Bayesian Ensembles of Crowds and Deep Learners for Sequence Tagging

Anonymous TACL submission

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 theoretical comparison 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. 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. We make the modular implementation of our proposed method freely available, along with our experimental code[1].

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 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 con-

[1] http://github.com/ukplab/arxiv2018-bayesian-ensembles

trast to previous work, we do not require neural networks to be adapted, nor assume that their predictions are reliable when aggregating annotations. Instead, we propose to learn the reliability of existing sequence taggers using a variational approach, allowing untrusted, off-the-shelf sequence taggers to 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 their individual reliability. Here, we describe several existing models that do not consider dependencies between annotations in a sequence, then provide an extension that captures sequential dependencies. Each of the approaches presented employs a particular function, A, to model the likelihood of the annotator choosing the label c_τ given the true label, t_τ, for token τ.

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

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

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). 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 nonetheless have a high π.

MACE spamming model (Hovy et al., 2013): assumes a constant annotator accuracy, π, but that when annotators are incorrect, they label according to a spamming distribution, $\boldsymbol{\xi}$, that is independent of the true label, t_τ.

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

This addresses the case where spammers choose the most common label when the classes are imbalanced. 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, for example, if an annotator frequently labels longer spans than the true spans by starting the spans early. In this case, they may more frequently mis-label the 'B' tokens than the 'I' or 'O' tokens, which cannot be modeled by MACE.

Confusion vector (CV): this approach learns a separate accuracy for each class label (Nguyen et al., 2017) using parameter vector, $\boldsymbol{\pi}$, of size J:

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

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 $J \times J$ matrix with values given by:

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

This requires a larger number of parameters, J^2, compared to the $J+1$ parameters of MACE or J parameters of the confusion vector. CM can model spammers who frequently chose one label regardless of the ground truth, as well as annotators in sequence tagging tasks with 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 dependencies between annotations in a sequence, such as the fact that an 'I' cannot immediately follow an '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, giving the following likelihood:

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

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_τ ='I', the value $\pi_{j,c_{\tau-1},c_\tau} = 0$, $\forall j$ is fixed *a priori*. 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 $\pi_{I,O,B}$.

Many commonly-used annotator models can therefore be seen as extensions of one another. The next section shows how these models can be used as part of a model for aggregating sequential annotations. The experiments in Section 5 test whether the more expressive seq annotator model, which has more parameters to learn, is beneficial in a realistic setting.

3 A Model for Bayesian Sequence Combination

The generative story for our approach, *Bayesian sequence combination (BSC)*, is as follows. We assume a transition matrix, $\boldsymbol{T}$, where each entry is $T_{j,\iota} = p(t_\tau = \iota | t_{\tau-1} = j)$. We draw each row of the transition matrix, $T_j \sim \mathrm{Dir}(\boldsymbol{\gamma}_j)$, where Dir is the Dirichlet distribution. For each document, n, in a set of N documents, we draw a sequence of class labels, $\boldsymbol{t}_n = [t_{n,1}, ..., t_{n,L_n}]$, of length L_n, from a categorical distribution: $t_{n,\tau} \sim \mathrm{Cat}(\boldsymbol{T}_{t_{n,\tau-1}})$. The set of all labels for all documents is referred to as $\boldsymbol{t} = \{\boldsymbol{t}_1, ..., \boldsymbol{t}_N\}$.

For each of K annotators, we choose one of the annotator models defined in Section 2. The number of parameters depends on the choice of model: for *acc*, only one parameter, $\pi^{(k)}$, is drawn for annotator k; for *MACE*, we draw a single value $\pi^{(k)}$ and a vector $\xi^{(k)}$ of length J, 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 $j \in \{1, ..., J\}$; in the case of *seq*, we draw vectors $\boldsymbol{\pi}_{j,\iota}^{(k)}$ for each true label value and each previous label value, ι. All parameters of these annotator models are probabilities, so are drawn from Dirichlet priors. We refer to the set of hyperparameters for k's annotator model as $\boldsymbol{\alpha}^{(k)}$. Given its parameters, the annotator model defines a likelihood function, $A^{(k)}(t_{n,\tau}, \boldsymbol{c}_{n,\tau}, \boldsymbol{c}_{n,\tau-1})$. The argument $\boldsymbol{c}_{n,\tau-1}$ is only required if $A^{(k)}$ is an instance of *seq* and is ignored by the other annotator models. We draw annotator k's label for each token τ in each document n according to:

$$c_{n,\tau}^{(k)} \sim \mathrm{Cat}([A^{(k)}(t_{n,\tau}, 1, \boldsymbol{c}_{n,\tau-1}^{(k)}), ..., A^{(k)}(t_{n,\tau}, J, \boldsymbol{c}_{n,\tau-1}^{(k)})]). \tag{6}$$

The annotators are assumed to be conditionally independent of one another given the true labels, $\boldsymbol{t}$, which means that their errors are assumed to be uncorrelated. This is a strong assumption when considering that the annotators have to make their decisions based on the same input data. However, in practice, dependencies do not usually cause the most probable label to change (Zhang, 2004), hence the performance of classifier combination methods is only slightly degraded, while avoiding the complexity of modeling dependencies between annotators (Kim and Ghahramani, 2012).

