Bayesian Ensembles of Crowds and Deep Learners for Sequence Tagging

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Abstract

Current methods for sequence tagging, a core task in NLP, are data hungry. Crowdsourcing is often used as a relatively cheap solution to obtain labeled data, but the annotators are unreliable, so noise must be mitigated through redundant labeling and aggregation techniques. Building on previous Bayesian approaches that have been shown to perform strongly on other crowdsourcing tasks, we develop a new model for combining unreliable 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 introducing a Bayesian wrapper for black-box sequence taggers that enables them to be trained with crowdsourced data and accounts for the unreliability of the black-box method as well as the crowd of annotators. We evaluate our model on named entity recognition and information extraction tasks, showing that our method improves on previous work. Our experiments show that by integrating the training and aggregation steps into a Bayesian framework, we can use active learning techniques to obtain data more efficiently without modifying the black-box method. A modular implementation of our method is published along with experimental code to encourage adaptation and reuse.

1 Introduction

The high demand for labeled training data in current NLP methods is widely recognized, with deep learning performance often improved by making use of larger training sets (e.g. (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* (also known as sequence labeling or sequential classification), which involves classifying spans of tokens to perform tasks such as named entity recognition (NER), part-of-speech tagging (POS), or information extraction (IE). Recent neural network approaches to sequence tagging are typically trained on tens of thousands of documents, containing hundreds of thousands of tokens (Ma and Hovy, 2016; Lample et al., 2016). However, this requirement for large labeled datasets presents a challenge when training models for new domains and tasks, where obtaining labels may be time-consuming or costly.

One way to obtain labeled data relatively cheaply is crowdsourcing, in which large numbers of untrained workers annotate documents in place of more expensive experts. We could also obtain training data by aggregating labels from models trained on different domains, from multiple experts, or from users of an application who click on and interact with data in various ways that can be interpreted as noisy labels. All of these cases require the aggregation of unreliable, redundant labels, potentially in small quantities. Probabilistic methods for aggregating unreliable labels, such as that proposed by Dawid and Skene (1979) have been shown to produce more reliable annotations than using simple heuristics such as majority voting (Raykar et al., 2010; Sheshadri and Lease, 2013; Rodrigues et al., 2013; Hovy et al., 2013).

Text spans can be annotated using a tagging scheme such as BIO, in which the first token in a span of type x is labeled 'B-x', subsequent tokens in the same span are labeled as 'I-x', and tokens outside of any spans are labeled as 'O'. This results in a sequence of labels, where each label depends on its predecessor. Aggregation methods have been proposed to exploit the sequential dependencies between these labels(Rodrigues et al., 2014; Nguyen et al., 2017), however, these methods use simplified models of annotators that differ from that of Dawid and Skene (1979), and does not capture the effect of sequential dependencies on the annotators' reliability. In this paper, we compare annotator models qualitatively and empirically, and introduce a sequential annotator model that outperforms previous approaches for sequence tagging.

The cost of labeling can also be reduced by choosing a smaller set of training examples that minimize redundancy without reducing the model's performance. This can be achieved using active learning (Settles, 2010), in which a model is trained iteratively, using its predictions at each iteration to guide selection of new data points to label and add to the training set. Active learning relies on identifying informative data points using heuristics such as *uncertainty sampling*, in which the most uncertain data points according to the model are selected for labeling in the next iteration. Bayesian methods provide a natural basis for decision making tasks, such as active learning, because their predictions account for the uncertainty in the model that arises from small or noisy training data. While Bayesian approaches place probability distributions over model parameters, alternatives such as maximum likelihood estimation optimize point values, and may produce overconfident predictions. Bayesian methods have successfully been applied to various crowdsourcing tasks in NLP, such as sentence fragment classification (Fang et al., 2014), sentiment analysis (Levenberg et al., 2014; Venanzi et al., 2014), intent classification (Yang et al., 2018) and argument ranking(Simpson and Gurevych, 2018), but have not been adapted to sequence tagging. Conversely, the methods proposed for sequence tagging (Rodrigues et al., 2014; Nguyen et al., 2017) do not use a fully Bayesian approach. We introduce a fully Bayesian approach for aggregating sequence tags from multiple sources and providing a modular inference method using variational Bayes that facilitates modifications to the model.

Active learning over a large dataset requires us to make predictions for unlabeled documents. For complex tasks such as sequence tagging, we may wish to take advantage of state-of-the-art models for the task in hand, including neural networks that do not account for model uncertainty, potentially forming an ensemble of multiple methods to boost performance. One approach is to modify these sequence taggers by adding a crowd layer (Nguyen et al., 2017; Rodrigues and Pereira, 2018). However, we argue that integrating existing methods into the aggregation model allows us to treat them as black boxes and facilitate ensemble construction. These black box methods may not always be trusted to perform well, particularly given small training datasets. In contrast to previous work, we address this by modeling the reliability of the black box sequence taggers.

