Bayesian Ensembles of Crowds and Deep Learners for Sequence Tagging

Edwin Simpson and Iryna Gurevych
Ubiquitous Knowledge Processing Lab
Department of Computer Science
Technische Universität Darmstadt
https://www.ukp.tu-darmstadt.de
{simpson,gurevych}@ukp.informatik.tu-darmstadt.de

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. To address this, we develop a modular Bayesian method for aggregating sequence labels from multiple annotators and evaluate different models of annotator errors and labeling biases. Our approach integrates black-box sequence taggers as components in the model to improve the quality of predictions. We evaluate our model on crowdsourced data for named entity recognition and information extraction tasks, showing that our sequential annotator model outperforms previous methods.

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, part-of-speech tagging, or information extraction. Neural network sequence taggers are typically trained on tens of thousands of documents (Ma and Hovy, 2016; Lample et al., 2016), which presents a challenge when facing new domains or tasks, where obtaining labels is often time-consuming or costly.

Labeled data can be obtained cheaply by crowdsourcing, in which large numbers of untrained workers annotate documents instead of more expensive experts. For sequence tagging, this results in multiple sequences of unreliable labels for each document. Probabilistic methods for aggregating these labels 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 limited and existing methods cannot model dependencies between the annotators’ labels and hence miss error patterns such as a tendency to label overly long spans (Rodrigues et al., 2014; Nguyen et al., 2017). In this paper, we remedy this by proposing a sequential annotator model and applying it to tasks that follow a beginning, inside, outside (BIO) scheme, in which the first token in a span of type ‘x’ is labeled ‘B-x’, subsequent tokens are labeled ‘I-x’, and tokens outside spans are labeled ‘O’.

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). In contrast, Bayesian inference accounts for model uncertainty when making predictions, and enables hyperparameter tuning in unsupervised scenarios through Bayesian model selection (Bishop, 2006). Unlike alternative methods that optimize the values for model parameters, Bayesian inference integrates over all possible values of a parameter, weighted by a prior distribution that captures background knowledge. The resulting posterior probabilities improve downstream decision making as they include the probability of errors due to a lack of knowledge. For example, during active learning, posterior probabilities assist with selecting the most informative data points (Settles, 2010). We therefore develop a Bayesian sequence combination method, building on prior work that has demonstrated the advantages of Bayesian inference for aggregating unreliable classifications (Kim and Ghahramani, 2012; Simpson et al., 2013; Felt et al., 2016; Paun et al., 2018).

Aggregated label quality can be improved 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 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:

- We propose Bayesian sequence combination (BSC), a method for aggregating sequence labels from multiple annotators that models sequential dependencies between tags
- A technique for wrapping existing black-box sequence taggers into the aggregation model to improve the quality of aggregated labels
- Theoretical and empirical comparisons of annotator models for sequence tagging, including a novel model that captures sequential dependencies between annotations (referred to later as seq)

The following sections discuss related work, annotator models for sequence tagging, our BSC model, and our variational inference approach that enables us to integrate existing sequence taggers. Then, we evaluate a range of Bayesian and non-Bayesian aggregation methods with simulated annotators and two crowdsourced NLP datasets, showing that our sequential model consistently outperforms the previous state-of-the-art, and benefits from the inclusion of automated sequence taggers. We make all of our code freely available\(^1\).

1.1 Related Work

Sheshadri and Lease (2013) benchmarked several aggregation models for non-sequential classifications, obtaining the most consistent performance from that of Raykar et al. (2010), who model the reliability of individual annotators using probabilistic confusion matrices, as proposed by Dawid and Skene (1979). Simpson et al. (2013) showed that a Bayesian variant of Dawid and Skene (1979)’s model, independent Bayesian classifier combination (IBCC) (Kim and Ghahramani, 2012) can outperform maximum likelihood approaches and simple heuristics when combining crowds of image annotators. To reduce the number of parameters in multi-class problems, Hoey et al. (2013) proposed MACE, and showed that it performed better under a Bayesian treatment on NLP tasks. Paun et al. (2018) further illustrated the advantages of Bayesian models of annotator ability on NLP classification tasks with different levels of annotation sparsity and noise. We expand this work by detailing the relationships between several annotator models and extending them to sequential classification. Here 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).

