A Bayesian Method for Combining Crowds and Ensembles for Annotating Text Sequences

Anonymous EMNLP submission

Abstract

VERSION 1: A common task in NLP is sequence labelling, which is performed by both human annotators to produce training data and by automatic classifiers that extract information from text. However, different annotators can often disagree and may have highly varying levels of reliability, particularly when crowdsourcing is used to annotate spans of text. High error rates can be mitigated by combining annotations from multiple annotators, a technique that is also used by ensembles of classifiers to boost performance. Existing approaches that model the biases and error rates of annotators have been shown to improve over simple heuristics such as majority voting. However, existing methods ignore the sequential nature of text span annotations and may therefore underperform. We propose a new Bayesian technique to combined multiple annotators of differing reliability and make the software available publicly. Using a series of simulations, we show how several different probabilistic and heuristic approaches perform under different conditions. We illustrate how our approach can improve sequential classification performance on a real-world argumentation mining task by using it to combine both human annotators and an ensemble of automated classifiers.

VERSION 2: We present a Bayesian method for combining sequence classifications from multiple annotators with different levels of noise and class bias. Sequential classification is an important problem in fields such as NLP, where many tasks involve annotating spans of text. In such tasks, crowdsourcing is often used to obtain training data for automated classifiers. However, individual human annotators have highly variable error rates and different automated classifiers often produce different patterns of errors. In both cases, errors can be reduced by combining multiple annotators. However, while Bayesian methods have proved effective in combining unreliable classifiers, they have not previously taken into account the sequence of classifications and are therefore unable to incorporate rules that restrict which labels may follow each other, such as with BIO encoding. We propose a new method that incorporates sequence information using hidden Markov models, and show how the priors can be set to capture sequence rules. We analyse performance against established classifier combination methods on synthetic data to show the effects of annotator accuracy, bias and crowd size on performance. We further evaluate the methods on two NLP datasets: crowdsourced annotations of argument components; and predictions of argument components from an ensemble of neural network classifiers. The results show the advantage of modelling sequential dependencies between labels. We make our source code and data available online.

VERSION 3: Despite sequences being core to NLP, scant work has considered how to handle noisy sequence labels from multiple annotators for the same text. Given such annotations, we consider two complementary tasks: (1) aggregating sequential crowd la- bels to infer a best single set of consen- sus annotations; and (2) using crowd an- notations as training data for a model that can predict sequences in unannotated text. For aggregation, we propose a novel Hid- den Markov Model variant. To predict se- quences in unannotated text, we propose a neural approach using Long Short Term Memory. We evaluate a suite of meth- ods across two different applications and text genres: Named-Entity Recognition in news articles and Information Extraction from biomedical abstracts. Results show improvement over strong baselines. Our source code and data are available online1.

VERSION 4: We present a Bayesian method for combining sequence classifications from multiple annotators with different levels of noise and class bias. Sequential classification is an important problem in fields such as NLP, where many tasks involve annotating spans of text. In such tasks, crowdsourcing is often used to obtain training data for automated classifiers. However, individual human annotators have highly variable error rates and different automated classifiers often produce different patterns of errors. In both cases, errors can be reduced by combining multiple annotators. However, while Bayesian methods have proved effective in combining unreliable classifiers, they have not previously taken into account the sequence of classifications and are therefore unable to incorporate rules that restrict which labels may follow each other, such as with BIO encoding. We propose a new method that incorporates sequence information using hidden Markov models, and show how the priors can be set to capture sequence rules. We analyse performance against established classifier combination methods on synthetic data to show the effects of annotator accuracy, bias and crowd size on performance. We further evaluate the methods on two NLP datasets: crowdsourced annotations of argument components; and predictions of argument components from an ensemble of neural network classifiers. The results show the advantage of modelling sequential dependencies between labels. We make our source code and data available online.

Bayesian classifier combination methods can be used both to obtain reliable classifications from crowdsourced annotations and to combine an ensemble of automated classifiers to reduce overall error rates.

TODO LIST: see notes.txt

1 Introduction

- sequential annotation problems are very frequent in NLP; high cost of labelling means we need crowdsourcing;
- Example of a sequential span and disagreement between workers
- ...we treat the crowd workers as classifiers and combine; can also do this with ensembles of ML classifiers
- ...current methods dont take advantage of sequential information
- Add in description of rival method non-Bayesian, missing sequential model for workers, has no way to set priors to specify IOB rules,
- (Put into a later related work section?) HMM_crowd includes features but we don't consider that aspect here because it is task-specific. Using a generic word-based model may be effective in some cases but could be problematic if using small datasets where the words are not actually good features, e.g. argument labelling. The best models for doing this are... Any problem-specific model can be incorporated into VB. Here, we focus on the combination of workers and sequential labelling.
- Bayesian approaches to classifier combination without sequential information are state-of-the-art
- We develop a Bayesian approach that takes full advantage of knowledge of sequential labelling rules, such as BIO.

Scientific research relies on humans to recognise important patterns in data even if we employ automated methods, these typically require training labels produced by human annotators. Natural language processing (NLP) often requires people to annotate segments of text, which we then use to train machine learning algorithms and evaluate our results. Many NLP tasks require training data in the form of annotations of phrases and propositions in text. These annotations are spans of varying length, and different pieces of text may contain different numbers of spans. An example is highlighting claims in argumentative text. Annotators will typically make mistakes and may disagree with each other about the correct annotation, even if they are experts. When processing large datasets we may use crowdsourcing to reduce costs/time of experts, which increases the amount of noise and disagreements as the annotators are non-experts. Therefore, we require a method for aggregating text span annotations from multiple annotators.