This paper provides the following contributions:

- A taxonomy of annotator reliability models and an empirical analysis of these models on sequence tagging tasks
- A Bayesian method for combining sequential classifications from multiple annotators that models sequential dependencies between tags and outperforms
- A technique for wrapping existing task-specific classifiers into the Bayesian model to improve the quality of aggregated data performance given sufficient amounts of crowdsourced data
- An empirical evaluation of our proposed approach in small data scenarios, with and without active learning, showing that our Bayesian aggregation method consistently outperforms the previous state-of-the-art
- Experimental code[1] including a modular implementation of Bayesian classifier combination methods

In the remainder of the paper, we begin with related work, then provide a description of annotator models for sequence tagging, then our variational approach that integrates existing classifiers, followed by an outline of the modular design of our implementation illustrating how this library can be extended to new types of aggregation problems We then provide an empirical comparison of each approach on two NLP datasets, showing performance in both active and passive learning scenarios, visualizing the models learned by each approach and analyzing their errors. Finally, we provide conclusions and avenues for future work.

1.1 Related Work

Sheshadri and Lease (2013) use a set of benchmarks to evaluate several different aggregation

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

methods, finding the most consistent performance from the method proposed by Raykar et al. (2010), which is an extension of the confusion matrix approach (Dawid and Skene, 1979). However, the methods they evaluate use different inference methods and apply prior distributions in various ways, making it unclear whether the differences in performance are due to the structure of the annotator model or these additional aspects. In this paper, we compare several annotator models on sequence tagging tasks, as components of a model that is otherwise the same and uses the same inference procedure. Our experiments include the annotator model used by the well-used MACE implementation(Hovy et al., 2013).

Several extensions have been proposed for IID classification that could also be adapted to any of the models we test: clustering annotators with similar behaviour (Venanzi et al., 2014; Moreno et al., 2015), adapting to task difficulty (Whitehill et al., 2009; Bachrach et al., 2012), tracking changing behavior over time (Simpson and Roberts, 2015), and learning from the time annotators spend on each task (Venanzi et al., 2016). However, our comparison focuses on the core representation of an annotator, while these works augment this model by sharing parameters between annotators or modifying their models between tasks.

Raykar et al. (2010) proposed a method for directly learning a logistic regression classifier from crowdsourced labels, but unlike our approach, it does not model the reliability of the classifier as it is being trained. Felt et al. (2016) evaluate several methods for incorporating text features into crowdsourcing models for classification, comparing generative with discriminative methods and improving performance using pre-trained word embeddings. However, their methods are designed for IID classification, rather than sequence tagging, and define only simple models of the text features. In contrast, our approach makes use of sequential dependencies between annotations and permits the integration of arbitrary sequence tagging models.

Previous works have applied crowdsourcing to sequence labeling tasks such as named entity recognition (Ritter et al., 2011) and POS-tagging (Hovy et al., 2014), but these do not develop new aggregation methods. Rodrigues et al. (2014) proposed a CRF-based model, CRF-MA, for sequence tagging that estimates true labels given multiple annotators, but their annotator model assumes only one annotator is correct for any given label. Recently, Nguyen et al. (2017) proposed an approach based on hidden Markov models, called HMM-Crowd, which outperformed CRF-MA and non-sequential baselines including MACE (Hovy et al., 2013) and Dawid-Skene (Dawid and Skene, 1979). HMM-Crowd considers the text data by modeling the distribution of tokens conditioned on the hidden state, More sophisticated LSTM-based sequence taggers must be trained separately given the true labels estimated by HMM-Crowd.

The goal of aggregating noisy sequence labels is often to train a model for predicting labels on unlabeled documents. Recently, deep neural methods based on Bi-LSTMs have achieved state-of-the-art performance for sequence tagging (Lample et al., 2016; Ma and Hovy, 2016). Both Rodrigues and Pereira (2018) and Nguyen et al. (2017) extend neural network sequence taggers using an additional *crowd layer* that learns weights for individual annotators when trained directly on crowdsourced data. While Nguyen et al. (2017) found that performance improved over training on the raw crowd labels without the crowd layer, although their best results were obtained using HMM-Crowd as a separate pre-processing step, then training the sequence tagger on its predictions.

Instead of modifying a neural network, Albarqouni et al. (2016) integrate a CNN classifier for image annotation into an aggregation method based on expectation maximization (EM) (Dempster et al., 1977). While this approach improves the CNN performance over using a separate pre-processing step, their method cannot model label dependencies in sequence tagging, does not consider the unreliability of the neural network classifier itself. The same EM approach was evaluated by Rodrigues and Pereira (2018), who found it was out-performed by a GRU with crowd layer. However, they did not adapt the EM method to sequence tagging.

