did not outperform either CRF-MA (Rodrigues and Pereira, 2018) or HMM-crowd(Nguyen et al., 2017). Albarqouni et al. (2016) integrate a CNN classifier for image annotation into an aggregation method based on expectation maximization (EM) (Dempster et al., 1977). Yang et al. (2018) adapt a Bayesian neural network so that it can be trained concurrently with an annotator model, also using EM. In contrast to previous work, we do not adapt neural net-

[1] http://github.com/***/***

works nor trust their predictions when aggregating annotations using EM. Instead, we propose to learn the reliability of existing sequence taggers using a variational approach, allowing untrusted, off-the-shelf sequence taggers to be enhance the performance of the aggregation method.

2 Modeling Sequential Annotators

When combining multiple annotators with varying skill levels, we can improve performance by modeling the reliability of individuals. Several models have previously been applied that do not consider dependencies between a sequence of annotations. In this section, we describe these existing models and provide an extension that captures sequential dependencies.

Accuracy model (acc): simply models the annotator's accuracy, π, as follows:

$$p(c_\tau = i | t_\tau = i, \pi) = \begin{Bmatrix} \pi & \text{where } i = j \\ \frac{1-\pi}{J-1} & \text{otherwise} \end{Bmatrix}, \quad (1)$$

where c_τ is the label given by the annotator for token τ, t_τ is its true label and J is the number of classes. This is the basis of several previous methods (Donmez et al., 2010; Rodrigues et al., 2013). The limitation of this approach is that it assumes reliability is constant, which means that when one class label is far more common than others, a spammer who always selects the most common label will have a high π.

MACE spamming model (Hovy et al., 2013): This method again assumes a constant annotator accuracy, but also models the case where annotators are incorrect by assuming they label according to a spamming distribution that is independent of the true label.

$$p(c_\tau = i | t_\tau = j, \pi, \xi) = \begin{Bmatrix} \pi + (1-\pi)\xi_j & \text{where } i = j \\ (1-\pi)\xi_j & \text{otherwise} \end{Bmatrix}. \quad (2)$$

While MACE can capture spamming patterns, it does not explicitly model different rates of errors per class. This could be an issue for sequence tagging using the BIO encoding: annotators who start labeling spans one or two tokens early more frequently mis-label the 'B' tokens than the 'I' or 'O' tokens, but this cannot be modeled by MACE.

Confusion vector (CV): learn separate accuracies for each class label (Nguyen et al., 2017) by assuming that $\boldsymbol{\pi}$ is a vector of size J:

$$p(c_\tau = i | t_\tau = j, \boldsymbol{\pi}) = \begin{Bmatrix} \pi_j & \text{where } i = j \\ \frac{1-\pi_j}{J-1} & \text{otherwise} \end{Bmatrix}. \quad (3)$$

For the incorrect label case where $i = j$, $p(c_\tau = i | t_\tau = j, \boldsymbol{\pi})$ is constant for all values of $i \neq j$. Therefore, this model does not explicitly capture spamming patterns where one of the incorrect labels has a much higher likelihood than the others.

Confusion matrix (CM) (Dawid and Skene, 1979): this model can be seen as an expansion of the confusion vector so that $\boldsymbol{\pi}$ becomes a JxJ matrix with values given by:

$$p(c_\tau = i | t_\tau = j, \boldsymbol{\pi}) = \pi_{j,i}. \quad (4)$$

This requires a larger number of parameters, $J \times J$, compared to the $J + 1$ parameters of MACE or J parameters of the confusion vector. The confusion matrix therefore represents the probability of each individual mistake, so it can model spammers who frequently chose one label regardless of the ground truth. It can also model annotators in sequence tagging tasks who have different error rates for 'B-x', 'I-x' and 'O' labels, for example, if an annotator is better at detecting type 'x' spans than type 'y', or if they frequently mis-label the start of a span as 'O' when the true label is 'B-x', but are otherwise accurate. However, the confusion matrix ignores the dependencies between annotations in a sequence that affect these probabilities. For instance, it is usually not possible for an annotator to assign an 'I' label that is preceded by 'O'.

Sequential Confusion Matrix (seq): we introduce a new extension to the confusion matrix to model the dependency of each label in a sequence on its predecessor. The likelihood of a label can now be written as follows:

$$p(c_\tau = i | c_{i-1}, t_\tau = j, \boldsymbol{\pi}) = \pi_{j, c_{\tau-1}, i}, \quad (5)$$

where $\boldsymbol{\pi}$ is now three-dimensional with size $J \times J \times J$. In the case of disallowed transitions, e.g. from $c_{\tau-1} =$'O' to $c_\tau =$'I', the value $\pi_{j, c_{i-1}, c_\tau} = 0, \forall j$ does not need to be learned. The sequential model can capture phenomena such as a tendency toward overly long sequences, by learning that $\pi_{O,O,O} > \pi_{O,I,O}$, or a tendency to split spans by inserting 'B' in place of 'I' by increasing the value of $\pi_{I,I,B}$ without affecting $\pi_{I,B,B}$ and $\pi_{I,O,B}$.