Black-box Sequence Taggers: As an optional extension to our model, we can integrate S automated methods as additional noisy annotators. In comparison to human annotators, sequence taggers can quickly label large numbers of documents, providing a cheap source of additional annotations across the whole dataset. We model each sequence tagger, s, using an annotator model, $B^{(s)}$, of one of the types described in Section 2 (analagous to $A^{(k)}$ for a human annotator), with hyperparameters $\boldsymbol{\beta}^{(s)}$. Each sequence tagger generates a sequence of labels, $\boldsymbol{d}_n^{(s)}$, for each document n (analogous to $\boldsymbol{c}_n^{(k)}$ produced by annotators) according to:

$$d_{n,\tau}^{(s)} \sim \mathrm{Cat}([B^{(s)}(\boldsymbol{t}_{n,\tau}, 1, d_{n,\tau-1}^{(s)}), ..., B^{(s)}(\boldsymbol{t}_{n,\tau}, J, d_{n,\tau-1}^{(s)})]). \tag{7}$$

In the generative model, we draw a sequence of text tokens, $\boldsymbol{x}_n$, from a likelihood, $p\left(\boldsymbol{x}_n | \boldsymbol{d}_n^{(s)}, \boldsymbol{\theta}^{(s)}\right)$, given internal parameters, $\boldsymbol{\theta}^{(s)}$, and label sequence, $\boldsymbol{d}_n^{(s)}$. This likelihood is defined by the black-box sequence tagger. If the sequence tagger is Bayesian, its parameters, $\boldsymbol{\theta}^{(s)}$, may also be drawn from an unknown prior distribution. However, since we are treating the tagger as a black box, we do not need to know these internal details. In the next section, we explain how we can avoid computing this likelihood explicitly during inference, and instead use only the sequence tagger's existing training and prediction functions to learn $\boldsymbol{\theta}^{(s)}$ in parallel with the parameters of the BSC model. Like the human annotators, each sequence tagger is assumed to produce labels that are conditionally independent of the other sequence taggers given $\boldsymbol{t}$. Due to the fact that sequence taggers will typically use the same features, i.e. the text of the documents, this independence assumption may be violated, yet this assumption in other models has been shown not to hamper performance in many practical situations (Zhang, 2004).

Joint distribution: the complete model can be represented by the joint distribution over its random variables, given by:

$$p(\boldsymbol{t}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{T}, \boldsymbol{\theta}, \boldsymbol{c}, \boldsymbol{d}, \boldsymbol{x} | \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}) \quad (8)$$
$$= \prod_{k=1}^{K} \left\{ p(A^{(k)}|\boldsymbol{\alpha}^{(k)}) \prod_{n=1}^{N} p(\boldsymbol{c}_n^{(k)}|A^{(k)}, \boldsymbol{t}) \right\}$$
$$\prod_{j=1}^{J} p(\boldsymbol{T}_j|\boldsymbol{\gamma}_j) \prod_{n=1}^{N} \prod_{\tau=1}^{L_n} p(\boldsymbol{t}_n|\boldsymbol{T}_{t_{n,\tau-1}}) \prod_{s=1}^{S} \left\{ p(\boldsymbol{\theta}^{(s)}) \right.$$
$$\left. p(B^{(s)}|\boldsymbol{\beta}^{(s)}) \prod_{n=1}^{N} \left\{ p(\boldsymbol{x}|\boldsymbol{d}^{(s)}, \boldsymbol{\theta}^{(s)}) p(\boldsymbol{d}^{(s)}|B^{(s)}, \boldsymbol{t}) \right\} \right\}$$

4 Inference using Variational Bayes

Given a set of annotations, $\boldsymbol{c} = \{\boldsymbol{c}^{(1)}, .., \boldsymbol{c}^{(K)}\}$ from K annotators, our aim is to obtain a posterior distribution over sequence labels, $\boldsymbol{t}$. To do this, we employ *variational Bayes* (*VB*) (Attias, 2000). In comparison to other Bayesian approaches such as Markov chain Monte Carlo (MCMC), VB is often faster, readily allows incremental learning, and provides easier ways to determine convergence (Bishop and Nasrabadi, 2007). Unlike maximum likelihood methods such as standard expectation maximization (EM), VB considers prior distributions and accounts for parameter uncertainty in a Bayesian manner. The trade-off is that VB requires us to approximate the posterior distribution:

$$p(\boldsymbol{t}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{T}, \boldsymbol{\theta} | \boldsymbol{c}, \boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}) \approx \prod_{k=1}^{K} q(A^{(k)})$$
$$\prod_{j=1}^{J} q(\boldsymbol{T}_j) \prod_{n=1}^{N} q(\boldsymbol{t}_n) \prod_{s=1}^{S} \left\{ q(B^{(s)}) q(\boldsymbol{\theta}^{(s)}) \right\}. \quad (9)$$

The variational approximation factorizes between subsets of parameters or latent variables, so that each subset, z, has a *variational factor*, $q(z)$. The labels produced by the sequence taggers, $\boldsymbol{d}$, have been marginalized. Due to our choice of conjugate priors, the variational factors for BSC are of the same types as their prior distributions defined in Section 3, and the parameters of each variational distribution can be computed in terms of expectations over the other subsets of variables. We perform approximate inference, using coordinate ascent to update each variational factor, $q(z)$, in turn, taking expectations with respect to the current estimates of the other variational factors. Our VB approximation therefore makes use of the *mean field* assumption. Each iteration reduces the KL-divergence between the true and approximate posteriors of Equation 9, and hence optimizes a lower bound on the log marginal likelihood, also called the evidence lower bound or ELBO (Bishop and Nasrabadi, 2007; Attias, 2000). The complete VB algorithm is described in Algorithm 1, which makes use of the update equations for the log variational factors given below.