Recent work has developed a method for actively learning approximately Bayesian neural networks from crowds for the task of classifying intent in user queries (Yang et al., 2018). The authors adopt a Bayesian deep learning method based on dropout (Gal and Ghahramani, 2016) to account for uncertainty in neural network parameters. They use an EM algorithm to train the neural network concurrently with an annotator model. However, in contrast to our method, the annotator model is not given a Bayesian treatment while the neural network is adapted rather than treating it as a black box. Their work follows earlier research on active learning from crowds that uses simpler models of independent data points (Fang et al., 2014; Simpson and Roberts, 2015).

2 Modeling Sequential Annotators

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

Accuracy model (Acc): one of the simplest ways to model the reliability of an annotator is simply to learn their accuracy, π, as follows:

$$p(c_\tau = j | t_\tau = \iota, \pi) = \left\{ \begin{matrix} \pi & \text{where } j = \iota \\ \frac{1-\pi}{J} & \text{otherwise} \end{matrix} \right\}, \tag{1}$$

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). The limitation of this approach is that it assumes reliability is constant, which means that when one class label is far more common than others, a spammer who always selects the most common label will have a high π.

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

$$p(c_\tau = j | t_\tau = \iota, \pi, \xi) = \left\{ \begin{matrix} \pi + (1-\pi)\xi_j & \text{where } j = \iota \\ (1-\pi)\xi_j & \text{otherwise} \end{matrix} \right\}. \tag{2}$$

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

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

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

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

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

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

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

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

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

where $\boldsymbol{\pi}$ is now three-dimensional with size $JxJxJ$. In the case of disallowed transitions, e.g.

from c_{i-1} ='O' to c_τ ='I', the value $\pi_{j,c_{i-1},c_\tau} = 0, \forall j$ need not be learned. The sequential model can capture phenomena such as a tendency toward overly long sequences, by learning that $\pi_{O,O,O} > \pi_{O,I,O}$, or a tendency to split spans by inserting 'B' in place of 'I' by increasing the value of $\pi_{I,I,B}$ without affecting $\pi_{I,B,B}$ and $\pi_{I,O,B}$.

The annotator models described above can be seen as extensions of one another, which can be used as part of a complete model for aggregating sequential annotations as described in the next section.

3 Bayesian Sequence Combination

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

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

In contrast to the Hidden Markov Model (HMM) approach used by Nguyen et al, (2017), we do not explicitly consider text features in our observation model. Instead, we defer to existing black-box methods to make use of text features. The next section describes how we learn the parameters of the model and integrate the existing methods into the model to boost performance. The experiments in Sections 6 and 7 then test whether the more expressive Seq annotator model, which has more parameters to learn, is beneficial in a realistic setting.

4 Variational Wrapper for Black-Box Sequence Taggers

We learn the model parameters, $\boldsymbol{\theta} = \{\boldsymbol{A}, \boldsymbol{B}\}$ and sequence labels $\boldsymbol{t}$ given a set of annotations, $\boldsymbol{c}$, using *variational Bayes (VB)*(Attias, 2000). VB is an approximate inference method that avoids the need for expensive sampling steps, while considering prior distributions and accounting for uncertainty over parameters in a Bayesian manner. Each

Input: Annotations, $\boldsymbol{c}$
1 Initialise $\mathbb{E}[\ln \boldsymbol{B}]$, $\mathbb{E}[\ln A]$ and $\hat{\boldsymbol{d}}$ randomly or to prior means;
while $\mathbb{E}[\boldsymbol{t}]$ *not converged* **do**
2 Update $q(t_{i,\tau} = j)$ and $q(t_{i,\tau-1} = j, t_{i,\tau} = j'), \forall i, \forall \tau, \forall j$, given $\mathbb{E}[\ln \boldsymbol{B}]$ and $\mathbb{E}[\ln \boldsymbol{A}]$ using the forward-backward algorithm (Ghahramani, 2001);
3 Set true label predictions $\mathbb{E}[t_{i,\tau} = j] = q(t_{i,\tau} = j)$;
4 Retrain sequence taggers using $\mathbb{E}[\boldsymbol{t}]$ as training labels;
5 Use sequence taggers to predict $\hat{\boldsymbol{d}}$;
6 Update $q(\boldsymbol{A})$ and recompute $\mathbb{E}[p(c_\tau{=}j | c_{i-1}, t_\tau{=}\iota, \boldsymbol{\pi})]$ given current $q(t_{i,\tau-1} = j, t_{i,\tau} = j')$;
7 Update $q(\boldsymbol{B})$ and recompute $\mathbb{E}[\ln \boldsymbol{B}]$ given current $q(t_{i,\tau-1} = j, t_{i,\tau} = j')$;
end
Output: Posterior predictions for the true labels, $\mathbb{E}[\boldsymbol{t}]$.