The annotator models described above are extensions of one another that can be used as part of the model for aggregating sequential annotations described in the next section. The experiments in Section 6 test whether the more expressive seq annotator model, which has more parameters to learn, is beneficial in a realistic setting.

3 Bayesian Sequence Combination

The generative story for our approach, *Bayesian sequence combination (BSC)*, is as follows. We assume a transition matrix, $\boldsymbol{B}$, where each entry is $B_{j,\iota} = p(t_\tau = \iota | t_{\tau-1} = j)$. We draw each row of the transition matrix, $B_j \sim \text{Dir}(\boldsymbol{\beta}_j)$, where Dir is the Dirichlet distribution. For each document, n, in a set of N documents, we draw a sequence of class labels, $\boldsymbol{t}_n = [t_{n,1}, ..., t_{n,T_n}]$, of length T_n, from $t_{n,\tau} \sim \text{Categorical}(\boldsymbol{B}_{t_{n,\tau-1}})$.

Given K annotators and a choice of the models defined in Section 2, we draw an annotator model for each annotator, k. All of the annotator models are parametrized by probabilities that we draw from Dirichlet distributions. For the acc model, only one parameter, $\pi^{(k)}$, is drawn for annotator k. For MACE, we draw a single value $\pi^{(k)}$ and a vector $\xi^{(k)}$, while for CV we draw J independent values of $\pi_j^{(k)}$, and for CM we draw a vector $\boldsymbol{\pi}_j^{(k)}$ of size J for each true label value $t_\tau = j$. In the case of seq, we draw vectors $\boldsymbol{\pi}_{j,\iota}^{(k)}$ for each true label and each previous label value, ι. We refer to the set of all parameters for the chosen annotator models as $\boldsymbol{A}$, whose prior has hyperparameters $\boldsymbol{\alpha}$.

4 Inference using Variational Bayes

We learn the parameters, $\boldsymbol{A}$ and $\boldsymbol{B}$ and sequence labels $\boldsymbol{t}$ given annotations, $\boldsymbol{c}$, using *variational Bayes*(*VB*) (Attias, 2000). VB is an approximate inference method that avoids the need for expensive sampling steps, while considering prior distributions and accounting for uncertainty over parameters in a Bayesian manner. Each latent variable in the generative model, z, has a variational distribution $q(z)$, that is of the same form as its prior distribution (Dirichlet for $\boldsymbol{B}_j$, Categorical for $t_{n,\tau}$, etc.), defined in Section 3. The parameters of each $q(z)$ are expectations over the other variables in the model. For reasons of space, we do not provide all variational update equations here. However, they can be derived given the generative model stated above.

The VB procedure for BSC is detailed in Algorithm 1, including a step for integrating existing sequence taggers to boost performance of the aggregation method. The sequence taggers act as additional noisy annotators who can also make predictions for unlabeled documents. We integrate a sequence tagger, s, by modeling it as an additional annotator that predicts a sequence of labels, $\boldsymbol{d}_n^{(s)}$, for document n. We treat these predictions as random variables whose joint distribution with the sequence of text tokens, $\boldsymbol{\phi}_n$, is given by:

Input: Annotations, $\boldsymbol{c}$

1. Initialise $\mathbb{E}[\ln \boldsymbol{B}]$, $\mathbb{E}[\ln A]$ and $\hat{\boldsymbol{d}}$ randomly or to prior means;

while $\mathbb{E}[\boldsymbol{t}]$ *not converged* **do**

2. Update $q(t_{n,\tau} = j)$ and $q(t_{n,\tau-1} = j, t_{n,\tau} = j')$, $\forall i, \forall \tau, \forall j$, given $\mathbb{E}[\ln \boldsymbol{B}]$ and $\mathbb{E}[\ln \boldsymbol{A}]$ using the forward-backward algorithm (Ghahramani, 2001);
3. Set true label predictions $\mathbb{E}[t_{n,\tau} = j] = q(t_{n,\tau} = j)$;
4. Retrain sequence taggers using $\mathbb{E}[\boldsymbol{t}]$ as training labels;
5. Use sequence taggers to predict $\hat{\boldsymbol{d}}$;
6. Update $q(\boldsymbol{A})$ and recompute $\mathbb{E}[p(c_{n,\tau}{=}j | c_{n,\tau-1}, t_{n,\tau}{=}\iota, \boldsymbol{\pi})]$ given current $q(t_{n,\tau-1} = j, t_{n,\tau} = j')$;
7. Update $q(\boldsymbol{B})$ and recompute $\mathbb{E}[\ln \boldsymbol{B}]$ given current $q(t_{n,\tau-1} = j, t_{n,\tau} = j')$;

end

Output: Posterior predictions for the true labels, $\mathbb{E}[\boldsymbol{t}]$.