Input: Annotations, $\boldsymbol{c}$
Randomly initialise $\mathbb{E} \ln A^{(k)}, \forall k$, $\mathbb{E} \ln B^{(s)}, \forall s$, $\mathbb{E} \ln \boldsymbol{T}_j, \forall j$ and $\hat{d}_{n,\tau}^{(s)}(i), \forall s, \forall n, \forall \tau, \forall i$.
while not_converged$(r_{n,\tau,j}, \forall n, \forall \tau, \forall j)$ **do**
  Update $r_{j,n,\tau}$, $s_{t_{j,n,\tau-1}, t_{\iota,n,\tau}}$, $\forall j, \forall \tau, \forall i, \forall \iota$, using forward-backward algorithm
  Retrain all sequence taggers using $\tilde{\boldsymbol{d}}^{(s)}$ as training labels for tagger s
  Use sequence taggers to predict $\hat{d}_{n,\tau}^{(s)}(i)$, $\forall s, \forall n, \forall \tau, \forall i$
  Update $\ln q(A^{(k)})$ and $\mathbb{E} \ln A^{(k)}, \forall k$
  Update $\ln q(B^{(s)})$ and $\mathbb{E} \ln B^{(s)}, \forall s$
  Update $\ln q(\boldsymbol{T}_j)$ and $\mathbb{E} \ln T_{j,\iota}, \forall j, \forall \iota$
end
Output: Label posteriors, $r_{n,\tau,j}, \forall n, \forall \tau, \forall j$, most probable sequence of labels, $\hat{\boldsymbol{t}}_n, \forall n$ using Viterbi algorithm

Algorithm 1: The VB algorithm for BSC.

For the true labels, $\boldsymbol{t}$, the variational factor is:

$$\ln q(\boldsymbol{t}_n) = \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} \sum_{s=1}^{S} \mathbb{E} \ln B^{(s)} \left(t_{n,\tau}, d_{n,\tau}^{(s)}, d_{n,\tau-1}^{(s)} \right)$$
$$+ \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} \sum_{k=1}^{K} \mathbb{E} \ln A^{(k)} \left(t_{n,\tau}, c_{n,\tau}^{(k)}, c_{n,\tau-1}^{(k)} \right)$$
$$+ \mathbb{E} \ln T_{t_{n,\tau-1}, t_{n,\tau}} + \text{const.} \quad (10)$$

From this factor, we compute the posterior probability of each true token label, $r_{n,\tau,j} = \mathbb{E}[p(t_{n,\tau} = j|\boldsymbol{c})]$, and of each label transition, $s_{n,\tau,j,\iota} = \mathbb{E}[p(t_{n,\tau-1} = j, t_{n,\tau} = \iota|\boldsymbol{c})]$, using the forward-backward algorithm (Ghahramani, 2001), which consists of two passes. The *forward pass* for each document, n, starts from $\tau = 1$ and computes:

$$\ln r_{n,\tau,j}^{-} = \ln \sum_{\iota=1}^{J} \left\{ r_{n,\tau-1,\iota}^{-} \mathrm{e}^{\mathbb{E} \ln T_{\iota,j}} \right\} + ll_{n,\tau}(j), \quad (11)$$

$$ll_{n,\tau}(j) = \sum_{k=1}^{K} \mathbb{E} \ln A^{(k)} \left(j, c_{n,\tau}^{(k)}, c_{n,\tau-1}^{(k)}\right) + \sum_{s=1}^{S} \sum_{i=1}^{J} \sum_{\iota=1}^{J} \mathbb{E} \ln B^{(s)}(j,i,\iota)\, \hat{d}_{n,\tau}^{(s)}(i) \hat{d}_{n,\tau-1}^{(s)}(\iota), \quad (12)$$

where $\hat{d}_{n,\tau}^{(s)}(i)$ is defined below in Equation 21, and $r_{n,0,\iota}^{-} = 1$ where $\iota =$'O' and 0 otherwise. The *backwards pass* starts from $\tau = L_n$ and scrolls backwards, computing:

$$\ln \lambda_{n,L_n,j} = 0, \qquad \ln \lambda_{n,\tau,j} = \ln \sum_{\iota=1}^{J} \exp\big\{ \ln \lambda_{i,\tau+1,\iota} + \mathbb{E} \ln T_{j,\iota} + ll_{n,\tau+1}(\iota)\big\}. \quad (13)$$

By applying Bayes' rule, we arrive at $r_{n,\tau,j}$ and $s_{n,\tau,j,\iota}$:

$$r_{n,\tau,j} = \frac{r_{n,\tau,j}^{-} \lambda_{n,\tau,j}}{\sum_{j'=1}^{J} r_{n,\tau,j'}^{-} \lambda_{n,\tau,j'}} \quad (14)$$

$$s_{n,\tau,j,\iota} = \frac{\tilde{s}_{n,\tau,j,\iota}}{\sum_{j'=1}^{J} \sum_{\iota'=1}^{J} \tilde{s}_{n,\tau,j',\iota'}} \quad (15)$$

$$\tilde{s}_{n,\tau,j,\iota} = r_{n,\tau-1,j}^{-} \lambda_{n,\tau,\iota} \exp\{\mathbb{E} \ln T_{j,\iota} + ll_{n,\tau}(\iota)\}.$$

Each row of the transition matrix has the factor:

$$\ln q(\boldsymbol{T}_j) = \ln \mathrm{Dir}\left([N_{j,\iota} + \gamma_{j,\iota}, \forall \iota \in \{1,..,J\}]\right), \quad (16)$$

where $N_{j,\iota} = \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} s_{n,\tau,j,\iota}$ is the expected number of times that label ι follows label j. The forward-backward algorithm requires the terms:

$$\mathbb{E} \ln T_{j,\iota} = \Psi(N_{j,\iota} + \gamma_{j,\iota}) - \Psi\left(\sum_{\iota=1}^{J} (N_{j,\iota} + \gamma_{j,\iota})\right), \quad (17)$$

where Ψ is the digamma function.