Algorithm 1: The VB algorithm for Seq-BCC.

latent variable in the generative model, z, has a variational distribution $q(z)$, that is of the same form as its prior distribution (Dirichlet for $\boldsymbol{B}_j$, Categorical for $t_{i,\tau}$, etc.), as defined in Section 3. The parameters of each $q(z)$ are functions of expectations over the other variables in the model. For reasons of space, we do not provide all variational update equations in this paper, however, they can be derived given the generative model stated above. The VB procedure for BSC is detailed in Algorithm 1, and includes an extension to integrate black-box sequence taggers using an additional expectation-maximization (EM) step.

We integrate each sequence tagger, s, by modeling it as an additional annotator that predicts a sequence of labels, $\boldsymbol{d}_i^{(s)}$, for document i. We treat these predictions as random variables whose joint distribution with the sequence of text tokens, ϕ_i, in document i is given by:

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

where the first term on the right-hand side is defined by the annotator model with parameters $\boldsymbol{A}^{(s)}$, and $\boldsymbol{\theta}^{(s)}$ are the parameters of the sequence tagger, s. Marginalizing $\boldsymbol{d}_i^{(s)}, \forall i$ permits us to train the sequence tagger on $\mathbb{E}[\boldsymbol{t}]$ given ϕ_i to obtain a prediction function for sequences of labels, $\hat{\boldsymbol{d}}_i^{(s)} = f(\phi_i)$, where $\hat{\boldsymbol{d}}_i^{(s)}$ is either the variational distribution $\hat{\boldsymbol{d}}_i^{(s)} = q(\boldsymbol{d}_i^{(s)})$ or the sequence of most likely values of $\hat{\boldsymbol{d}}_i^{(s)} = \operatorname{argmax}_{\boldsymbol{d}_i^{(s)}} p\left(\phi_i | \boldsymbol{d}_i^{(s)}, \hat{\boldsymbol{\theta}^{(s)}}\right)$, and training may either marginalize $\boldsymbol{\theta}^{(s)}$ or optimize it using maximum likelihood. Since we require only f to perform variational updates for $\boldsymbol{d}_i^{(s)}$, $\boldsymbol{A}^{(s)}$ and $\boldsymbol{t}$, we can treat s as a black box inside a variational wrapper, ignoring its internal details. Therefore, the sequence tagger need not implement a generative model but can be discriminative, as is the case for many neural networks. Note, however, that if $f(\phi_i)$ approximates $\hat{\boldsymbol{d}}_i^{(s)}$, convergence may not be guaranteed. Where the sequence tagger uses a maximum likelihood rather than Bayesian training procedure, the complete model also does not account for uncertainty in the model of the text sequence.

This variational wrapper allows us to potentially exploit multiple existing sequence taggers, or indeed other existing classifiers useful for recognising tag types, with only the requirement that they provide training and prediction functions. Our approach learns the reliability of each sequence tagger, hence does not require them to be optimized for the current domain, and provides confidence estimates based on their reliability. As with the annotators, we assume the taggers to be conditionally independent of one another given the true labels. While this assumption has not proven a large drawback in previous works on combining annotators (Dawid and Skene, 1979; Kim and Ghahramani, 2012; Simpson and Roberts, 2015), it remains a strong assumption when multiple taggers depend on the same text features.

5 Modular Implementation of Variational Inference

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

The true label model exposes methods to compute $q(t_{i,\tau} = j)$ and $q(t_{i,\tau-1} = j, t_{i,\tau} = j')$, $\forall i, \forall \tau, \forall j$ given $\boldsymbol{c}$ and $\mathbb{E}[p(c_\tau = j | c_{i-1}, t_\tau = \iota, \boldsymbol{\pi})]$. In our implementation of BSC, the true label model contains methods for learning a transition matrix over labels, $\boldsymbol{B}$, which assumes first-order Markov chain. Other underlying models could also be used, such as a model with longer memory.

The worker models must provide methods to initialise the variational distribution $q(\boldsymbol{A})$, update $q(\boldsymbol{A})$ given $\boldsymbol{c}$, $\hat{\boldsymbol{d}}$, and $\mathbb{E}[\boldsymbol{t}]$, and compute $\mathbb{E}[p(c_\tau = j | c_{i-1}, t_\tau = \iota, \boldsymbol{\pi})]$.

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

6 Experiments with Simulated Annotators

We run several method comparisons using two NLP datasets to test whether the quality of aggregated labels is improved by (a) the more sophisticated worker models described in Section 3, (b) the inclusion of text features into the graphical model or (c) a Bayesian approach. We further test whether Bayesian approach facilitates more efficient active learning of sequential annotations from crowds and whether integrating the LSTM into the ensemble of annotators improves performance further. Our experiments consist of three tasks: (1) aggregating crowdsourced labels, (2) training the LSTM sequence tagger of Lample et al. (2016) using aggregated labels, and (3) actively selecting batches of documents for crowdsourced annotation.