Algorithm 1: The VB algorithm for Seq-BCC.

$$p\left(d_{n,\tau}^{(s)}, \boldsymbol{\phi}_n | \boldsymbol{t}, \boldsymbol{\theta}^{(s)}\right) = p\left(d_{i,\tau}^{(s)} | \boldsymbol{t}, d_{n,\tau-1}^{(s)}, \boldsymbol{A}^{(s)}\right) p\left(\boldsymbol{\phi}_n | d_{n,\tau}^{(s)}, \boldsymbol{\theta}^{(s)}\right), \quad (6)$$

where the first term on the right-hand side is defined by the annotator model with parameters $\boldsymbol{A}^{(s)}$, and $\boldsymbol{\theta}^{(s)}$ are the parameters of the sequence tagger, s. Marginalizing $\boldsymbol{d}_n^{(s)}$ permits us to train the sequence tagger using labels $\mathbb{E}[\boldsymbol{t}]$ and features $\boldsymbol{\phi}_n$, to obtain a prediction function for sequences of labels, $\hat{\boldsymbol{d}}_n^{(s)} = f(\boldsymbol{\phi}_n)$. If we use a Bayesian sequence tagger, $\hat{\boldsymbol{d}}_n^{(s)}$ is the variational distribution, $f(\boldsymbol{\phi}_n) = q(\boldsymbol{d}_n^{(s)})$. However, neural network sequence taggers typically maximize likelihood, so that $\hat{\boldsymbol{d}}_n^{(s)} = \text{argmax}_{\boldsymbol{d}_n^{(s)}} p\left(\boldsymbol{\phi}_n | \boldsymbol{d}_n^{(s)}, \boldsymbol{\theta}^{(s)}\right)$ is the sequence of most likely values. Since we require only f to perform variational updates for

$\boldsymbol{d}_n^{(s)}$, $\boldsymbol{A}^{(s)}$ and $\boldsymbol{t}$, we can treat s as a black box inside a variational wrapper, ignoring its internal details. Therefore, the sequence tagger need not implement a generative model. Where the sequence tagger does not use Bayesian inference, the complete model also does not account for uncertainty in its parameters $\boldsymbol{\theta}^{(s)}$.

Our variational approach allows us to exploit existing sequence taggers to improve the quality of aggregated labels, requiring only that they provide training and prediction functions. By modeling sequence taggers as additional annotators, our approach accounts for their reliability when aggregating labels, and permits the use of noisy sequence taggers, such as those that are not optimized for the current domain.

5 Modular Implementation of Variational Inference

The variational inference method described in Section 4 is naturally suited to a modular implementation. We divide the model into three modules: (a) the true label model, (b) the annotator model, and (c) black-box sequence taggers. The true label model defines the distribution over sequences of labels, $q(\boldsymbol{t}_n)$, and implements lines 2, 3 and 7 in Algorithm 1. The annotator model may be one of those described in Section 2 and implements line 6. The black-box sequence taggers are existing implementations that provide training and prediction functions to predict true labels given text features, and are used in lines 4 and 5.

The true label model exposes methods to compute $q(t_{n,\tau} = j)$ and $q(t_{n,\tau-1} = j, t_{n,\tau} = j')$, $\forall n, \forall \tau, \forall j, \forall j'$ given $\boldsymbol{c}$ and $\mathbb{E}[p(c_{n,\tau} = i | c_{n,\tau-1}, t_{n,\tau} = j, \boldsymbol{\pi})]$. In BSC, the true label model learns a transition matrix, $\boldsymbol{B}$, which assumes a first-order Markov chain. True label models with longer memory could also be used could be used here. The worker models must provide methods to initialise the variational distribution $q(\boldsymbol{A})$, update $q(\boldsymbol{A})$ given $\boldsymbol{c}$, $\hat{\boldsymbol{d}}$, and $\mathbb{E}[\boldsymbol{t}]$, and compute $\mathbb{E}[p(c_{n,\tau}{=}i | c_{n,\tau-1}, t_{n,\tau}{=}j, \boldsymbol{\pi})]$.

By allowing individual functions to be replaced without rewriting the inference method, the modular implementation makes it easier to adapt the model to different types of annotations, such as continuous values or pairwise preferences, to evaluate annotator or true label models, incorporate existing taggers, and even tailor the model to tasks other than sequence tagging, such as regression.