Heuristic rules could be applied, such as taking intersections of annotations, or majority labels for individual words to determine whether they form part of a span or not. However, this does not account for differing reliability between workers (e.g. there may be spammers, people who do not understand the task) and the theoretical justification for these rules is often unclear. Therefore it may not be possible to apply simple heuristics to obtain gold-standard labels from a crowd.

In this paper develop a Bayesian machine learning algorithm for combining multiple unreliable text annotations. The method we propose is based on the classifier combination method described by (Kim and Ghahramani, 2012), which was shown to be effective for handling the unreliable classifications provided by a crowd of workers. A scalable implementation of this method using variational Bayes was described by (Simpson et al., 2013), which we use as the basis for our implementation in the current work. This paper provides the following contributions:

- Novel Bayesian methodology
  - Propose a probabilistic model for combining classifications to combine annotations over sequences of words
  - Describes and tests a scalable inference algorithm for the proposed model that adapts the existing variational Bayes implementation for classifier combination
  - Analysis of priors and how to choose them
  - Guidelines for NLP crowdsourcing users on why and when to use MACE/IBCC (spam probability vs. confusion matrix) models for workers (this requires a task with many classes to show value of MACE, e.g. from the MACE paper itself)
- Compares the approach on real-world NLP datasets with simple heuristic methods (e.g. mode) and alternatives such as weighted combinations
  - Demonstrate the technique outperforms previous methods on two crowdsourcing problems?
  - Show that the technique also works well for forming ensembles of classifiers
- Evaluates the different possibilities for integrating a task-specific classifier using one of the following methods:
  - (1) an additional base classifier (retrained on soft/hard labels after crowdsourced labels have been combined; predictions then made as a combination of crowd+newly trained classifier)
  - (2) an additional base classifier (iteratively retrained on soft labels inside the VB loop)
  - (3) using the probabilities output by the classifier as a q() distribution inside the graphical model (as in WWW 16 paper) (retraining inside the VB loop until convergence).
  - (4) Other approach taken in ACL 2017 paper?
  - The distinction is important because intuitively many people use a pipeline: first, get gold or soft-gold labels by applying MACE to the crowdsourced labels, then train a classifier. We show how iterative training improves things.
- Demonstrates how using the proposed Bayesian model enables an active learning approach that improves crowdsourcing efficiency

1.1 Related Work

A model for aggregating sequential annotations was recently introduced by (Nguyen et al., 2017). Their approach assumes a simplified worker model that captures only a worker's overall accuracy, rather than modelling their skills separately for different tasks. A Bayesian treatment is not provided, meaning that it is not possible to use background knowledge of worker accuracy, for example, by transferring a worker model from a previous task. Furthermore, the method does not have a means of handling workers with few annotations, whose reliability may be estimated poorly, as we show in this paper.

Nugyen et al. (2017) experimented with two main tasks:

1. Predicting the ground truth for items labelled by the crowd, i.e. finding the true label given multiple noisy crowdsourced labels
2. Predicting the ground truth for new items not labelled by the crowd, i.e. they use crowdsourced labels for a training set of items to train a model to predict labels for a test set

We show that with our Bayesian approach, a validation set for tuning hyperparameters is not required as they can be tuned in an unsupervised manner to give comparable performance.

The model proposed by Nguyen et al. (2017), called *HMMcrowd*, estimates the sequential labels for a document given unreliable crowdsourced labels. For their first task, HMM-Crowd gave the best overall performance, closely followed in one dataset by the DS-then-HMM method, a pipeline method that first combines crowdsourced labels using Dawid and Skene's model (DS), then uses these to train an HMM to predict the sequence labels given the input text. In the second dataset the runner up was another HMM-based method that models the sequential dependencies between the annotators' labels as well as the true labels. However, DS without using the textual features also performs well in this task, much better than DS-then-HMM.

For the second task, the authors propose two other methods, both using an LSTM classifier: (1) HMMCrowd is used as a pre-processing step and the most likely sequence of labels predicted by HMMCrowd predictions is used as training labels; (2) the crowdsourced labels are used directly to train the LSTM classifier, using a vector representation for each annotator's labelling noise. It is unclear why they do not use the HMM-Crowd model directly to predict the class labels. The first approach performed marginally better in practice, but both methods were substantially better than the alternatives they tested for both datasets. We show that separate approaches are not required for the different tasks, by proposing a Bayesian approach that can integrate any classifier (such as the LSTM classifier used by Nguyen et al. (2017), into its inference loop and train it using classifier with soft, probabilistic labels, where possible. This results in improved performance for tasks 1 and 2, and enables simple, widely-applicable active learning approaches that can reduce the cost of crowdsourcing. We demonstrate this in our experiments by integrating the LSTM into our model for task 1, and by applying the complete model to task 2. We further demonstrate the active learning potential of our method against a pure neural network approach by showing task 2 performance with active learning (F1-score on unlabelled items, corresponding to figure 4 in (Nguyen et al., 2017)), and also task 1 performance with active learning (F1-score on all items in task 1 dataset, whether labelled by crowd or not).

We show the ability to incorporate different classifiers by testing our method with the LSTM as well as naive Bayes, a GP classifier, and a multinomial model (Simpson et al., 2015), the state-of-the-art for another task such as argumentation mining?