To account for disagreement between annotators when training a sequence tagger, Plank et al. (2014) modify the loss function of the learner. However, typical cross entropy loss naturally accommodates probabilities of labels as well as discrete labels (Bekker and Goldberger, 2016). A contrasting approach is CRF-MA (Rodrigues et al., 2014), a CRF-based model that assumes only one annotator is correct for any given label. Recently, Nguyen et al. (2017) proposed a hidden Markov model (HMM) approach that outperformed CRF-MA, 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. In this paper, we develop a sequential annotator model and a fully Bayesian method for aggregating sequence labels.

While HMM-crowd uses only a simple conditional independence model of text features, Nguyen et al. (2017) and Rodrigues and Pereira (2018) also train neural network sequence taggers directly on crowdsourced data by adding a layer to handle worker reliability. However, the proposed approaches did not outperform either CRF-MA (Rodrigues and Pereira, 2018) or HMM-crowd (Nguyen et al., 2017). A similar approach by Albarqouni et al. (2016) integrates 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 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, allowing untrusted, off-the-shelf 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 different function, $A$, to model the likelihood of the annotator choosing the label $c_{\tau}$ given the true label, $t_{\tau}$, for token $\tau$.

Accuracy model (acc): simply models the annotator’s accuracy, $\pi$, as follows:

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

(1)

where $c_{\tau}$ is the label given by the annotator for token $\tau$, $t_{\tau}$ 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 $\pi$.

MACE (Hovy et al., 2013): assumes constant accuracy, $\pi$, but when an annotator is incorrect, they label according to a spamming distribution, $\xi$, that is independent of the true label, $t_{\tau}$.

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

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, $\pi$, of size $J$:

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

This model does not 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 $\pi$ becomes a $J \times J$ matrix with values given by:

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

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 with different error rates for each type of ‘B-x’, ‘I-x’ and ‘O’ label. 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:

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

where $\pi$ 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 $\pi_{j,c_{\tau-1},c_{\tau}} = 0$, $\forall j$ 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 $\pi_{I,O,B}$.
The annotator models we presented, which include the most widespread models for NLP annotation tasks, can therefore be seen as extensions of one another. The choice of annotator model for a particular annotator depends on the developer’s understanding of the annotation task: if the annotations have sequential dependencies, this suggests the seq model; for non-sequential classifications CM may be effective with small (≤ 5) numbers of classes; MACE may be more suitable if there are more classes. However, there is also a trade-off between the expressiveness of the model and the number of parameters that must be learned. Simpler models with fewer parameters, such as acc, which may be effective if there are only small numbers of annotations from each annotator. Our experiments in Section 5 investigate this trade-off on NLP tasks involving sequential annotation. The next section shows how these models can be used as part of a model for aggregating sequential annotations.

3 A Generative Model for Bayesian Sequence Combination

The generative story for our approach, Bayesian sequence combination (BSC), is as follows. We assume a transition matrix, $T$, where each entry is $T_{j,k} = p(t_{\tau} = j|t_{\tau-1} = k)$. We draw each row of the transition matrix, $T_j \sim \text{Dir}(\gamma_j)$, where Dir is the Dirichlet distribution. For each document, $n$, in a set of $N$ documents, we draw a sequence of class labels, $t_n = \{t_{n,1},...,t_{n,L_n}\}$, of length $L_n$, from a categorical distribution: $t_{n,\tau} \sim \text{Cat}(T_{n,\tau-1})$. The set of all labels for all documents is referred to as $t = \{t_1,...,t_N\}$.