6 Experiments

We evaluate Bayesian sequence combination (BSC) against alternative methods to test (a) the different annotator models described in Section 3, (b) the performance of BSC on unreliable or small training sets, and (c) the benefits of including sequence taggers into the graphical model. The first experiment uses simulated annotators to investigate the effects of different annotator flaws on aggregation methods. We then introduce two NLP datasets to test aggregation performance in passive and active learning scenarios, analyze errors, visualize the learned annotator models, and test LSTM sequence taggers (Lample et al., 2016) trained using our proposed method.

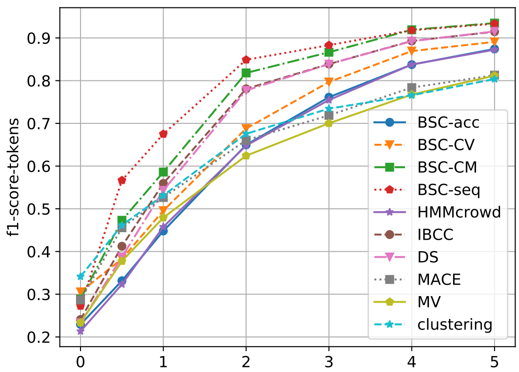
6.1 Evaluated Methods

As established non-sequential baselines, we include token-level majority voting (*MV*), *MACE* (Hovy et al., 2013), Dawid-Skene (*DS*) (Dawid and Skene, 1979) and independent Bayesian classifier combination (*IBCC*) (Kim and Ghahramani, 2012), a Bayesian treatment of Dawid-Skene. We also test the sequential *HMM-crowd* method (Nguyen et al., 2017), which uses a combination of maximum *a posteriori* (or smoothed maximum likelihood) estimates for a confusion vector (CV) annotator model and variational inference for an integrated hidden Markov model. We also introduce a *clustering* baseline, that aggregates spans from multiple annotators by grouping them together using kernel density estimation(Rosenblatt, 1956).

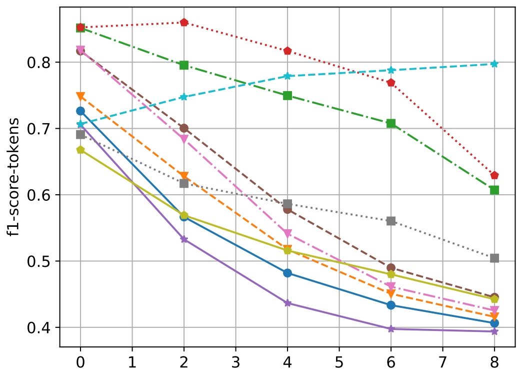
BSC is tested with each of the different annotator models described in Section 2 and integrating different text models. As the default set-up, we integrate a simple black-box classifier that treats all text features as conditionally independent of each other and of the sequence of labels. This set-up is tested with all annotator models. The BSC-seq variant is also tested without a text model (*notext*), and with an integrated LSTM (Lample et al., 2016), labeled *BSC-seq+LSTM*. We also use HMM-crowd and BSC-seq to produce training labels for the LSTM as a separate pre-processing step, labeled in our results as →LSTM.

6.2 Simulated Annotators

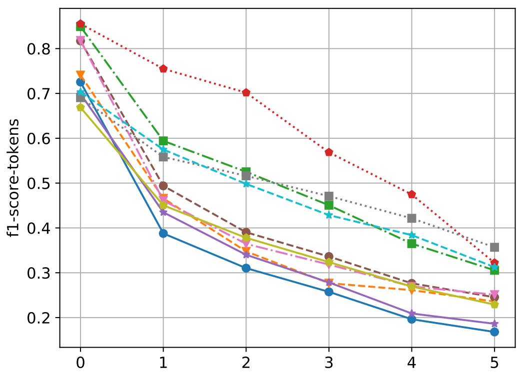
Simulated data allows us to test the effect of one type of error in the crowdsourced data, while keeping other characteristics of the data constant. We



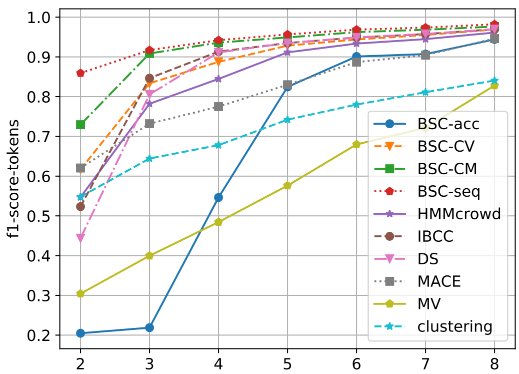
(a) Average annotator accuracy



(b) Short span bias



(c) Missed span bias



(d) Number of good workers out of a crowd of 10, where the rest are random.