We demonstrate the diversity of NLP task types to which the approach is applicable by also testing on ...

- Check the Christian Stab argumentation data from his paper again?
- Don't we really need a good dataset for classifier combination instead? There won't be space for so many experiments.
- Check with Christian briefly if the argumentation sequential dataset is available
- Check with Tobias or Avinesh about extractive summarisation? But if it is whole sentences, may not work
- Is there any data for SRL or POS tagging? If not, it may be a useful one to crowdsource.

1.2 Notes on Applications and Datasets

There are several annotation tasks for NLP or information retrieval that we are interested in:

- Argument component labelling – identifying claims and premises that form an argument. This requires marking individual sentences, clauses, or spans that cross sentence boundaries. Some schemas allow for the component to be split so that it consists of multiple spans with excluded text between the spans. – check Steffen's ensemble work again to see if there is anything else we can do with that paper. I think the 7-class problem failed? Ideally, we combine heterogeneous classifiers. See http://www.aclweb.org/anthology/P/P17/P17-1002.pdf. We don't have a comparable metric to the paper implemented? Another option is to introduce some training data for BAC/IBCC/MACE. We can also try the argumentative essays corpus for an additional result with expert annotators.
- Semantic role labelling (SRL) – e.g. A Joint Sequential and Relational Model for Frame-Semantic Parsing
- Extractive summarisation – marking the important spans.

- Named entity recognition – Ma and Hovy 2016; uses same dataset as Nguyen et al 2017, except with the complete dataset. Could we combine the Nguyen LSTM with the Ma and Hovy one + crowd labels? Could also combine other work such as Empower Sequence Labeling with Task-Aware Neural Language Model and other papers that cite Hovy. Perhaps worth testing whether the complex sequential models are necessary if our model is providing that part, or if IBCC is sufficient if the base classifiers capture sequential patterns? Or we apply the Ma and Hovy and the Lample models and the some feature-engineered baselines (?) in an ensemble to an arbitrary task.
- POS-tagging
- Information extraction – marking relevant spans given an information requirement
- Sentiment analysis – e.g. Neural Networks for Open Domain Targeted Sentiment, Meishan Zhang and Yue Zhang and Duy-Tin Vo. The paper presents a sequential classification problem (”targeted sentiment analysis”, tokens referring to entities with that are target of particular sentiment) and compares CRF and NN models, but publishes code in C++... Could look whether the results are available as we can just use these as input.
- Unsupervised Aspect Term Extraction with B-LSTM and CRF using Automatically Labelled Datasets – Semeval task. Code not available but others might be?
- Bidirectional LSTM-CRF for Clinical Concept Extraction (2016) – code available; 2010 i2b2/VA Natural Language Processing Challenges for Clinical Records concept extraction task; compares 3 versions of their method against 5 other methods with performance around 78 - 85 f score.
- Semantic slots – End-to-End Task-Completion Neural Dialogue Systems; code available at https://github. com/MiuLab/TC-Bot; 2017; can't clearly find the results of methods compared
- Results of the WNUT2017 Shared Task on Novel and Emerging Entity Recognition; 7 systems with low F1 scores around 40.
- Event extraction? NILs?
- action sequence extraction

Note that for classifier combination, a good use case is where we the annotations are difficult to model with a single method, hence we combine several specialised models. This may not apply to NER or POS tagging because the sequential classifier gets information from the pattern of types, so a classifier specialised in one type is unlikely to work better. However, for argument claim detection, we could train models on different datasets and combine later, rather than simply dumping all datasets together – this may work because we know that there are different text types, but putting the data together into one dataset would lose that information. Could debate topics be a good way to split datasets? If the way we identify claims in each topic differs, then yes. However, it could be confused by topic-specific features and not learn a model that generalises at all. Better would be text types, e.g. argumentative essays, reviews, tweets. Imagine that I need to reuse a set of pre-trained models to discover arguments on a new topic. The new topic is slightly different, but could still be the same text type, e.g. Tweets. So perhaps trying either topic-specific models, or even random dataset splits could produce a set of models that we can combine. The combination should be better than a single one of the classifiers, including a classifier trained on everything.

AUTOML?

2 Modelling Text Span Annotations

We model annotations using the IOB schema, in which each token in a document is labelled as either I (in), O (out), or B (begin). The IOB schema requires that the label I cannot directly follow a label O, since a B token must precede the first I in any span. The IOB schema allows us to identify whether a token forms part of an annotation or not, and the use of the B label enables us to separate annotations when one annotation span begins immediately after another without any gap. This schema does not permit overlapping annotations, which are typically undesirable in crowdsourcing tasks where the crowd is instructed to provide one type of annotation. The schema also does not consider different types of annotation, although it is trivial to extend both the schema and our model to permit this case. Using a single model for different types of annotation may be desirable if the annotators are likely to have consistent confusion patterns betweeen different annotation types.