In the generative model, we assume one of the annotator models described in Section 2 for each of $K$ annotators. The number of parameters depends on the choice of annotator 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 $\pi(j)$, and for CM we draw a vector $\pi(k)$ of size $J$ for each true label value $j \in \{1,...,J\}$; in the case of seq, we draw vectors $\pi_j(k)$ for each true label value for each previous label value, $i$. 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 $\alpha(k)$. Given its parameters, the annotator model defines a likelihood function, $A(k)(t_{n,\tau}, c_{n,\tau}, c_{n,\tau-1})$, where $c_{n,\tau}$ is the $\tau$th label of document $n$. The argument $c_{n,\tau-1}$ 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 $\tau$ in each document $n$ according to:

$$c_{n,\tau}^{(k)} \sim \text{Cat}(\{A(k)(t_{n,\tau}, 1, c_{n,\tau-1}), ..., A(k)(t_{n,\tau}, J, c_{n,\tau-1})\}).$$  

The annotators are assumed to be conditionally independent of one another given the true labels, $t$, 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 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 (analogous to $A(k)$ for a human annotator), with hyperparameters $\beta(s)$.

We extend the generative model for BSC with additional steps as follows. Each sequence tagger generates a sequence of labels, $d_{n,\tau}^{(s)}$, for each document $n$ (analogous to $c_{n,\tau}^{(k)}$ produced by human annotators) according to:

$$d_{n,\tau}^{(s)} \sim \text{Cat}(\{B(s)(t_{n,\tau}, 1, d_{n,\tau-1}^{(s)}), ..., B(s)(t_{n,\tau}, J, d_{n,\tau-1}^{(s)})\}).$$

In the generative model, we draw a sequence of text tokens, $x_n$, from a likelihood, $p \left( x_n | d_n^{(s)}, \theta(s) \right)$, given internal parameters, $\theta(s)$, and label sequence, $d_n^{(s)}$. This likelihood is defined by the black-box sequence tagger. If the sequence tagger is Bayesian, its parameters, $\theta(s)$, 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 \( \theta^{(s)} \) 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 \( t \).

**Joint distribution:** the complete model can be represented by the joint distribution, given by:

\[
p(t, A, B, T, \theta, c, d, x|\alpha, \beta, \gamma) = \prod_{k=1}^{K} \left\{ p(A^{(k)}|\alpha^{(k)}) \prod_{n=1}^{N} p(e^{(n)}_k|A^{(k)}, t) \right\} \prod_{j=1}^{J} p(T_j|\gamma_j) \prod_{n=1}^{N} p(t_n|T_{n,\tau-1}) \prod_{s=1}^{S} \left\{ p(\theta^{(s)}) \right\} \prod_{n=1}^{N} \prod_{\tau=1}^{L_n} p(B^{(s)}|\beta^{(s)}), \]

where each term is defined by the distributions of the generative model described in this section.

4 Inference using Variational Bayes

Given a set of annotations, \( c = \{c^{(1)}, \ldots, c^{(K)}\} \), from \( K \) annotators, our aim is to obtain a posterior distribution over sequence labels, \( t \). 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, 2006). 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. Here, we apply the mean field assumption to assume a variational approximation that factorizes between subsets of parameters or latent variables, so that each subset, \( z \), has a variational factor, \( q(z) \):

\[
p(t, A, B, T, \theta|c, x, \alpha, \beta, \gamma) \approx \prod_{k=1}^{K} q(A^{(k)}) \prod_{j=1}^{J} q(T_j) \prod_{n=1}^{N} q(t_n) \prod_{s=1}^{S} \left\{ q(B^{(s)})q(\theta^{(s)}) \right\}.
\]

The labels produced by the sequence taggers, \( d \), can be marginalized analytically so do not require a separate factor. Each variational factor has the form \( \ln q(z) = \mathbb{E} \ln p(z|c, -z) \), where \(-z\) contains all the latent variables except \( z \). We perform approximate inference by 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. 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, 2006; 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, \( c \)

1 Randomly initialize \( \mathbb{E} \ln A^{(k)}, \forall k \), \( \mathbb{E} \ln B^{(s)}, \forall s \), \( \mathbb{E} \ln T_j, \forall j \) and \( \tilde{d}^{(s)}(i), \forall s, \forall n, \forall \tau, \forall i \), \( \forall \).

2 While not_converged \( r_{n,\tau,j}, \forall n, \forall \tau, \forall j \) do

3 Update \( r_{j,n,\tau}, s_{j,n,\tau-1}, \forall n, \forall \tau, \forall i \), \( \forall \), using forward-backward algorithm

4 Use sequence taggers to predict \( \tilde{d}^{(s)}(i), \forall s, \forall n, \forall \tau, \forall i \), \( \forall \).