The variational factor for each annotator model is a distribution over its parameters, which differs between models. For *seq*, the variational factor is:

$$\ln q\left(A^{(k)}\right) = \sum_{j=1}^{J} \sum_{l=1}^{J} \mathrm{Dir}\left(\left[\boldsymbol{N}_{j,l,m}^{(k)} \forall m \in \{1,..,J\}\right]\right)$$

$$N_{j,l,m}^{(k)} = \alpha_{j,l,m}^{(k)} + \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} r_{n,\tau,j} \delta_{l,c_{n,\tau-1}^{(k)}} \delta_{m,c_{n,\tau}^{(k)}}, \quad (18)$$

where δ is the Kronecker delta. For *CM*, *MACE*, *CV* and *acc*, the factors follow a similar pattern of summing pseudo-counts of correct and incorrect answers. The forward-backward passes also require the following expectation terms for *seq*, which can be simplified for the other annotator models:

$$\mathbb{E} \ln A^{(k)}(j,l,m) = \Psi\left(N_{j,l,m}^{(k)}\right) - \Psi\left(\sum_{m'=1}^{J} \left(N_{j,l,m'}^{(k)}\right)\right). \quad (19)$$

The variational factor, $q(B^{(s)})$, for each sequence tagger's annotator model has the same form as $q(A^{(k)})$, substituting $\delta_{l,c_{n,\tau-1}^{(k)}}$ for $\hat{d}_{n,\tau}^{(s)}(i)$, as defined in below in Equation 21.

Black-box sequence taggers: the parameters of tagger s have the following variational factor:

$$\ln q\left(\boldsymbol{\theta}^{(s)}\right) = \ln p\left(\boldsymbol{x} | \boldsymbol{\theta}^{(s)}, \tilde{\boldsymbol{d}}^{(s)}\right) + \ln p\left(\boldsymbol{\theta}^{(s)}\right) + \text{const},$$

$$\tilde{d}_{n,\tau} = \mathbb{E}\left[p(d_{n,\tau}^{(s)} = i | B^{(s)}, t_{n,\tau})\right] = \sum_{j=1}^{J} \sum_{\iota=1}^{J} r_{n,\tau,j} \tilde{d}_{n,\tau-1} \mathbb{E} B^{(s)}(j,i,\iota). \quad (20)$$

The expecations, $\tilde{\boldsymbol{d}}_n^{(s)}$, fill the role of training labels, allowing us to use the training function of the black-box sequence taggers to update the variational factor, $q\left(\theta^{(s)}\right)$. Many black-box sequence taggers, including most neural networks, use maximum likelihood (ML) to find optimal point values, $\hat{\boldsymbol{\theta}}^{(s)}$, rather than their posterior distribution. If we integrate such sequence taggers, our complete inference procedure becomes a hybrid between VB and ML expectation maximization (EM) (Bishop and Nasrabadi, 2007). The sequence tagger may also require training using discrete labels, in which case we introduce a further ML step and approximate $\tilde{\boldsymbol{d}}_n^{(s)}$ by the most probable values at each token.

The update equations for other factors require expectations of $\boldsymbol{d}_n$ with respect to $\boldsymbol{\theta}^{(s)}$, or their ML approximation:

$$\hat{d}_{n,\tau}^{(s)}(i) = \mathbb{E}\left[p(d_{n,\tau}^{(s)} = i | \boldsymbol{x}_n, \boldsymbol{\theta}^{(s)})\right] \approx p\left(d_{n,\tau}^{(s)} = i | \boldsymbol{x}_n, \hat{\boldsymbol{\theta}}^{(s)}\right) \quad (21)$$

These values are the predictions obtained from the black-box sequence tagger given tokens $\boldsymbol{x}$. Therefore, our method requires only training and prediction functions to integrate a sequence tagger, while its annotator model, $B^{(s)}$, accounts for

the sequence tagger's reliability. This means we can treat sequence taggers as black boxes, even if their predictions are noisy or over-confident. Pre-trained taggers can also be used, for example, to make use of taggers that were trained on different domains with more annotated data.

4.1 Predicting the Sequence Labels

The approximate posterior probabilities of the true labels, $r_{j,n,\tau}$, provide confidence estimates for the labels. However, it is often useful to compute the most probable sequence of labels, $\hat{\boldsymbol{t}}_n$, using the Viterbi algorithm (Viterbi, 1967). To apply the algorithm, we use the converged variational factors to compute $\mathbb{E}[\boldsymbol{T}], \mathbb{E}[A^{(k)}], \forall k, \mathbb{E}[B^{(s)}], \forall s$ and $\hat{d}^{(s)}_{n,\tau}(i), \forall s, \forall n, \forall \tau, \forall i$. The most probable sequence is particularly useful because, unlike $r_{j,n,\tau}$, the sequence will be consistent with any transition constraints imposed by the priors on the transition matrix $\boldsymbol{T}$, such as preventing 'O'→'I' transitions by assigning them zero probability. We can also make predictions for unlabelled documents in a similar manner, simply omitting the human annotations, $\boldsymbol{c}$, and relying only on the predictions of the black-box sequence taggers, $\hat{\boldsymbol{d}}^{(s)}$.