We propose an extension of the independent Bayesian classifier combination (IBCC) model (Kim and Ghahramani, 2012) for combining annotations provided by a crowd of unreliable annotators. We refer to our model as Sequential Bayesian classifier combination or Seq-BCC. In Seq-BCC, we model the text annotation task as a sequential classification problem, where the true class, t_i, of token i may be I, O, or B, and is dependent on the class of the previous token, t_{i-1}. This dependency is modelled by a transition matrix, A, as used in a hidden markov model. Rows of the transition matrix correspond to the class of the previous token, t_{i-1}, while columns correspond to values of t_i. Each row is therefore a categorical distribution. Seq-BCC also extends IBCC by incorporating an arbitrary classifier to model the relationship between text features and the true class labels, providing a generalisation of the method proposed by Simpson et al. (2015). In this case, we assume that the integrated classifier can be used to model the likelihood of the text features, $\boldsymbol{V}$, of a document (a sequence of words or word embedding vectors) given its sequence of true labels: $p(\boldsymbol{V}|t_0, ..., t_N)$.

We model the annotators using a confusion matrix similar to that used in (Simpson et al., 2013), which captures the likelihood that annotator k labels token i with class $c_i^{(k)}$, given the true class label, t_i, and the previous annotation from k, $c_{i-1}^{(k)}$. The dependency between $c_i^{(k)}$ and t_i allows us to infer the ground truth from noisy or biased crowdsourced annotations. There is also a dependency on the previous worker annotation, since these are constrained in a similar way to the true labels, i.e. the class I cannot follow immediately from class O. Furthermore, mistakes in the class labels are likely to be correlated across several neighbouring tokens, since annotations cover continuous spans of text. The confusion matrix, $\boldsymbol{\pi}^{(k)}$, is therefore expanded in our model to a three dimensional transition-confusion mtrax, where the element $\pi_{j,l,m}^{(k)} = p(c_i^{(k)} = m | c_{i-1}^{(k)} = l, t_i = j)$. Within $\boldsymbol{\pi}^{(k)}$, the vector $\boldsymbol{\pi}_{j,l}^{(k)} = \{\pi_{j,l,1}^{(k)}, ..., \pi_{j,l,L}^{(k)}\}$, where L is the number of class labels, represents a categorical distribution over the worker's annotations conditioned on the ground truth and their previous annotation.

2.1 Generative Model

In the Seq-BCC approach, the model described above is given a Bayesian treatment by placing prior distributions over the state transition matrix A and worker confusion matrices $\boldsymbol{\pi}^{(k)}$. The generative process is as follows.

Ground truth: For each class label $j = \{I, O, B\}$, we draw a row of the transition matrix, $A_j \sim \mathrm{Dir}(\boldsymbol{\beta}_j)$, where Dir is the Dirichlet distribution. For each document i in a set of N documents, we now draw a sequence of class labels $\boldsymbol{t_i} = [t_{i,1}, ..., t_{i,T_i}]$ of length T_i. For $\tau = 1$, we draw the first label in each sequence from $t_{i,\tau} \sim \mathrm{Categorical}(\boldsymbol{A}_O)$, then for $\tau > 1$, we draw subsequent labels from $t_{i,\tau} \sim \mathrm{Categorical}(\boldsymbol{A}_{t_{i,\tau-1}})$. The first label in each sequence uses hyperparameters $\boldsymbol{A}_O$ because there is no previous annotation, so we assume that the state $t_{i,0}$ prior to the document start is not part of an annotation, and therefore $t_{i,0} = O$ is an outside or O token.

Worker annotations: For each worker $k \in \{1, ..., K\}$, true label $j \in \{1, ..., L\}$, and previous worker label $l = \{1, ..., L\}$, we draw vectors $\boldsymbol{\pi}_{j,l}^{(k)} \sim \mathrm{Dir}(\boldsymbol{\alpha}_{j,l}^{(k)})$, which make up the three-dimensional transition-confusion matrix. We now draw annotations for each worker k for each document i, starting with the first token, $c_{i,1}^{(k)} \sim \mathrm{Categorical}(\boldsymbol{\pi}_{t_{i,1},O}^{(k)})$ (assuming that the annotation prior to token 1 is equivalent to an O annotation), then for subsequent tokens, τ, we draw $c_{i,\tau}^{(k)} \sim \mathrm{Categorical}(\boldsymbol{\pi}_{t_{i,\tau}, c_{i,\tau-1}^{(k)}}^{(k)})$.

Text features: we model the relationship between the true class labels $\boldsymbol{t}_i$ of document i, and its sequence of text tokens, $\boldsymbol{V}_i$, using a text classifier chosen for the specific task in hand. In the generative process, we treat the text classifier in a similar way to the workers, assuming it produces annotations $c_{i,\tau}^{(b)} \sim \mathrm{Categorical}(\boldsymbol{\pi}_{t_{i,1}, c_{i,\tau-1}^{(b)}}^{(b)})$, where b is the index of the black-box classifier. We assume that the sequence of text tokens are drawn from $v_{i,\tau} \sim f(c_{i,\tau}^{(b)}, \boldsymbol{\theta}_v)$, where f is an arbitrary likelihood determined by the text classifier that is parametrised by $\boldsymbol{\theta}_v$. Modelling the text classifier in a similar way to the workers allows us to integrate classifiers that output either discrete predictions or probabilities, and to ignore the internal details of the classifier by treating it as a black-box. In practice, the text classifier need not implement a generative model, as discriminative methods can also be used to estimates the terms we need for approximate inference, as we show in the next section.