5 Update \( \ln q(A^{(k)}) \) and \( \mathbb{E} \ln A^{(k)}, \forall k \), given current \( c, r_{j,n,\tau} \).

6 Update \( \ln q(B^{(s)}) \) and \( \mathbb{E} \ln B^{(s)}, \forall s \), given current \( d, r_{j,n,\tau} \).

7 Update \( \ln q(T_j) \) and \( \mathbb{E} \ln T_{j,t}, \forall j, \forall t \), given current \( s_{j,n,\tau-1}, t_{j,n,\tau} \).

end

**Output:** Label posteriors, \( r_{n,\tau,j}, \forall n, \forall \tau, \forall j \), most probable sequence of labels, \( t_{n} \), \( \forall n \) using Viterbi algorithm

**Algorithm 1:** The VB algorithm for BSC.

The prior distributions chosen for our generative model are conjugate to the distributions over the latent variables and model parameters, meaning that each \( q(z) \) is the same type of distribution as the corresponding prior distribution defined in Section 3. The parameters of each variational distribution can be computed in terms of expectations over the other subsets of variables. For the true label...
bles, \( t \), the variational factor is:

\[
\ln q(t_n) = \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} \sum_{i=1}^{S} \mathbb{E} \ln B^{(s)}(t_n, \tau, d^{(s)}_{n,\tau-1}) \\
+ \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} \sum_{k=1}^{K} \mathbb{E} \ln A^{(k)}(t_n, \tau, \epsilon^{(k)}_{n,\tau}, \epsilon^{(k)}_{n,\tau-1}) \\
+ \mathbb{E} \ln T_{n,\tau-1,t_n,\tau} + \text{const.} \quad (10)
\]

From this factor, we compute the posterior probability of each true token label, \( r_{n,\tau,j} = \mathbb{E}[p(t_n = j|\epsilon)], \) and of each label transition, \( s_{n,\tau,j'} = \mathbb{E}[p(t_{n,\tau-1} = j, t_n = j'|\epsilon)], \) 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:

\[
\ln r_{n,\tau,j} = \ln\left\{ r_{n,\tau-1,j} e^{\mathbb{E} \ln T_{n,\tau}} \right\} + \ln l_{n,\tau}(j), \\
\ln l_{n,\tau}(j) = \sum_{k=1}^{K} \mathbb{E} \ln A^{(k)}(j, \epsilon^{(k)}_{n,\tau}, \epsilon^{(k)}_{n,\tau-1}) + \sum_{s=1}^{S} \mathbb{E} \ln B^{(s)}(j, i, \epsilon^{(s)}_{n,\tau-1}(i), \epsilon^{(s)}_{n,\tau-1}(i)), \quad (11)
\]

where \( \epsilon^{(s)}_{n,\tau}(i) \) is defined below in Equation 20, and \( r_{n,0,i} = 1 \) when \( i = 'O' \) and 0 otherwise. The backwards pass starts from \( \tau = L_n \) and scrolls backwards, computing:

\[
\ln \lambda_{n,L_n,\tau} = 0, \quad \ln \lambda_{n,\tau,j} = \ln \sum_{i=1}^{J} \exp\left\{ \ln \lambda_{i,\tau+1,j} + \mathbb{E} \ln T_{j,\tau} + \ln l_{n,\tau+1}(i) \right\}. \quad (12)
\]

By applying Bayes’ rule, we arrive at \( r_{n,\tau,j} \) and \( s_{n,\tau,j'} \):

\[
r_{n,\tau,j} = \frac{r_{n,\tau-1,j} \lambda_{n,\tau,j}}{\sum_{j'=1}^{J} r_{n,\tau-1,j'} \lambda_{n,\tau,j'}} \quad (13)
\]

\[
s_{n,\tau,j'} = \frac{s_{n,\tau,j'}}{\sum_{j'=1}^{J} \tilde{s}_{n,\tau,j'}} \quad (14)
\]

\[
\tilde{s}_{n,\tau,j'} = r_{n,\tau-1,j} \lambda_{n,\tau,j'} \exp[\mathbb{E} \ln T_{j,\tau} + \ln l_{n,\tau}(i)].
\]

Each row of the transition matrix has the factor:

\[
\ln q(T) = \ln \text{Dir}(\{N_{j,\tau} + \gamma_{j,\tau}, \forall \tau \in \{1, ..., J\})]. \quad (15)
\]

where \( N_{j,\tau} = \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} s_{n,\tau,j} \) is the expected number of times that label \( \ell \) follows label \( j \).