4.2 Modular Implementation of Variational Inference

The variational inference method described in Section 4 is naturally suited to a modular implementation. We divide the BSC model, as defined in Section 3 and Equation 8, into three modules: (a) the true label model, which defines the distribution over sequences of labels, $q(\boldsymbol{t}_n)$; (b) the annotator model, which may be one of those described in Section 2 and implements $q(A^{(k)})$ and $q(B^{(s)})$; and (c) black-box sequence taggers, which are existing implementations that provide training and prediction functions to predict true labels given text tokens, $\boldsymbol{x}$. The true label model exposes methods to compute $r_{n,\tau,j}$ and $s_{n,\tau,j,\iota}, \forall n, \forall \tau, \forall j, \forall \iota$, while the annotator models provide methods to initialise and update $q(A^{(k)})$ and $q(B^{(s)})$, and compute expectations according to Equation 19.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, and to test each component part. For example, new annotator models could, in future, be introduced to aggregate continuous-valued ratings or pairwise preferences.

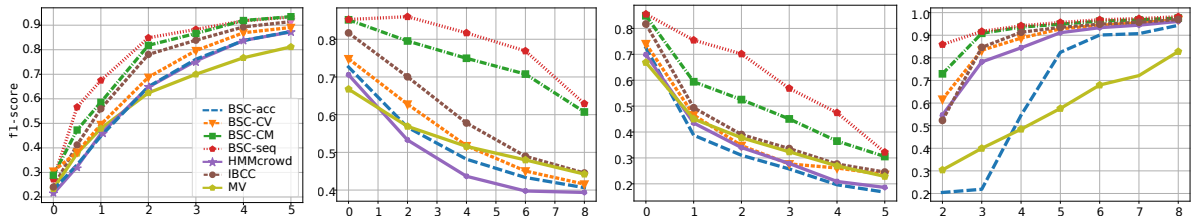
5 Experiments

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 probabilistic 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.

5.1 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.

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 BiLSTM-LSTM-CRF, (Lample et al., 2016), labeled *BSC-seq+LSTM*. We also use the output predictions of HMM-crowd and BSC-seq as training labels for the same LSTM-based method, then evaluate its predictions (labeled in our results as →LSTM). In our experiments we evaluate the benefits of integrating black-box sequence taggers as part of an ensemble, rather than tuning for optimal performance on a particular task. Therefore, we reuse the hyperparameters determined by Lample



(a) Average annotator accuracy (b) Short span bias (c) Missed span bias (d) Good workers out of 10

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

Data -set	Sentences with crowd total	dev	test	without crowd dev	test	Tokens /sent.	Workers total	/doc	Span type	Gold spans	Span length 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	pop.	700	7.74	7.38

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

et al. (2016) for all instances of BiLSTM-LSTM-CRF, except for the optimizer, for which we use Adam to improve the convergence rate, as recommended by Reimers and Gurevych (2017). We apply early stopping if the development set score does not improve after 5 iterations. For the integrated BSC-seq+LSTM, we found better development set performance for both our datasets if the other parameters are allowed to converge before training the LSTM to convergence. This is intended to reduce over-fitting, which is a likely consequence of using a maximum likelihood step to integrate the LSTM as a black-box sequence tagger.

The MACE and IBCC methods are non-sequential variants of BSC-MACE and BSC-CM, and serve to show the benefits of the sequential BSC model. The HMM-Crowd and DS methods also allow us to compare non-Bayesian methods against their Bayesian variants, BSC-CV and IBCC, respectively.

5.2 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 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.

5.3 Crowdsourced Datasets

We use two datasets containing both crowdsourced and gold sequential annotations.

	NER				Hyperparams.			PICO				Hyperparams.		
	Prec.	Rec.	F1	CEE	γ_0	ϵ_0	α_0	Prec.	Rec.	F1	CEE	γ_0	ϵ_0	α_0
Best worker	76.4	60.1	67.3	17.13				64.8	53.2	58.5	17.03			
Worst worker	55.7	26.5	35.9	31.94				50.7	52.9	51.7	40.96			
MV	79.9	55.3	65.4	6.24				82.5	52.8	64.3	2.55			
MACE	74.4	66.0	70.0	1.01	.1	.1	0	25.4	84.1	39.0	58.23	.1	.1	0
DS	79.0	70.4	74.4	2.84				71.3	66.3	68.7	0.44			
IBCC	79.0	70.4	74.4	0.49	.1	1	.1	72.1	66.0	68.9	0.27	.1	10	10
HMM-crowd	80.5	69.4	74.6	1.04	0	.1	0	76.5	66.2	71.0	0.79	0	.1	0
HMM-crowd→LSTM	81.8	69.5	75.2	12.20	0	.1	0	76.5	66.5	71.2	12.94	0	.1	0
BSC-acc	83.4	54.3	65.7	0.96	10	.1	10	**89.4**	45.2	60.0	1.59	.1	.1	10
BSC-MACE	67.9	74.1	70.9	0.89	10	10	1	46.7	84.4	60.1	1.98	.1	100	.1
BSC-CV	81.4	64.7	72.1	0.89	10	1	1	74.9	67.2	71.1	0.84	.1	1	.1
BSC-CM	79.9	72.2	75.8	1.46	.1	100	.1	60.1	78.8	68.2	1.49	.1	100	1
BSC-seq	80.3	74.8	77.4	0.65	.1	1	1	72.9	77.6	75.1	1.10	100	1	1
BSC-seq-notext	81.0	69.8	75.0	0.52	.1	1	1	81.2	59.2	68.5	0.73	.1	.1	.1
BSC-seq-noHMM														
BSC-seq→LSTM	80.2	75.3	77.7	11.02	.1	1	1	75.7	75.4	75.5	25.48	100	1	1
BSC-seq+LSTM	**82.3**	**75.9**	**78.9**	0.59	.1	1	1	78.7	**78.6**	**78.7**	1.15	100	1	1

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

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 5. Note that NER spans are typically much shorter than those in PICO.