2.2 Variational Bayes (VB) Algorithm

We propose a mean-field variational Bayes (VB) algorithm for approximate inference, with an expectation-maximisation (EM) step used to integrate an arbitrary text classifier. The VB algorithm assumes an approximate posterior distribution that factorises between the parameters and latent variables, given by:

$$q(\boldsymbol{t}, \boldsymbol{A}, \boldsymbol{\pi}^{(1)}, ..., \boldsymbol{\pi}^{(K)} | \hat{\boldsymbol{c}}^{(b)}) = \prod_{d=1}^{D} q(\boldsymbol{t}_d)$$

$$\prod_{j=1}^{L} \left\{ q(\boldsymbol{A}_j) \prod_{l=1}^{L} q(\boldsymbol{\pi}_{j,l}^{(b)}) \prod_{k=1}^{K} q(\boldsymbol{\pi}_{j,l}^{(k)}) \right\}, \quad (1)$$

where $\boldsymbol{t}$ contains ground truth labels for all documents, and $\hat{\boldsymbol{c}}^{(b)}$ contains the text classifier's current predictions for all tokens in all documents. We optimise this distribution using Algorithm 1 to obtain approximate posterior distributions over $\boldsymbol{t}$, $\boldsymbol{\pi}^{(k)}, \forall k$ and $\boldsymbol{A}_j, \forall j$. The algorithm iteratively increases the lower bound on the model evidence, $\mathcal{L}$, by optimising one variational factor given the current estimates of the others. Convergence can be checked cheaply by comparing values of $\mathbb{E}[t_{i,\tau}]$ between iterations. However, a more reliable method is to check $\mathcal{L}$ for convergence.

Depending on the implementation of the text classifier, the training step of the text classifier may correspond to the maximisation step in an EM-algorithm, if the parameters of the classifier, θ_v, are optimised to their maximum likelihood or maximum a-posteriori solution, as is typical of neural network methods. In this case, our complete algorithm would incorporate a non-Bayesian text classification step. In contrast, a Bayesian classifier integrates out the parameters θ_v and outputs marginal probabilities over class labels. If a Bayesian classifier is integrated, retraining the text classifier becomes a VB step, in which a variational factor, $q(\boldsymbol{c}^{(b)}$, is updated, making the complete algorithm a fully Bayesian approximation. We now present equations for the variational factors and expectation terms required by the algorithm, followed by the lower bound, $\mathcal{L}$.

2.3 Variational Factors

For the sequence of true labels, $\boldsymbol{t}$, the optimal variational factor given the current estimates of $q(\boldsymbol{A}_j)$

Input: Crowdsourced annotations, $\boldsymbol{c}$
Initialise $\mathbb{E}[\ln \boldsymbol{A}]$, $\mathbb{E}\left[\ln \boldsymbol{\pi}^{(k)}\right], \forall k$ $\mathbb{E}\left[\ln \boldsymbol{\pi}^{(b)}\right]$ $\hat{\boldsymbol{c}}^{(b)}$ randomly or to prior means;
while *not converged* **do**
- Update $q^*(t_{i,\tau} = j)$ and $q^*(t_{i,\tau-1} = j, t_{i,\tau} = j'), \forall i, \forall \tau, \forall j$, given $\mathbb{E}[\ln \boldsymbol{A}]$ and $\mathbb{E}\left[\ln \boldsymbol{\pi}^{(k)}\right], \forall k$ using the forward-backward algorithm;
- Retrain text classifier using $\mathbb{E}[\boldsymbol{t}]$ as training labels;
- Update predictions $\hat{\boldsymbol{c}}^{(b)}$;
- Update $q^*\left(\boldsymbol{\pi}_j^{(k)}\right), \forall j, \forall k$ given current $q^*(t_{i,\tau-1} = j, t_{i,\tau} = j')$;
- Update $q^*(\boldsymbol{A}_j), \forall j$ given current $q^*(t_{i,\tau} = j)$;
- Recompute $\mathbb{E}[\ln \boldsymbol{A}]$ and $\mathbb{E}\left[\ln \boldsymbol{\pi}^{(k)}\right], \forall k$ given current estimates of $q(\boldsymbol{A}_j)$ and $q(\boldsymbol{\pi}_j^{(k)})$;

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

Algorithm 1: The VB algorithm for Seq-BCC.

and $q(\boldsymbol{\pi}_j^{(k)})$, is:

$$\ln q^*(\boldsymbol{t}) = \mathbb{E}_q \left[\sum_{i=1}^{N} \sum_{\tau=1}^{T_i} \left\{ \ln p(t_{i,\tau} | t_{i,\tau-1}, \boldsymbol{A}) \right.\right.$$

$$\left.\left. + \sum_{k=1}^{K} p(c_{i,\tau}^{(k)} | t_{i,\tau}, c_{i,\tau-1}^{(k)}, \boldsymbol{\pi}^{(k)}) \right\} \right] + \text{const},$$

$$= \sum_{i=1}^{N} \sum_{\tau=1}^{T_i} \mathbb{E}[\ln A_{j,t_{i,\tau}}] + \sum_{k=1}^{K} \ln \tilde{\pi}_{i,\tau,t_{i,\tau}}^{(k)} + \text{const}, \quad (2)$$

where for notational convenience we define $\ln \tilde{\pi}_{i,\tau,j}^{(k)} = \mathbb{E}\left[\ln \pi^{(k)}_{j,c_{i,\tau-1}^{(k)},c_{i,\tau}^{(k)}}\right]$. In the VB algorithm, the parameters updates to $q(\boldsymbol{A}_j)$ and $q(\boldsymbol{\pi}_j^{(k)})$ require expectations for the individual true labels and transitions from one each label to the next:

$$r_{i,\tau,j} = q^*(t_{i,\tau} = j) = \mathbb{E}_q[p(t_{i,\tau} = j | \boldsymbol{c})], \quad (3)$$

$$s_{i,\tau,j,j'} = q^*(t_{i,\tau-1} = j, t_{i,\tau} = j') = \mathbb{E}_q[p(t_{i,\tau-1} = j, t_{i,\tau} = j' | \boldsymbol{c})]. \quad (4)$$