Figure 1: F1 scores with simulated annotators. Each plot shows the effect of varying one characteristic.

generate crowds of 10 annotators for four experiments, which test the effect of varying (a) average annotator accuracy, (b) short span bias, i.e. the probability of not including the last tokens in a span, (c) missed span bias, i.e. the probability of missing a span entirely, and (d) the ratio of good to uninformative annotators in the crowd. We simulate annotators using the generative model of BSC-seq, drawing annotator labeling probabilities from Dirichlet distributions. By default, Dirichlet parameters corresponding to incorrect answers are 1, those for correct answers are 2.5, and disallowed transitions (O→I) are close to 0. We then change the parameters of these Dirichlet distributions to obtain the variations described above. We repeat each experiment 25 times, in each case generating 25 documents of 100 tokens each.

Figure 1 shows the F1-scores for our tested methods. Where annotator accuracy is high, majority voting and clustering are less accurate than methods that model individual annotator behavior, although the difference decreases as we introduce more errors. Clustering performs better with high short span bias, as density estimation can compensate for short spans but may over-estimate those of the correct length. Among the BSC variants, performance increases with the complexity of the annotator model, from BSC-acc to BSC-seq, suggesting that this richer model can be successfully learned on a small dataset. There are some benefits for the Bayesian approaches, IBCC and BSC-CV, over the similar models, DS and HMM-crowd, respectively, in handling all four types of annotator error.

6.3 Crowdsourced Datasets

We use two datasets containing both crowdsourced and gold sequential annotations. The CoNLL 2003 named-entity recognition dataset (Tjong Kim Sang and De Meulder, 2003), *NER*, contains gold labels for four named entity categories (PER, LOC, ORG, MISC), with crowdsourced labels provided by (Rodrigues et al., 2014). *PICO* (Nguyen et al., 2017), consists of medical paper abstracts that have been annotated by a crowd to indicate text spans that identify the population enrolled in a clinical trial. Further information about the datasets is shown in Table 6.2. Note that NER spans are typically much shorter than those in PICO.

Dataset	Docs			Sent	Tokens	Workers		Span	Gold	Span length	
	total	gold	crowd	-ences		total	/doc	type	spans	mean	std.
NER	1393	1393	415	6503	179323	47	4.9	PER	6282	1.19	0.49
								LOC	6482	1.73	0.57
								ORG	5789	1.55	0.92
								MISC	3059	1.44	0.80
PICO	4740	191	4740	9480	1424721	312	6.0	population	700	7.74	7.38

Table 1: Numbers of documents, spans, annotators, tokens and sentences for our test datasets.

6.4 Evaluation Metrics

For NER we use the CoNLL 2003 F1-score, which considers only exact span matches to be correct. For PICO, we use the relaxed F1-measure (Nguyen et al., 2017), which counts the matching fractions of spans when computing precision and recall. Since the spans in PICO are longer than those of NER, partial matches may still contain much of the required information. We also compute the cross entropy error (*CEE*) at the level of tokens to compare the probability estimates produced by aggregation methods, which are useful for decision-making tasks such as active learning.

6.5 Aggregating Crowdsourced Labels

In this task, we use the aggregation methods to combine multiple crowdsourced labels and predict the true labels for the same documents. For both datasets, we provide all the crowdsourced labels as input to the aggregation method. In both cases, we split the gold-labelled documents into 50% validation and test sets. For NER, we use the split given by Nguyen et al. (2017), while for PICO, the split was not available so our results are not directly comparable to theirs.

To limit the number of hyperparameters to tune, we optimize only three values for BSC. Hyperparameters of the transition matrix, $\boldsymbol{\beta}_j$, are set to the same value, β_0, except for disallowed transitions, (O→I, transitions between types, e.g. I-PER→I-ORG), which are set to 0.1. For the annotator models, all values are set to α_0, except for disallowed transitions, which are set to 0.1, then γ_0 is added to hyperparameters corresponding to correct annotations (e.g. diagonal entries in a confusion matrix). We use validation set F1-scores to choose values from $[0.1, 1, 10, 100]$, training on a small subset of 250 documents for NER and 500 documents for PICO.