5.4 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.

5.5 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.

We tune the hyperparameters using a validation set. To limit the number of hyperparameters to tune, we optimize only three values for BSC. Hyperparameters of the transition matrix, $\boldsymbol{\gamma}_j$, are set to the same value, γ_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 (both $\boldsymbol{A}$ and $\boldsymbol{B}$), all values are set to α_0, except for disallowed transitions, which are set to 0.1, then ϵ_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

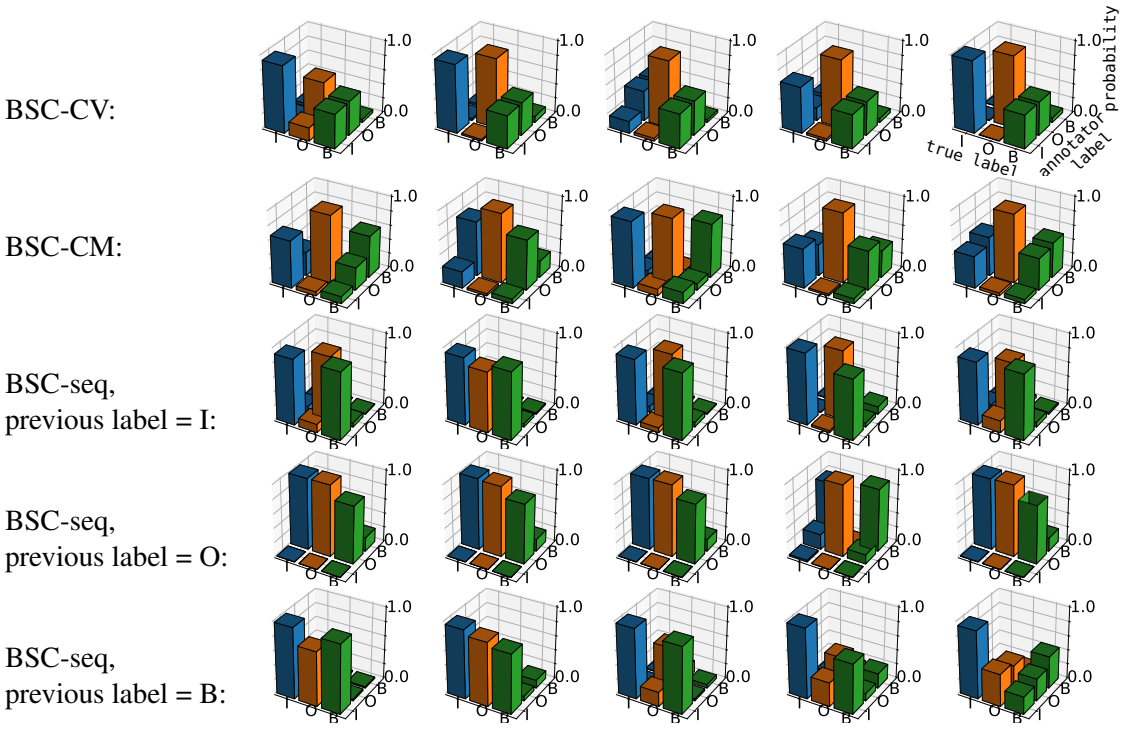


Figure 2: Clusters of confusion matrix representations from each BSC-*** annotator model trained on PICO.

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 expected 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

Method	Data-set	exact match	type wrong only	partial match	mis-sing span	false +ve	late start	early start	late fin-ish	early fin-ish	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.

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.

5.6 Active Learning

Active learning iteratively selects informative data points to be labeled so that a model can be trained using less labeled data. The posterior probabilities that are output by a Bayesian methods account for uncertainty in the model parameters, hence can be used to choose data points for labeling that most rapidly reduce that uncertainty and improve the model's confidence. In contrast, frequentist methods such as maximum likelihood, output probabilities that do not account for parameter uncertainty due to small datasets or noisy labels. We therefore hypothesize that BSC will learn more quickly than HMMCrowd, which uses only partially-Bayesian inference, and majority voting, which is not probabilistic and also does not benefit from a sequential model. When the labeled dataset is small and many documents have few labels, the integration of an LSTM may improve performance as it acts as an additional annotator. To test these hypotheses, we simulate active learning using *uncertainty sampling* (Settles, 2010), as described in Algorithm 2: Here we compute entropy over token labels independently so that the method is applicable to non-sequential models such as majority voting.

Input: A random $initial\_set$ of training labels, the same for all methods.