These terms can be computed using the forward-backward algorithm (Ghahramani, 2001), which consists of two passes. The forward pass starts from $\tau = 1$ and computes for each value of τ the posterior given crowdsourced annotations for tokens up to and including τ.

$$\ln r^-_{i,\tau,j} = \mathbb{E}\left[\ln p(t_{i,\tau} = j|\boldsymbol{c}^{(1)}_{i,1:\tau}, ..., \boldsymbol{c}^{(K)}_{i,1:\tau})\right]$$
$$= \sum_{j'=1}^{L} \left\{\ln r^-_{i,\tau-1,j'} + \mathbb{E}[\ln A_{j',j}]\right\} + \sum_{k=1}^{K} \ln \tilde{\pi}^{(k)}_{i,\tau,j}, \quad (5)$$

where $\boldsymbol{c}^{(k)}_{i,1:\tau}$ is the set of labels from 1 to τ in document i. For the first token in each sequence, we compute $\ln r^-_{i,1,j}$ as follows:

$$\ln r^-_{i,1,j} = \mathbb{E}[\ln p(t_{i,1})] + \sum_{k=1}^{K} \ln \tilde{\pi}^{(k)}_{i,1,j}, \quad (6)$$

where $p(t_{i,1})$ gives the class probability for the first token in the sequence. The backwards pass starts from $\tau = T_i$ and scrolls backwards, computing the likelihood of the annotations at positions from $\tau + 1$ to T_i given the true label $t_{i,\tau}$, as follows:

$$\ln \lambda_{i,T_i,j} = 0$$
$$\ln \lambda_{i,\tau,j} = \mathbb{E}_q\left[\ln p(\boldsymbol{c}^{(1)}_{i,\tau+1:T_i}, ..., \boldsymbol{c}^{(K)}_{i,\tau+1:T_i}|t_{i,\tau} = j)\right]$$
$$= \ln \sum_{j'=1}^{L} \exp\left\{\ln \lambda_{i,\tau+1,j'} + \mathbb{E}[\ln A_{j,j'}] + \sum_{k=1}^{K} \ln \tilde{\pi}^{(k)}_{i,\tau+1,j'}\right\} \quad (7)$$

$\forall \tau < T_i$. Since the terms may become small over a long sequence, $\ln r^-_{i,\tau,j}$ and $ln\lambda_{i,\tau,j}$ can be normalised by subtracting the corresponding sum over j. By taking the exponents and applying Bayes' rule we arrive at the terms $r_{i,\tau,j}$ and $s_{i,\tau,j,j'}$:

$$r_{i,\tau,j} = \mathbb{E}\left[p(t_{i,\tau} = j)\right] = \frac{1}{Z} r^-_{i,\tau,j} \lambda_{i,\tau,j} \quad (8)$$
$$s_{i,\tau,j,j'} = \frac{1}{Z} r^-_{i,\tau-1,j} \lambda_{i,\tau,j'} \exp(\mathbb{E}[\ln A_{j,j'}] + \ln \tilde{\pi}^{(k)}_{i,\tau,j'}) \quad (9)$$

The $r_{i,\tau,j}$ terms are normalised by a sum, Z, over j, and the $s_{i,\tau,j,j'}$ terms are normalised by a sum, Z, over j and j'. The $r_{i,\tau,j}$ terms provide the output predictions of the class labels.

The optimal variational factor for each row of the ground truth transition matrix is:

$$\ln q^*(\boldsymbol{A}_j)$$
$$= \sum_{i=1}^{N} \sum_{\tau=1}^{T_i} \sum_{j'=1}^{L} s_{i,\tau,j,j'} \ln \boldsymbol{A}_{j,j'} + \ln p(\boldsymbol{A}_j|\boldsymbol{\beta}_j) + \text{const}$$
$$= \sum_{j'=1}^{L} N_{j,j'} \ln \boldsymbol{A}_{j,j'} + \ln p(\boldsymbol{A}_j|\boldsymbol{\beta}_j) + \text{const}, \quad (10)$$

where $N_{j,j'} = \sum_{i=1}^{N} \sum_{\tau=1}^{T_i} s_{i,\tau,j,j'}$ are pseudo-counts of the number of times that class j follows class j'. Since we assumed Dirichlet priors over $\boldsymbol{A}_j$, the variational factor for $\boldsymbol{A}_j$ is Dirichlet distribution with parameters $\boldsymbol{b}_j = \boldsymbol{\beta}_j + \boldsymbol{N}_j$, where $\boldsymbol{N}_j = \{N_{j,j'}, \forall j'\}$. The class probability for the first token in each sequence, $p(t_i, 1)$, can be treated as an additional row of the transition matrix, $\boldsymbol{A}_0$. Dirichlet priors can then be applied in the same manner, and the posterior parameters can also by computed by adding pseudo-counts of the initial class labels.