7 Experiments with Real Data

7.1 Datasets

We use two datasets containing both crowdsourced sequential annotations and gold annotations. The *NER* dataset contains $1,393$ English documents from the CoNLL 2003 named-entity recognition dataset (Tjong Kim Sang and De Meulder, 2003), all of which contain gold labels for four named entity categories (PER, LOC, ORG, MISC). Of these, we use crowdsourced labels provided by (Rodrigues et al., 2014) for 415 documents. We also test on the *PICO* dataset, introduced by Nguyen et al. (Nguyen et al., 2017), containing $4,740$ medical paper abstracts, all of which have been annotated by a crowd to indicate text spans that identify the population enrolled in a clinical trial. There are gold labels for 191 documents.

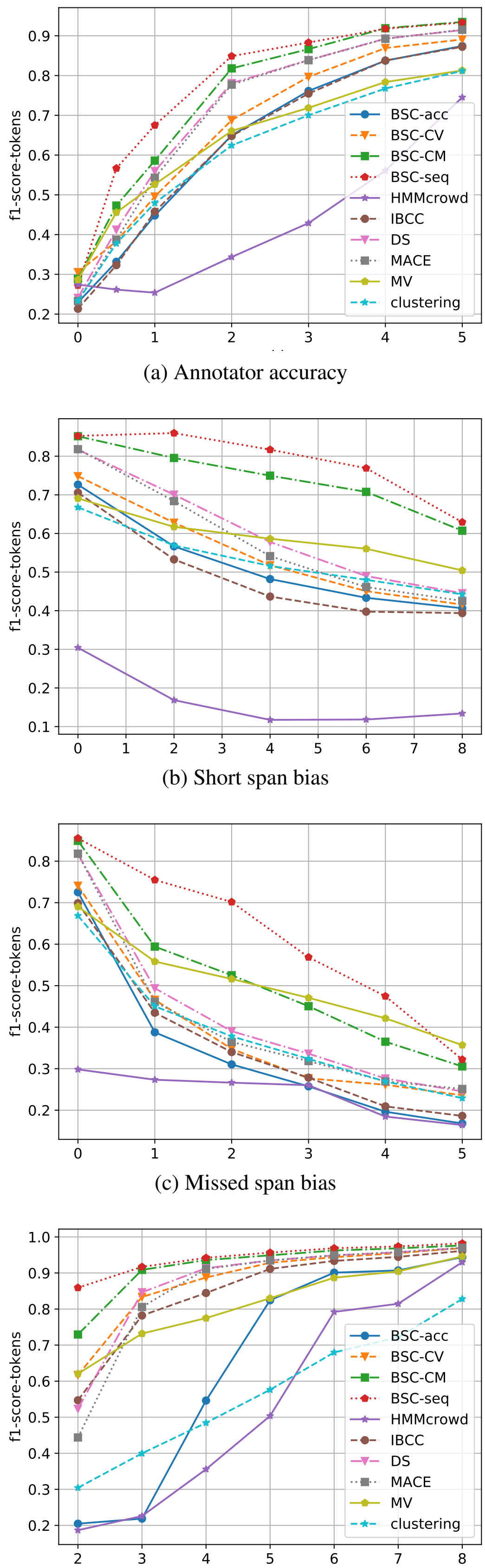
7.2 Evaluation metrics

For NER we use the established CoNLL 2003 F1-score, which is computed at the level of annotated spans that must match exactly to be considered correct. This measure is intuitive because complete named entities must be marked to be of value. For PICO, we use the relaxed F1-measure defined in (Nguyen et al., 2017), which counts the matching fractions of spans when computing precision and recall. To evaluate the probabilities produced by each aggregation method, which may be useful for decision-making tasks such as active learning, we also compute the cross entropy error.

7.3 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). We also test independent Bayesian classifier combination (*IBCC*) (Kim and Ghahramani, 2012), which can be seen as a Bayesian treatment of Dawid-Skene.

Next, we test the sequential *HMM-Crowd* method (Nguyen et al., 2017). This method uses a mixture of maximum *a posteriori* (or smoothed maximum likelihood) estimates for the worker



(a) Annotator accuracy

(b) Short span bias

(c) Missed span bias

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

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

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

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

model, and variational inference for the transition matrix and feature model. The worker model uses a simplification of the DS confusion matrix that models only the probability that a worker labels correctly given each true label class. HMM-Crowd is the current state-of-the-art and allows us to compare our approach against a model without a fully Bayesian treatment.

We test our proposed method, Bayesian sequence classifier combination (BSCC) in several configurations. Firstly, with the different worker models described in Section 2. Secondly, integrating different text models:

1. Independent text features (the default setup): the probability of a token is independent of the sequence conditioned on the true label of the token. This is a standard emission model for an HMM.