The forward-backward algorithm requires expectations of \( \ln T \) that can be computed using standard equations for a Dirichlet distribution:

\[
\mathbb{E} \ln T_{j,\tau} = \Psi(N_{j,\tau} + \gamma_{j,\tau}) - \Psi\left( \sum_{\tau=1}^{J} (N_{j,\tau} + \gamma_{j,\tau}) \right), \quad (16)
\]

where \( \Psi \) 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:

\[
\ln q(\Lambda^{(k)}_{j,l,m}) = \sum_{j=1}^{J} \sum_{l=1}^{L} \text{Dir}(\{N_{j,l,m}^{(k)} \forall m \in \{1, ..., J\}])
\]

\[
N_{j,l,m}^{(k)} = \alpha_{j,l,m}^{(k)} \sum_{n=1}^{N} \sum_{\tau=1}^{L_n} r_{n,\tau,j} \delta_{l,v,n-1} \delta_{m,v'}, \quad (17)
\]

where \( \delta \) 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 are standard equations for Dirichlet distributions and can be simplified for the other annotator models:

\[
\mathbb{E} \ln A^{(k)}(j, l, m) = \Psi\left( N_{j,l,m}^{(k)} \right) - \Psi\left( \sum_{m' \neq m}^{J} N_{j,l,m'}^{(k)} \right). \quad (18)
\]

The variational factor, \( q(B^{(s)}) \), for each sequence tagger’s annotator model has the same form as \( q(A^{(k)}), \) substituting \( \delta_{l,v,n-1} \) for \( \tilde{d}_{n,\tau}^{(s)}(i), \) as defined in below in Equation 20.

**Black-box sequence taggers:** the parameters of tagger \( s \) have the following variational factor:

\[
\ln q(\Theta^{(s)}_{\log}) = \ln p(\Theta^{(s)}_{\log} \cdot \tilde{d}^{(s)}_{\log}) + \ln p(\Theta^{(s)}_{\log}) + \text{const}, \quad (19)
\]

The expectations, \( \tilde{d}^{(s)}_{\log}(i), \) fill the role of training labels, allowing us to use the training function of the black-box sequence taggers to update the variational factor, \( q(\Theta^{(s)}_{\log}). \) Many black-box sequence taggers, including most neural networks, use maximum likelihood (ML) to find optimal point values, \( \hat{\Theta}^{(s)}_{\log}, \) 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) (see Bishop (2006)). The sequence tagger may also require training using discrete labels, in which case we introduce a further ML step and approximate \( \hat{d}_{n}^{(s)} \) by the most probable values at each token.

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

\[
\bar{d}_{n,\tau}(i) = \mathbb{E} \left[ p(d_{n,\tau}^{(s)} = i \mid x_{n}, \theta^{(s)}) \right] \\
\approx p \left( d_{n,\tau}^{(s)} = i \mid x_{n}, \hat{\theta}^{(s)} \right)
\]

These values are the predictions obtained from the black-box sequence tagger given tokens \( x \). 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, \( t_{n} \), using the Viterbi algorithm (Viterbi, 1967). To apply the algorithm, we use the converged variational factors to compute \( \mathbb{E}[T], \mathbb{E}[A^{(k)}], \forall k, \mathbb{E}[B^{(s)}], \forall s \) and \( \bar{d}_{n,\tau}^{(s)}(i), \forall s, \forall n, \forall \tau, \forall i \). 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 \( T \), such as preventing ‘O’→‘T’ transitions by assigning them zero probability. We can also make predictions for unlabeled documents in a similar manner, simply omitting the human annotations, \( c \), and relying only on the predictions of the black-box sequence taggers, \( \hat{d}^{(s)} \).