The VB algorithm requires a term $\mathbb{E}[\ln A]$ to update the variational factors for the ground truth labels. We can compute each element using:

$$\mathbb{E}[\ln A_{j,j'}] = \Psi\left(b_{j,j'}\right) - \Psi\left(\sum_{j'=1}^{L} b_{j,j'}\right), \quad (11)$$

where Ψ is the digamma function.

For the three-dimensional worker transition-confusion matrices, $\boldsymbol{\pi}^{(k)}$, the optimal variational factors are given by:

$$\ln q^*\left(\boldsymbol{\pi}^{(k)}_{j,l}\right) = \sum_{m=1}^{J} N^{(k)}_{j,l,m} \ln \pi^{(k)}_{j,l,m}$$
$$+ \ln p\left(\boldsymbol{\pi}^{(k)}_{j,l}|\alpha^{(k)}_{j,l}\right) + \text{const}, \quad (12)$$

where $N^{(k)}_{j,l,m} = \sum_{i=1}^{N} \sum_{\tau=1}^{T_i} r_{i,\tau,j} \delta_{m,c^{(k)}_{i,\tau}}$ are pseudo-counts and δ is the Kronecker delta. The variational factor is also a Dirichlet distribution with parameters $\boldsymbol{a}^{(k)}_{j,l} = \boldsymbol{\alpha}^{(k)}_{j,l} + \boldsymbol{N}^{(k)}_j$, where $\boldsymbol{N}^{(k)}_j = \left\{N^{(k)}_{j,l,m}, \forall m\right\}$.

To update the variational factor for the true class, the VB algorithm requires a three-dimensional expectation term, $\mathbb{E}[\ln \pi^{(k)}]$, whose elements are computed using the following:

$$\mathbb{E}\left[\ln \pi_{j,l,m}^{(k)}\right] = \Psi\left(a_{j,l,m}^{(k)}\right) - \Psi\left(\sum_{m=1}^{L} a_{j,l}^{(k)}\right). \quad (13)$$

2.4 Variational Lower Bound

The VB algorithm optimises the lower bound on model evidence, so it is useful to compute the lower bound to check for convergence, or to compare models with different hyperparameters when performing model selection. The lower bound for Bayesian annotator combination is:

$$\mathcal{L} = \mathbb{E}_q\left[\ln p\left(\boldsymbol{c}, \boldsymbol{t} | \boldsymbol{A}, \boldsymbol{\pi}^{(1)}, ..., \boldsymbol{\pi}^{(K)}\right) - \ln q(\boldsymbol{t})\right]$$
$$+ \sum_{j=1}^{L} \Bigg\{ \mathbb{E}_q\left[\ln p\left(\boldsymbol{A}_j | \boldsymbol{\beta}_j\right) - \ln q(\boldsymbol{A}_j)\right]$$
$$+ \sum_{l=1}^{J}\sum_{k=1}^{K} \mathbb{E}_q\left[\ln p\left(\boldsymbol{\pi}_{j,l}^{(k)} | \boldsymbol{\alpha}_{j,l}^{(k)}\right) - \ln q\left(\boldsymbol{\pi}_{j,l}^{(k)}\right)\right] \& \quad nonumber \quad (14)$$
$$+ \mathcal{L}_v\left(\boldsymbol{\theta}_v; \boldsymbol{V}, \boldsymbol{c}^{(b)}\right) \Bigg\}, \quad (15)$$

where $\mathcal{L}_v$ is provided by the text classifier implementation and is the marginal log-likelihood of the text data $\boldsymbol{V}$, either given the maximum likelihood estimate of parameters θ_v, or, in the case of a Bayesian classifier, an expectation over θ. The lower bound computation uses the equations described in the previous section for the variational factors, $q(\boldsymbol{A}_j)$ and $q\left(\boldsymbol{\pi}_{j,l}^{(k)}\right)$, and the prior distributions for the parameters, and inserts the expectations $\mathbb{E}\left[\ln \boldsymbol{A}_j\right]$ and $\mathbb{E}\left[\ln \boldsymbol{\pi}_{j,l}^{(k)}\right]$. The first term of $\mathcal{L}$ makes use of auxiliary variables from the forward-backward algorithm:

$$\mathbb{E}_q\left[\ln p\left(\boldsymbol{c}, \boldsymbol{t} | \boldsymbol{A}, \boldsymbol{\pi}^{(1)}, .., \boldsymbol{\pi}^{(K)}\right)\right] = \sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\sum_{j=1}^{L} r_{i,\tau,j} \ln r_{i,\tau,j}^{-} \quad (16)$$

3 Alternative Methods

To date, a number of methods have been used to reduce annotations from multiple workers to a single gold-standard set. These approaches make use of both heuristic and statistical techniques. This section outlines commonly-used baselines and state-of-the-art methods that we later compare against our method.

3.1 Majority/Plurality Voting

For classifications, a simple heuristic is to take the majority label, or for multi-class problems, the most popular label. Examples for NLP classification problems include sentiment analysis(Sayeed et al., 2011),.... With text spans, we can use the IOB classes and choose the most popular label for each word, but there are a number of cases where the resulting spans would not follow the constraints of the schema, and an additional step is required to resolve these issues. The problems occur when annotators disagree about the starting and ending points of an annotation:

- The votes for a token being inside a span can be split between the classes I and B, which could lead to tokens being excluded from spans even when most have marked them as inside.
- The voting process can lead to spans of I tokens with no preceding B token if there is only a minority of annotators who marked did not agree on the first token.
- The spans from different annotators could partly overlap, causing the overlap area itself to be marked as a separate span. In some cases, this may be a valid annotation, while in others it would be obvious to anyone reviewing the annotation that it is an artefact of the aggregation method. There does not seem to be a simple fix here, except for requesting more annotations from other workers. With a sufficient number of annotations, we expect the problem to be resolved.