2. No text features (*notext*): only the crowd-sourced labels are taken into account when labelling each token. Has the advantage of being task-independent and hence may be more suitable for cases where individual words are uninformative.

3. Integrated LSTM (*+LSTM*): the LSTM is integrated into the variational inference loop as described in Section 3.

7.4 Aggregating Crowdsourced Labels

In this task, we use the aggregation methods to combine crowdsourced labels and evaluate their outputs against the gold standard. For NER, we split the 415 crowd-labelled documents into 50% validation and test sets as in Nguyen et al. (2017). We run the methods on crowd labels from all 415 documents, then evaluate on either the validation or test set. For PICO, we also split the gold-labelled documents randomly into 50% validation and test sets. However, in this case, we run the methods on all $4,740$ crowd-labelled documents. The results for this dataset are not directly comparable with those of Nguyen et al. (2017), since their test and train splits were not available and they appear to have used a subset of the publicly-available dataset with on average 5 annotators per documents, rather than the 6 per document in the complete dataset.

Note that the token-level F1-score can be skewed upwards by matching a few long spans correctly, but is useful for PICO because it shows up cases where the spans matched but the predictions were split, i.e. B is used instead of I. With non-strict entity matching, the precision and recall can be 100% even though the prediction is split into multiple spans. Token-level F1-score catches this because it penalises the erroneous B tokens. With strict entity-level F1-score, the matches must be exact, so split spans would receive no credit.

To get a deeper understanding of our proposed method, we examine the types of errors it makes in comparison to the previous state-of-the-art, HMM-Crowd, and the majority vote baseline. Table 3 lists counts for different types of span annotation error for these three methods on both NER and PICO datasets. Compared to HMM-Crowd, BSC-Seq reduces errors of type ..., which is ... but increases errors of type ..., which is ... This corroborates with the higher precision or recall? in tables ... The majority baseline suffers from a large number of type ... errors.

The results show a benefit to using a sequential annotator model over CM, CV and Acc. To understand how BSC uses the richer model in practice, we plot learned the annotator models for PICO as probabilistic confusion matrices in Figure 2. To enable us to visualize the large number of annotator models, we clustered them into five groups by applying K-means to their expected values. ...

7.5 Active Document Selection

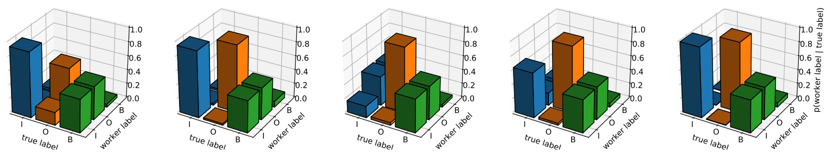
We run an active learning simulation to evaluate whether the proposed Bayesian approach and in-

	NER				Hyperparam.			PICO				Hyperparam.		
	Prec.	Rec.	F1	CEE	ν_0	acc. bias	α_0	Prec.	Rec.	F1	CEE	ν_0	acc. bias	α_0
Best worker	76.4	60.1	67.3	17.1				64.8	53.2	58.5	17.0			
Worst worker	55.7	26.5	35.9	31.9				50.7	52.9	51.7	41.0			
MV	79.9	55.3	65.4	6.2				82.5	52.8	64.3	2.6			
MACE	74.4	66.0	70.0	1.0	.1	.1	0	25.4	84.1	39.0	58.2	.1	.1	0
DS	79.0	70.4	74.4	2.8				71.3	66.3	68.7	0.4			
IBCC	79.0	70.4	74.4	**0.5**	.1	1	.1	72.1	66.0	68.9	**0.3**	.1	10	10
HMMcrowd	80.5	69.4	74.6	1.0	0	.1	0	76.5	66.2	71.0	0.8	0	.1	0
"→LSTM	81.8	69.5	75.2	12.2	0	.1	0	76.5	66.5	71.2	12.9	0	.1	0
BSC-acc	83.4	54.3	65.7	1.0	10	.1	10	**89.4**	45.2	60.0	1.6	.1	.1	10
BSC-MACE	67.9	74.1	70.9	0.9	10	10	1	46.7	84.4	60.1	2.0	.1	100	.1
BSC-CV	81.4	64.7	72.1	0.9	10	1	1	74.9	67.2	71.1	0.8	.1	1	.1
BSC-CM	79.9	72.2	75.8	1.5	.1	100	.1	60.1	78.8	68.2	1.5	.1	100	1
BSC-seq	80.3	74.8	77.4	0.7	.1	1	1	72.9	77.6	75.1	1.1	100	1	1
”-notext	81.0	69.8	75.0	0.5	.1	1	1	81.2	59.2	68.5	0.7	.1	.1	.1
"→LSTM	80.2	75.3	77.7	11.0	.1	1	1	75.7	75.4	75.5	25.5	100	1	1
"+LSTM	**82.3**	**75.9**	**78.9**	0.6	.1	1	1	78.7	**78.6**	**78.7**	1.2	100	1	1