Set training set $\boldsymbol{c} = initial\_set$

while *training set size* < max_no_labels **do**

  Train on $\boldsymbol{c}$

  Compute the mean entropy of the sequence labels of each document: $-\frac{1}{L_n}\sum_{\tau=1}^{L_n}\sum_{j=1}^{J} p(t_{n,\tau} = j|\boldsymbol{c}) \ln p(t_{n,\tau} = j|\boldsymbol{c})$

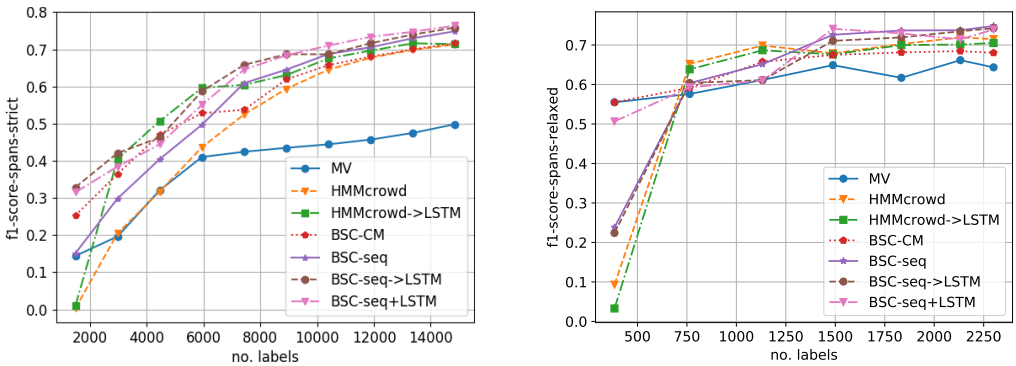
  Select $batch\_size$ documents with highest mean entropy, add their annotations to $\boldsymbol{c}$

end

Algorithm 2: Active learning simulation for each method using uncertainty sampling.

However, for sequential models such as HMM-crowd and BSC, the entropy could in future take into account the label dependencies, which may improve performance.

Figure 3 plots the mean F1 scores over ten repeats of the active learning simulation. BSC variants perform best with smaller datasets, where they may benefit from the Bayesian approach. 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, possibly because the dataset is too small to train the LSTM reliably. BSC-seq+LSTM accounts for the unreliability of the predictions of the integrated LSTM, enabling it to outperform BSC-seq→LSTM on NER with more than 10000 labels and on PICO at almost all points. We ob-



(a) NER, active learning simulation

(b) 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	77.6	75.3	76.5	too few training labels				

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

serve that

5.7 Prediction with Crowd-Trained LSTMs

In this scenario, we evaluate two ways to train a sequence tagger: (1) the more traditional approach of first aggregating crowdsourced labels to produce a gold standard, then training the model on the gold labels (BSC-seq->LSTM and HMM-crowd->LSTM), or (2) using BSC-seq+LSTM to form an ensemble of crowd annotators with a sequence tagger, allowing us to exploit the Bayesian framework to output confidence estimates that account for model uncertainty. For NER, we evaluate on the CoNLL English test set (Tjong Kim Sang and De Meulder, 2003), while for PICO, we train the aggregators on the 3,649 documents without gold labels, then evaluate on the gold-labelled test data split used in Section 5.5.

The results in Table 4 show that for F1-scores, BSC-seq->LSTM outperforms the previous state-of-the-art, HMM-crowd->LSTM (Nguyen et al., 2017). F1-scores for BSC-seq+LSTM are lower than those of BSC-seq→LSTM, although it also outperforms HMM-crowd→LSTM. However, BSC-seq+LSTM produces a far lower cross entropy error than either of the other methods, indicating that the probabilities it outputs are a better reflection of confidence and are likely to be more suitable to downstream decision-making tasks than the raw outputs from the LSTM sequence tagger. The benefits of Bayesian ensemble methods such as BSC for decision-making tasks is therefore a promising topic for future work.

6 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, which 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 integrate existing sequence taggers, such as deep neural networks, into our variational inference approach as black-box training and prediction functions. 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 testing them on other training sets of similar size.

References

Shadi Albarqouni, Christoph Baur, Felix Achilles, Vasileios Belagiannis, Stefanie Demirci, and Nassir Navab. 2016. Aggnet: deep learning from crowds for mitosis detection in breast cancer histology images. *IEEE transactions on medical imaging*, 35(5):1313–1321.

Hagai Attias. 2000. A variational Bayesian framework for graphical models. In *Advances in Neural Information Processing Systems 12*, pages 209–215. MIT Press.

Yoram Bachrach, Tom Minka, John Guiver, and Thore Graepel. 2012. How to grade a test without knowing the answers: a Bayesian graphical model for adaptive crowdsourcing and aptitude testing. In *Proceedings of the 29th International Coference on International Conference on Machine Learning*, pages 819–826. Omnipress.

C. M Bishop and N. M Nasrabadi. 2007. Pattern recognition and machine learning. *Journal of Electronic Imaging*, 16(4):9901.

A. P. Dawid and A. M. Skene. 1979. Maximum likelihood estimation of observer error-rates using the EM algorithm. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 28(1):20–28.

A. P. Dempster, N. M. Laird, and D. B. Rubin. 1977. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38.

Pinar Donmez, Jaime Carbonell, and Jeff Schneider. 2010. A probabilistic framework to learn from multiple annotators with time-varying accuracy. In *Proceedings of the 2010 SIAM International Conference on Data Mining*, pages 826–837. SIAM.

Paul Felt, Eric K. Ringger, and Kevin D. Seppi. 2016. Semantic annotation aggregation with conditional crowdsourcing models and word embeddings. In *International Conference on Computational Linguistics*, pages 1787–1796.