### 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, \( q(t_{n}) \); (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, \( x \). The true label model exposes methods to compute \( r_{n,\tau,j} \) and \( s_{n,\tau,j}, \forall n, \forall \tau, \forall j, \forall i \), while the annotator models provide methods to initialize and update \( q(A^{(k)}) \) and \( q(B^{(s)}) \), and compute expectations according to Equation 18.

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) with each of the annotator models described in Section 3 to assess whether the sequential annotator model, \( \text{seq} \), improves the quality of the inferred sequence tags. The first experiment uses simulated annotators to investigate the effects of different types of error on aggregation methods. We then introduce two NLP datasets to test performance in passive and active learning scenarios, analyze errors, and visualize the learned annotator models. The experiments also assess whether including sequence taggers into the probabilistic model improves the aggregated sequence tags as well as the sequence taggers’ predictions on test data.

### 5.1 Evaluated Methods

As well-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 Ghaframani, 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 \textit{a posteriori} (or smoothed maximum likelihood) estimates for the confusion vector (CV) annotator model and variational inference for an integrated hidden Markov model (HMM). MACE and IBCC are variants...
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. This can be seen as a sanity check to ensure that both our model and the proposed inference method can handle certain types of error when we know them to be present. 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 is less accurate than methods that model individual annotator behavior, although the difference decreases as we introduce more errors.
Among the BSC variants, performance increases with the complexity of the annotator model, from BSC-acc to BSC-seq, suggesting that the richer seq 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. This experiment on simulated data showed that our inference technique was able to handle certain types of error when generated from a BSC model. The following sections describe experiments test whether the benefits apply when BSC is used with real crowdsourced data.

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

### Table 2: Aggregating crowdsourced labels: estimating true labels for documents labeled by the crowd.

| Method         | Prec. | Rec. | F1   | CEE γ0 | ϵ0 | α0 | Prec. | Rec. | F1   | CEE γ0 | ϵ0 | α0 |
|----------------|-------|------|------|--------|-----|----|-------|------|------|--------|-----|----|
| 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 | 6.24   |     |    | 82.5  | 52.8 | 64.3 | 2.55   |     |    |
| MACE           | 74.4  | 66.0 | 70.0 | 1.01   | .1  | 0  | 25.4  | 84.1 | 39.0 | 58.2   | .1  | 0  |
| DS             | 79.0  | 70.4 | 74.4 | 2.80   |     |    | 71.3  | 66.3 | 68.7 | 0.44   |     |    |
| IBCC           | 79.0  | 70.4 | 74.4 | 0.49   | .1  | 1  | 72.1  | 66.0 | 68.9 | 0.27   | .1  | 10 |
| MV-crowd       | 80.5  | 69.4 | 74.6 | 1.04   | 0   | .1 | 76.5  | 66.2 | 71.0 | 0.79   | .1  | 0  |
| MV-crowd-LSTM  | 81.8  | 69.5 | 75.2 | 12.2   | 0   | .1 | 76.5  | 66.5 | 71.2 | 13.0   | .1  | 0  |
| BSC-acc        | 83.4  | 54.3 | 65.7 | 0.96   | 10  | 10 | 89.4  | 45.2 | 60.1 | 1.98   | .1  | 100|
| BSC-MACE       | 67.9  | 74.1 | 70.9 | 0.89   | 10  | 1  | 46.7  | 84.4 | 60.1 | 1.98   | .1  | 100|
| BSC-CV         | 81.4  | 64.7 | 72.1 | 0.89   | 10  | 1  | 74.9  | 67.2 | 71.1 | 0.84   | .1  | 1  |
| BSC-CM         | 79.9  | 72.2 | 75.8 | 1.46   | .1  | 100| 60.1  | 78.8 | 68.2 | 1.49   | .1  | 100|
| BSC-seq        | 80.3  | 74.8 | 77.4 | 0.65   | .1  | 1  | 72.9  | 77.6 | 75.1 | 1.10   | 100 | 1  |
| BSC-CM-notext  | 74.7  | 69.7 | 72.1 | 1.48   | .1  | 1  | 62.7  | 74.8 | 68.2 | 1.32   | 100 | 1  |
| BSC-CM\T       | 80.0  | 73.0 | 76.3 | 0.99   | .1  | 100| 65.8  | 66.7 | 66.2 | 0.28   | .1  | 100|
| BSC-seq-notext | 81.0  | 69.8 | 75.0 | 0.52   | .1  | 1  | 81.2  | 59.2 | 68.5 | 0.73   | .1  | 1  |
| BSC-seq\T      | 60.5  | 42.3 | 49.8 | 0.93   | .1  | 1  | 51.2  | 70.4 | 59.8 | 1.04   | .1  | 1  |
| BSC-seq\LSTM   | 80.2  | 75.3 | 77.7 | 11.0   | .1  | 1  | 75.7  | 75.4 | 75.5 | 25.5   | 100 | 1  |
| BSC-seq\LSTM   | 80.0  | 76.0 | 78.0 | 0.99   | .1  | 1  | 78.7  | 78.6 | 78.7 | 1.15   | 100 | 1  |