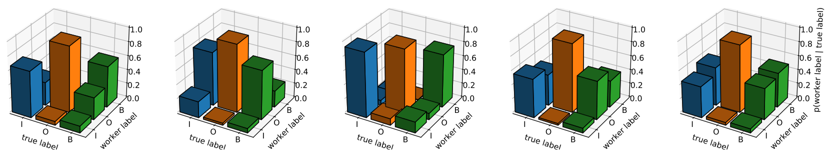
Table 2: NER dataset: estimating true labels for documents that have been labelled by the crowd.

Method	Data-set	exact match	type wrong only	partial match	mis-sing span	not a span	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

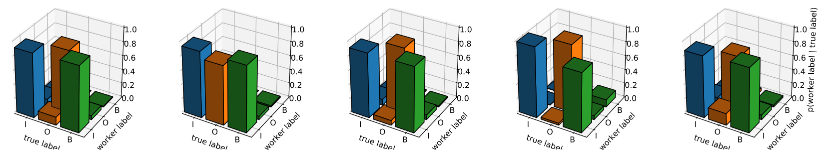
Table 3: Counts of different types of span errors.



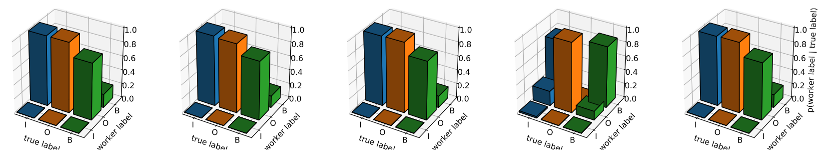
(a) BSCC-Vec-IF



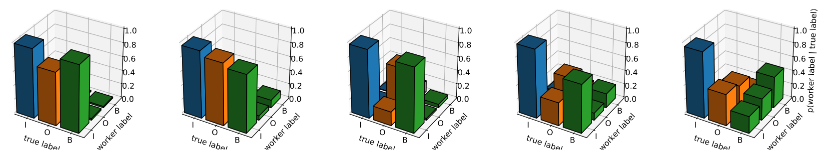
(b) BSCC-IBCC-IF



(c) BSCC-seq-IF, previous label = I



(d) BSCC-seq-IF, previous label = O



(e) BSCC-seq-IF, previous label = B

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

tegrated LSTM can improve the efficiency of a crowdsourcing process. The simulation is run separately for each method tested, and begins with the same initial set of randomly-chosen documents taken from the same crowd-labelled sets used in Section 7.4. We retrieve the crowdsourced labels for the selected documents, run the aggregation method, then use its posterior probabilities to select a new batch of the $N_{batchsize}$ most uncertain documents that have not yet been labelled. We retrieve the annotations for the selected batch of documents, then repeat the process until all of the available crowd labels have been used. We set $N_{batchsize}$ to one tenth of the crowd-labelled dataset size for each of the datasets. At each iteration, we monitor progress by training an LSTM on the current output of the aggregation method, and testing its performance as in Section 7.4. With the NER dataset we also evaluate the output of aggregation method on the test set for the crowd-labelled documents. This is not possible with PICO datas because we do not have gold labels for documents labelled by the crowd.

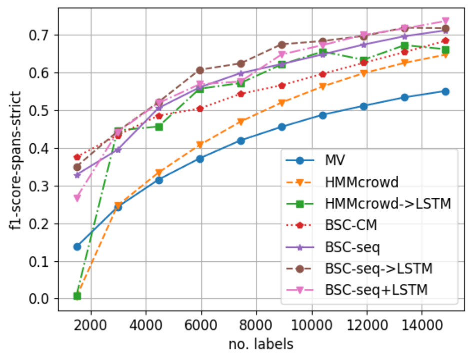
The active learning process tested here employs *uncertainty sampling*, which is a well-established heuristic (Settles, 2010). The selection method and batch size could be fine-tuned for future applications – the goal of our experiment in this paper was to test the benefits of the proposed aggregation methods, rather than to establish a robust active learning approach.