Zoubin Ghahramani. 2001. An introduction to hidden markov models and Bayesian networks. *International Journal of Pattern Recognition and Artificial Intelligence*, 15(01):9–42.

Matthew R. Gormley, Margaret Mitchell, Benjamin Van Durme, and Mark Dredze. 2014. Low-resource semantic role labeling. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1177–1187. Association for Computational Linguistics.

Dirk Hovy, Taylor Berg-Kirkpatrick, Ashish Vaswani, and Eduard H Hovy. 2013. Learning whom to trust with MACE. In *HLT-NAACL*, pages 1120–1130.

Hyun-chul Kim and Zoubin Ghahramani. 2012. Bayesian classifier combination. In *International Conference on Artificial Intelligence and Statistics*, pages 619–627.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. 2016. Neural architectures for named entity recognition. In *Proceedings of NAACL-HLT*, pages 260–270.

Xuezhe Ma and Eduard Hovy. 2016. End-to-end sequence labeling via bi-directional LSTM-CNNs-CRF. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, volume 1, pages 1064–1074.

Pablo G. Moreno, Yee Whye Teh, and Fernando Perez-Cruz. 2015. Bayesian nonparametric crowdsourcing. *Journal of Machine Learning Research*, 16:1607–1627.

An T Nguyen, Byron C Wallace, Junyi Jessy Li, Ani Nenkova, and Matthew Lease. 2017. Aggregating and predicting sequence labels from crowd annotations. In *Proceedings of the conference. Association for Computational Linguistics. Meeting*, volume 2017, page 299. NIH Public Access.

Pushpendre Rastogi, Ryan Cotterell, and Jason Eisner. 2016. Weighting finite-state transductions with neural context. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 623–633.

V. C. Raykar, S. Yu, L. H. Zhao, G. H. Valadez, C. Florin, L. Bogoni, and L. Moy. 2010. Learn-

ing from crowds. *Journal of Machine Learning Research*, 11:1297–1322.

Nils Reimers and Iryna Gurevych. 2017. Optimal hyperparameters for deep lstm-networks for sequence labeling tasks. *arXiv preprint arXiv:1707.06799*.

Filipe Rodrigues, Francisco Pereira, and Bernardete Ribeiro. 2013. Learning from multiple annotators: distinguishing good from random labelers. *Pattern Recognition Letters*, 34(12):1428–1436.

Filipe Rodrigues, Francisco Pereira, and Bernardete Ribeiro. 2014. Sequence labeling with multiple annotators. *Machine learning*, 95(2):165–181.

Filipe Rodrigues and Francisco Camara Pereira. 2018. Deep learning from crowds. In *The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI), 2018*.

Burr Settles. 2010. Active learning literature survey. *University of Wisconsin, Madison*, 52(55-66):11.

Aashish Sheshadri and Matthew Lease. 2013. Square: A benchmark for research on computing crowd consensus. In *First AAAI Conference on Human Computation and Crowdsourcing*.

E. Simpson, S. Roberts, I. Psorakis, and A. Smith. 2013. Dynamic Bayesian combination of multiple imperfect classifiers. *Intelligent Systems Reference Library series*, Decision Making with Imperfect Decision Makers:1–35.

Edwin D Simpson, Matteo Venanzi, Steven Reece, Pushmeet Kohli, John Guiver, Stephen J Roberts, and Nicholas R Jennings. 2015. Language understanding in the wild: Combining crowdsourcing and machine learning. In *Proceedings of the 24th International Conference on World Wide Web*, pages 992–1002. International World Wide Web Conferences Steering Committee.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. *The Journal of Machine Learning Research*, 15(1):1929–1958.

Erik F Tjong Kim Sang and Fien De Meulder. 2003. Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition. In *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4*, pages 142–147. Association for Computational Linguistics.

Matteo Venanzi, John Guiver, Gabriella Kazai, Pushmeet Kohli, and Milad Shokouhi. 2014. Community-based Bayesian aggregation models for crowdsourcing. In *23rd international conference on World wide web*, pages 155–164.

Matteo Venanzi, John Guiver, Pushmeet Kohli, and Nicholas R Jennings. 2016. Time-sensitive Bayesian information aggregation for crowdsourcing systems. *Journal of Artificial Intelligence Research*, 56:517–545.

Andrew Viterbi. 1967. Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *IEEE transactions on Information Theory*, 13(2):260–269.

Jacob Whitehill, Ting-fan Wu, Jacob Bergsma, Javier R Movellan, and Paul L Ruvolo. 2009. Whose vote should count more: Optimal integration of labels from labelers of unknown expertise. In *Advances in neural information processing systems*, pages 2035–2043.

Hui Yuan Xiong, Yoseph Barash, and Brendan J Frey. 2011. Bayesian prediction of tissue-regulated splicing using rna sequence and cellular context. *Bioinformatics*, 27(18):2554–2562.

Jie Yang, Thomas Drake, Andreas Damianou, and Yoelle Maarek. 2018. Leveraging crowdsourcing data for deep active learning an application: Learning intents in Alexa. In *Proceedings of the 2018 World Wide Web Conference on World Wide Web*, pages 23–32. International World Wide Web Conferences Steering Committee.

Harry Zhang. 2004. The optimality of naïve Bayes. In *Proceedings of the Seventeenth International Florida Artificial Intelligence Research Society Conference, FLAIRS 2004*. AAAI Press.

Barret Zoph, Deniz Yuret, Jonathan May, and Kevin Knight. 2016. Transfer learning for low-

resource neural machine translation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1568–1575.