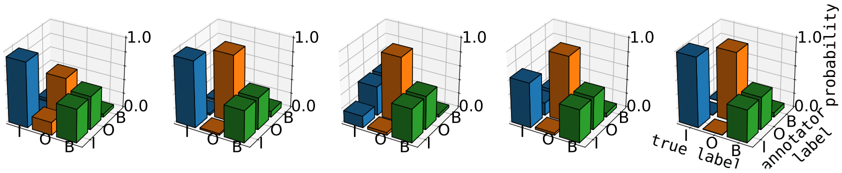
The results of this task are shown in Table 2. Although DS and IBCC do not consider sequence information nor the text itself, they both perform well against HMM-crowd on NER, and BSC-CM variants on PICO. The improvement of DS over the results given by Nguyen et al. (2017) may be due to implementation differences. Neither BSC-acc nor BSC-MACE perform strongly, with F1-scores sometimes falling below MV. The annotator models of BSC-CV and BSC-CM are better, although BSC-CM performs worse on PICO. The sequential annotator model of BSC-seq performs strongly, despite having a larger number of parameters to learn. When the text model is removed, BSC-seq-notext performs worse than BSC-seq, suggesting that incorporating even a simple text model provides a valuable boost. Using the predictions from HMM-crowd or BSC-seq to train an LSTM produces a small improvement, but is outperformed by BSC-seq+LSTM.

To get a deeper understanding of the key methods, we categorize the errors they make and list the counts for each category in Table 3. All machine learning methods shown reduce the number of spans that were completely missed by majority voting. BSC-seq+LSTM increases the number of exact span matches on NER, but reduces this number substantially on PICO while increasing the number of partial matches and false postives (where no true span was present). This appears to be due to a larger number of split spans, where a 'B' token is inserted incorrectly inside a span. Therefore, while BSC-seq outperforms the alternatives in terms of F1-score and missing spans, further work may be required to improve the distinction between 'B' and 'I' tokens.

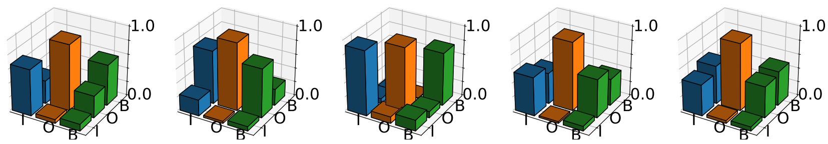
Table 2 shows a benefit of using the sequential annotator model over CM, CV and acc. To understand how BSC uses the richer model in practice, we plot the learned annotator models for PICO as probabilistic confusion matrices in Figure 2. To enable us to visualize the large number of annotator models, we clustered annotators into five groups by applying K-means to their posterior ex-

	NER				Hyperparams.			PICO				Hyperparams.		
	Prec.	Rec.	F1	CEE	β_0	γ_0	α_0	Prec.	Rec.	F1	CEE	β_0	γ_0	α_0
Best worker	76.4	60.1	67.3	17.1				64.8	53.2	58.5	17.0			
Worst worker	55.7	26.5	35.9	31.9				50.7	52.9	51.7	41.0			
MV	79.9	55.3	65.4	6.2				82.5	52.8	64.3	2.6			
MACE	74.4	66.0	70.0	1.0	.1	.1	0	25.4	84.1	39.0	58.2	.1	.1	0
DS	79.0	70.4	74.4	2.8				71.3	66.3	68.7	0.4			
IBCC	79.0	70.4	74.4	**0.5**	.1	1	.1	72.1	66.0	68.9	**0.3**	.1	10	10
HMM-crowd	80.5	69.4	74.6	1.0	0	.1	0	76.5	66.2	71.0	0.8	0	.1	0
HMM-crowd→LSTM	81.8	69.5	75.2	12.2	0	.1	0	76.5	66.5	71.2	12.9	0	.1	0
BSC-acc	83.4	54.3	65.7	1.0	10	.1	10	**89.4**	45.2	60.0	1.6	.1	.1	10
BSC-MACE	67.9	74.1	70.9	0.9	10	10	1	46.7	84.4	60.1	2.0	.1	100	.1
BSC-CV	81.4	64.7	72.1	0.9	10	1	1	74.9	67.2	71.1	0.8	.1	1	.1
BSC-CM	79.9	72.2	75.8	1.5	.1	100	.1	60.1	78.8	68.2	1.5	.1	100	1
BSC-seq	80.3	74.8	77.4	0.7	.1	1	1	72.9	77.6	75.1	1.1	100	1	1
BSC-seq-notext	81.0	69.8	75.0	0.5	.1	1	1	81.2	59.2	68.5	0.7	.1	.1	.1
BSC-seq→LSTM	80.2	75.3	77.7	11.0	.1	1	1	75.7	75.4	75.5	25.5	100	1	1
BSC-seq +LSTM	**82.3**	**75.9**	**78.9**	0.6	.1	1	1	78.7	**78.6**	**78.7**	1.2	100	1	1

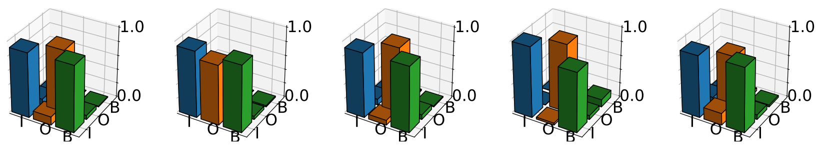
Table 2: Aggregating Crowdsourced Labels: estimating true labels for documents labelled by the crowd.