7.6 Prediction using an LSTM Trained by the Crowd

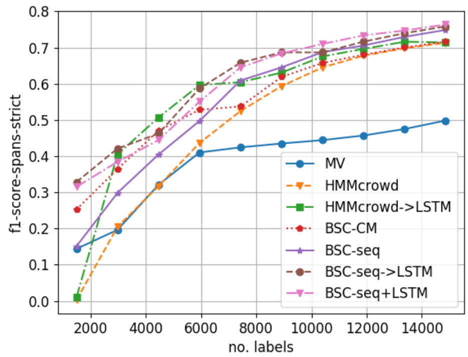
In this task, we use the aggregation methods to train an LSTM sequence tagger (Lample et al., 2016) to show whether integrating the LSTM with the aggregation method improves performance. For the NER dataset, we train the aggregation methods on the 415 crowd-labelled documents, as before, then use the outputs to train the LSTM. We then evaluate the LSTM on the validation and test sets in the original CoNLL dataset. With the PICO dataset, we run the aggregators on the $3,649$ documents without gold labels, use the outputs to train the LSTM, then evaluate the LSTM on the validation and test splits from the gold-labelled data.

7.7 Discussion

The benefits of sequential models are more evident on the PICO dataset than on NER, which may be due to the longer sequences or the smaller num-



(a) Random sampling



(b) Active learning simulation

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

	NER					PICO				
	Prec.	Recall	F1	CEE	N_{inv}	Prec.	Recall	F1	CEE	N_{inv}
HMM-Crowd→LSTMd	**78.7**	59.0	67.5	15.88	0	**75.6**	61.6	67.9	13.46	0
BSC-seq→LSTMd	74.3	**62.8**	**68.1**	15.65	0	82.3	**66.4**	**73.5**	19.62	0
BSC-seq+LSTM	73.4	62.0	67.3	0.48	0	**87.4**	57.9	69.7	**0.93**	0
gold→LSTMd	76.4	77.0	76.7	11.10	3					

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

No. Tokens	I	O	B
1486	0.22	0.978	0.648
14860	0.502	0.819	0.612
29704	0.695	0.539	0.533

Table 5: Accuracies for the integrated LSTM estimated by BSC-Seq+LSTM for NER.

ber of labels, since PICO target classes are only B, I, or O, whereas the B and I tags for NER are compounded with PER, LOC, ORG or MISC tags. <show an example from each dataset, with our predictions from HMM, BAC...>

8 Conclusions

Previous work has demonstrated the benefits of modeling annotator reliability when aggregating noisy data, such as crowdsourced labels. We proposed a sequential annotator model for sequence tagging, BSC-Seq, and showed how it improves the state-of-the-art. To further improve the quality of aggregated labels, we design a Bayesian wrapper that allows developers to integrate existing sequence taggers, such as deep neural networks, into BSC-Seq while treating them as black boxes. Our results show that integrating an LSTM in this manner can outperform an LSTM trained using labels that were aggregated in a separate pre-processing step. However, for active learning from crowds or learning with small datasets, we find that our purely Bayesian aggregation method, i.e. BSC-Seq without integrating the LSTM, outperforms both LSTM-based approaches. This hints at the value of uncertainty information in text models when data-efficient learning is required.

Future work will investigate the integration of approximate Bayesian variants of neural network sequence taggers, which may address the need for uncertainty information during active learning. We will also consider alternative data selection strategies, and how to include prior information about the reliability of black-box classifiers on a given training set size.

Acknowledgments

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.

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.

Meng Fang, Jie Yin, and Dacheng Tao. 2014. Active learning for crowdsourcing using knowledge transfer. In *AAAI*, volume 7, pages 7–4.

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.

Yarin Gal and Zoubin Ghahramani. 2016. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In *international conference on machine learning*, pages 1050–1059.

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.

Dirk Hovy, Barbara Plank, and Anders Søgaard. 2014. Experiments with crowdsourced re-annotation of a pos tagging data set. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (volume 2: Short Papers)*, volume 2, pages 377–382.

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.

Abby Levenberg, Stephen Pulman, Karo Moilanen, Edwin Simpson, and Stephen Roberts. 2014. Predicting economic indicators from web text using sentiment composition. *International Journal of Computer and Communication Engineering*, 3(2):109–115.

Huma Lodhi, Craig Saunders, John Shawe-Taylor, Nello Cristianini, and Chris Watkins. 2002. Text classification using string kernels. *Journal of Machine Learning Research*, 2(Feb):419–444.

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.

Nitika Mathur, Timothy Baldwin, and Trevor Cohn. 2017. Sequence effects in crowdsourced annotations. In *Emerging methods in natural language processing*.

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

Alan Ritter, Sam Clark, Oren Etzioni, et al. 2011. Named entity recognition in tweets: an experimental study. In *Proceedings of the conference on empirical methods in natural language processing*, pages 1524–1534. Association for Computational Linguistics.

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*.

Edwin Simpson and Stephen Roberts. 2015. Bayesian methods for intelligent task assignment in crowdsourcing systems. In *Decision Making: Uncertainty, Imperfection, Deliberation and Scalability*, pages 1–32. Springer.

Edwin D Simpson and Iryna Gurevych. 2018. Finding convincing arguments using scalable bayesian preference learning. *Transactions of the Association for Computational Linguistics*, 6:357–371.

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.

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.

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.

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.