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.

5.4 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-labeled 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
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, $\gamma_j$, are set to the same value, $\gamma_0$, 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 $A$ and $B$), all values are set to $\alpha_0$, except for disallowed transitions, which are set to 0.1, then $\epsilon_0$ is added to hyperparameters corresponding to correct annotations (e.g. diagonal entries in a confusion matrix). We use $\epsilon_0$ to encode the prior assumption that annotators are more likely to have an accuracy greater than random. This avoids the non-identifiability problem, in which the class labels become switched around. 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. For the integrated BSC-seq+LSTM, we found better validation set performance for both our datasets if the LSTM is first excluded while the other parameters converge before training the LSTM. This simply means that we follow Algorithm 1, but omit steps 3, 4 and 6 in the first few iterations. Note that we use the dev set at each VB iteration to select the best LSTM model after each epoch. These steps reduce over-fitting resulting from the maximum likelihood step used to integrate the LSTM as a black-box sequence tagger.

The results of the aggregation task are shown in Table 2. Although DS and IBCC do not consider sequence information nor the text itself, they both perform well on both datasets, with IBCC reaching better cross-entropy error than DS due to its Bayesian treatment. The improvement of DS over the results given by Nguyen et al. (2017) may be due to implementation differences. Neither MACE, BSC-acc nor BSC-MACE perform strongly, with F1-scores sometimes falling below MV. The acc and MACE annotator models may be a poor match for the sequence labeling task if annotator competence varies greatly depending on the true class label.

BSC-seq outperforms the other approaches, although without the text model (BSC-seq-notext) or the transition matrix (BSC-seq\(T\)), its performance decreases. However, for BSC-CM, the results are less clear: BSC-CM-notext differs from IBCC only in the inclusion of the transition matrix, $T$, yet IBCC outperforms BSC-CM-notext. This suggests that the combination of these elements is important: the seq annotator model is effective in
combination with the transition matrix and simple text model. Integrating an LSTM improves performance further in both datasets, and outperforms an LSTM trained on the output of HMM-crowd or BSC-seq.

We categorize the errors made by key methods 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 positives (where no true span was present). This is 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.

To determine whether BSC-seq learns distinctive confusion matrices depending on the previous labels, we plot the learned annotator models for PICO as probabilistic confusion matrices in Figure 2. As the dataset contains a large number of annotators, we clustered the confusion matrices inferred by each model into five groups by applying K-means to their posterior expected values. In all clusters, BSC-CV learns different accuracies for B, I and O (the diagonal entries). These differences may explain its improvement over BSC-acc. BSC-CM differs from BSC-CV in that the first, fourth and fifth clusters have off-diagonal values with different heights for the same true label value. The second cluster for BSC-CM encodes likely spammers who usually choose ‘O’ regardless of the ground truth. The confusion matrices for BSC-seq 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.