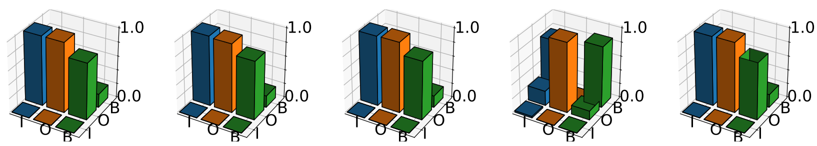
(a) BSC-CV



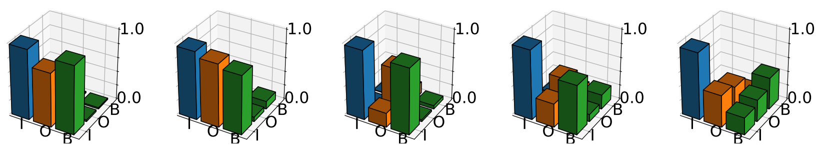
(b) BSC-CM



(c) BSC-seq, previous label = I



(d) BSC-seq, previous label = O



(e) BSC-seq, previous label = B

Figure 2: Clusters of confusion matrix representations from each BSC-*** annotator model trained on PICO.

Method	Dataset	exact match	type wrong only	partial match	missing span	false +ve	late start	early start	late finish	early finish	fused spans	split span
MV	NER	4307	304	228	1773	100	96	10	15	85	17	26
HMM-crowd	NER	4519	361	256	924	182	101	15	26	97	28	22
BSC-CV	NER	4431	275	243	1245	177	100	17	23	89	29	16
BSC-CM	NER	4534	387	258	734	269	111	23	37	86	39	12
BSC-seq+LSTM	NER	4581	351	261	564	195	93	42	33	85	39	17
MV	PICO	168	0	32	185	48	9	11	1	0	3	9
HMM-crowd	PICO	190	0	47	124	81	13	21	0	0	5	8
BSC-CV	PICO	196	0	46	117	81	10	25	0	0	11	0
BSC-CM	PICO	203	0	54	77	192	18	15	8	0	4	18
BSC-seq+LSTM	PICO	81	0	421	75	216	20	6	232	3	24	393

Table 3: Counts of different types of span errors.

pected values. In all clusters, BSC-CV has different heights for the diagonal entries for B, I and O, showing that it learns differences in accuracy for each of these label values. BSC-CM has more distinctive clusters and the first, fourth and fifth have off-diagonal values with different heights for the same true label value. The second cluster for BSC-CM appears to encode very weakly informative labelers who usually choose 'O' regardless of the ground truth. Unlike BSC-CM, BSC-seq improved performance on PICO over BSC-CV. Its confusion matrices are very different depending on the worker's previous annotation. Each column in the figure shows the confusion matrices corresponding to the same cluster of annotators. The first column, for example, shows annotators with a tendency toward I→I or O→O transitions, while the following clusters indicate very different labeling behavior. The model therefore appears able to learn distinct confusion matrices for different workers given previous labels, which supports the use of sequential annotator models.

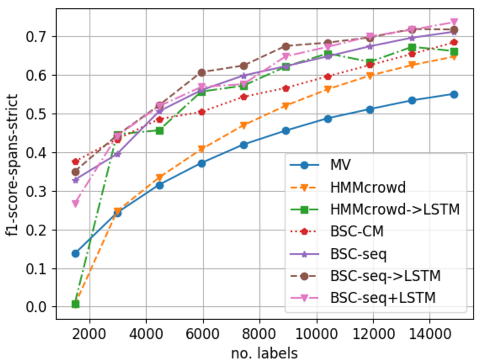
6.6 Small Data and Active Learning

We investigate the performance of the aggregation methods with smaller datasets, and the effectiveness of active learning at improving performance with fewer annotations. Two set-ups were evaluated on NER and PICO: the first tests our methods on random subsamples of crowdsourced data of increasing size; the second starts with a random initial subsample, then uses *uncertainty sampling*, a well-established active learning heuristic (Settles, 2010), to iteratively select additional crowd labels given posterior label predictions from a model trained on the previous subset. We used the same random samples for all methods and repeated the experiments ten times with different initializations.

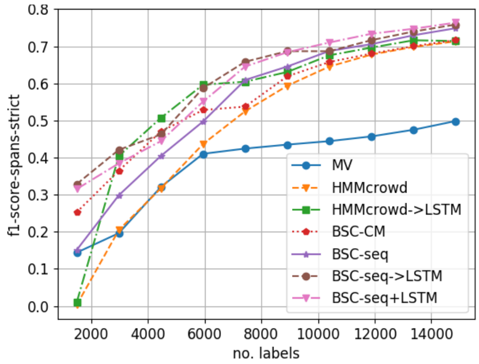
Figure 3 plots the F1 score at each iteration of the random sampling and active learning procedures. BSC performs best with smaller datasets, where it may benefit from a Bayesian approach. Uncertainty sampling appears to have a greater improvement over random sampling on NER after around 7000 labels have been obtained, suggesting that a different strategy could be beneficial while the dataset is very small. On PICO, with its smaller sample sizes, the effect of active learning is only observed with BSC-seq+LSTM. BSC-seq→LSTM and HMM-crowd→LSTM are effective on NER with smaller datasets, improving over BSC-seq and HMM-crowd methods that use only a simple independent text model to make predictions for unlabeled data. However, on PICO, they underperform BSC-seq and HMM-crowd respectively. BSC-seq+LSTM accounts for uncertainty in the predictions of the integrated LSTM, enabling it to outperform BSC-seq→LSTM when active learning aquires more than 10000 labels. We observe that BSC-seq→LSTM learns different values for the accuracy of the integrated LSTM depending on the true class label, even with only 1486 tokens labeled by the crowd.

6.7 Prediction with Crowd-Trained LSTMs

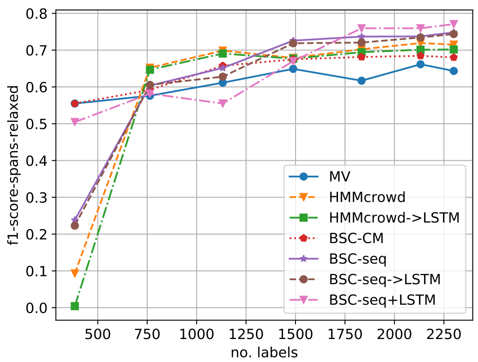
We compare the LSTM sequence taggers (Lample et al., 2016) trained by HMM-crowd and BSC-seq on test data from NER and PICO. For NER, we use the original CoNLL English test set (Tjong Kim Sang and De Meulder, 2003), while for PICO, we train the aggregators on the $3,649$ doc-



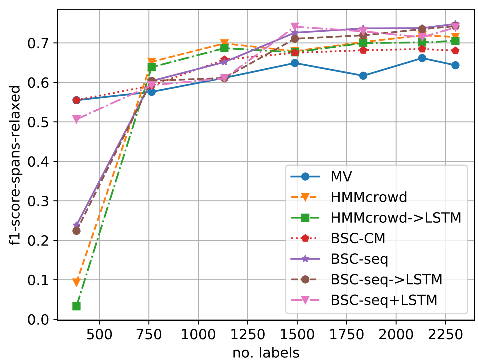
(a) NER, random sampling



(b) NER, active learning simulation



(c) PICO, random sampling



(d) PICO, active learning simulation

Figure 3: Small data subsamples: increasing span-level F1-score.

	NER				PICO			
	Prec.	Recall	F1	CEE	Prec.	Recall	F1	CEE
HMM-crowd→LSTM	**78.7**	59.0	67.5	15.9	**75.6**	61.6	67.9	13.5
BSC-seq→LSTM	74.3	**62.8**	**68.1**	15.65	82.3	**66.4**	**73.5**	19.6
BSC-seq+LSTM	72.3	64.2	68.0	**0.6**	**87.4**	57.9	69.7	**0.9**
LSTM trained on gold labels	76.4	77.0	76.7	11.10				

Table 4: Prediction performance on test datasets with training on crowdsourced labels.

uments without gold labels, then evaluate on the gold-labelled test data split used in Section 6.5.

The results in Table 4 show that the LSTM trained with BSC-seq predictions outperforms that trained using the outputs of HMM-crowd, the previous state-of-the-art (Nguyen et al., 2017). However, while BSC-seq+LSTM also outperforms HMM-crowd→LSTM and produces the lowest cross entropy error, its F1-scores are lower than those of BSC-seq→LSTM.

7 Conclusions

Previous work has demonstrated the benefits of modeling annotator reliability when aggregating noisy data, such as crowdsourced labels. We proposed BSC-Seq, a fully Bayesian approach to aggregating sequence labels, that models the effect of label sequences on annotator reliability, and showed how it improves the state-of-the-art, particularly with small datasets. To further improve the quality of aggregated labels, we designed a variational wrapper for integrating existing black-box sequence taggers, such as deep neural networks. Our results show that this technique can improve aggregated data quality on both active and passive learning tasks.

Future work will evaluate integrating sequence taggers that use Bayesian methods for deep learning, which may improve active learning. We will also investigate alternative data selection strategies to bootstrap active learning, and how to set priors for the reliability of black-box methods by experimenting on other training sets of similar size.

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