5.5 Active Learning
Active learning iteratively selects informative data points to be labeled so that a model can be trained using less labeled data. Posterior probabilities output by Bayesian methods account for uncertainty in the model parameters, hence can be used to choose data points that rapidly reduce uncertainty. We hypothesize that BSC will learn more quickly than non-sequential methods in an active learning scenario. While various active learning methods could be applied here, in this paper we wish to demonstrate only that BSC may serve as a good foundation for active learning, and defer a deeper investigation of active learning techniques to future work. We therefore simulate active learning using a well-established technique, uncertainty sampling (Settles and Craven, 2008; Settles, 2010), as described in Algorithm 2. The LSTM implementation provided by Lample et al. (2016) outputs discrete label predictions, so to allow direct comparison of BSC against a neural sequence tagger, we modify the network to output probabilities for the active learning simulation. For MV, probabilities are estimated by fractions of votes.

Figure 3 plots the mean F1 scores over ten repeats of the active learning simulation. IBCC learns more rapidly than DS on NER due to its Bayesian approach, which may also explain the stronger performance of BSC-CV compared to the similar HMM-crowd model, although this does not hold for the PICO dataset. BSC variants outperform non-sequential IBCC. BSC-CM and
### Table 3: Counts of different types of span errors.

| Method               | Data-set | exact match | type wrong | 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        |

BSC-CV are strongest on PICO with small numbers of labels, but are later overtaken by BSC-seq, which may require more data to learn its more complex model. On NER, BSC-CM continues to outperform the more complex BSC-seq, but the integrated LSTM clearly improves BSC-seq+LSTM. BSC-seq+LSTM performs strongly on NER but poorly on PICO, where fewer labels were provided, while BSC-seq+LSTM appears more robust to this problem.

#### 5.6 Prediction with Crowd-Trained LSTMs

In previous work (Nguyen et al., 2017), HMM-crowd–LSTM produced better predictions for documents not labeled by the crowd, compared with training an LSTM directly on crowdsourced data, or training on labels obtained from non-sequential aggregation methods. We evaluate whether the performance gains of BSC-seq–LSTM for aggregation also result in better predictions on unannotated documents. We also test whether BSC-seq+LSTM can provide meaningful confidence estimates when the sequence tagger it integrates produces only discrete labels. For NER, we evaluate on the CoNLL English test set (Tjong Kim Sang and De Meulder, 2003).

The results in Table 4 show that for F1-scores, BSC-seq–LSTM outperforms the previous state-of-the-art, HMM-crowd–LSTM. BSC-seq+LSTM produces a low cross entropy error, indicating that the probabilities it outputs are a good reflection of confidence and are likely to be more suitable to downstream decision-making tasks than the raw outputs from the LSTM sequence tagger.

### 6 Discussion and Conclusions

We proposed BSC-Seq, a Bayesian approach to aggregating sequence labels, which models the effect of label sequences on annotator reliability. Our results reinforce previous work that has demonstrated the benefits of modeling annotator reliability when aggregating noisy data, such as crowdsourced labels. We showed that sequential models outperform non-sequential baselines and that BSC-seq improves the state-of-the-art over HMM-crowd. Its performance depends on the combination of sequential annotator model, la-
bel transition matrix, and text model. We further improved the quality of aggregated labels, by integrating existing sequence taggers into our variational inference approach as black-box training and prediction functions. This technique performed well with larger amounts of labeled data, but may benefit from the use of pre-trained neural sequence taggers when the dataset is very small. Future work will evaluate integrating sequence taggers built on Bayesian deep learning, which may improve active learning. We will also investigate 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 Conference on International Conference on Machine Learning*, pages 819–826. Omnipress.

Alan Joseph Bekker and Jacob Goldberger. 2016. Training deep neural-networks based on unreliable labels. In *Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on*, pages 2682–2686. IEEE.

C. M. Bishop. 2006. *Pattern recognition and machine learning*, 4th edition. Information Science and Statistics. Springer.

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. Learn-
ing 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.

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 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. *Computer Sciences Technical Report 1648, University of Wisconsin-Madison*, 52(55-66):11.

Burr Settles and Mark Craven. 2008. An analysis of active learning strategies for sequence labeling tasks. In *Proceedings of the conference on empirical methods in natural language processing*, pages 1070–1079. Association for Computational Linguistics.

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*
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.