In our experiments, we define a baseline *majority voting* method, which addresses the problems described above as follows. We resolve the first problem using a two-stage voting process. First, we combine the I and B votes and determine whether each token should be labelled as O or not. Then, for each token marked as I or B, we and perform another voting step to determine the correct label. This resolves cases where annotators disagree about whether a span should be split into two annotations. To resolve the second problem of aggregated spans without a B token at the start, we mark the first I token in any aggregate span as B.

The voting procedure outlined above produces annotations where the annotations of at least 50% of workers intersect. A stricter approach can be used, which requires that all the annotators mark a token for it to be included (e.g. (Farra et al., 2015)). We refer to this approach as the *intersect* method. For tasks where workers are likely to miss many spans, it is also possible to lower the threshold so that we do not require a majority of workers to mark a token as I/B before we accept it as such during aggregation.

3.2 Item-response Methods

this should be moved to an earlier section and used to build up to the proposed method

The current state-of-the-art methods are termed *Item-response* models (Felt et al., 2016), which are based on the approach by (Dawid and Skene, 1979). These approaches use a confusion matrix to model the likelihood that annotator k gives response c to an item i. This approach naturally accounts for bias toward a particular answer and varying accuracy depending on the true class, and has been shown to outperform techniques such as majority voting and weighted sums(Simpson et al., 2013; Raykar and Yu, 2012; Kim and Ghahramani, 2003). Recent extensions follow the Bayesian treatment of (Kim and Ghahramani, 2003), called IBCC, to deal with specific problems in crowdsourcing with large numbers of workers: (Moreno et al., 2015; Venanzi et al., 2014) identify clusters of crowd workers with shared confusion matrices to improve performance when information about individual workers is sparse; (Venanzi et al., 2016) account for the time each worker takes to complete a task; (Felt et al., 2016; Simpson et al., 2015) additionally model language features in text classification tasks to improve performance when data is sparse. However, none of these methods consider the sequential nature of classifications and treat each item as i.i.d. Therefore, they cannot take advantage of the dependencies between each token's annotation to improve predictions and ensure valid sequences. In this paper, we propose and evaluate a method that resolves this problem. The modular nature of graphical models means that the extensions described above could in future be combined with our approach in suitable situations.

A method that simplifies the confusion matrix, *MACE*, was proposed by (Hovy et al., 2013) to reduce the cost of learning. This is particularly suitable for tasks with a large number of classes since the number of parameters in the confusion matrix typically grows $\mathcal{O}(J^2)$, where J is the number of classes.

* show mathematically how this method is related to IBCC *

However, there are some potential downsides to this simplification. Bias toward a particular class is fixed, and skill level no longer depends on the ground-truth class. The class proportions distribution is also omitted in both (Hovy et al., 2013) and the accompanying published software implementation, which could lead to reduced performance when classes are highly imbalanced. In our experiments, we compare MACE to both standard IBCC and our proposed method, Seq-BCC to illustrate the types of situation where each approach may be advantageous.

3.3 Clustering Methods

Cluster the annotations, e.g. using a mixture model with annotation centre and spread, or by merging the boundaries somehow. See Zooniverse annotation work – could discretize this?

3.4 Other Solutions

The level of disagreement in annotations for a particular piece of text can be used to determine whether an annotation is of a insufficient quality to keep (e.g. (Sayeed et al., 2011; Hsueh et al., 2009). This can be achieved using the majority voting method, but adjusting the threshold for classifying a token as I/B from 50% to something higher.

Human resolution: an additional worker selects the correct answer from the annotations provided by the initial set of workers, e.g. (Dagan, 2016). To reduce costs, the human resolution step could be applied only to text with large amounts of disagreement.

3.5 How to Include Text Features into the Crowdsourcing Model

Modelling the text features as part of the aggregation method has been shown to improve classification performance, particularly when few labels are available, allows classification of unlabelled items without training a separate classifier, and provides a basis for active selection of documents for further labelling (Settles, 2010).

The difficulty of modelling text features is that it requires a suitable classifier for the task at hand, and so it may not be effective to design a generic crowdsourcing model that describes the relationship between text features and class labels. Instead, we propose a solution that allows us to include task-specific classifiers, e.g. if the task at hand is NER, we show how to integrate a neural network designed specifically for NER.

The modular nature of variational Bayesian inference allows us to reusing the existing inference steps when extending the graphical model. This means that we can add additional components to the model to model the relationship between text features and classifications. This section shows how we can treat task-specific classifiers as black-box extensions to the graphical model, and integrate them into the VB inference procedure.

4 Experiments with Synthetic Data

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 2, (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. (**?**) using aggregated labels, and (3) actively selecting batches of documents for crowdsourced annotation.

5 Experiments with Real Data

6 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 (**?**), all of which contain gold labels for four named entity categories (PER, LOC, ORG, MISC). Of these, we use crowdsourced labels provided by (**?**) 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 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.

8 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 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 different worker models:

1. Accuracy model (*BSCC-ACC*): each worker is represented by a single parameter encoding $p(correctlabel)$
2. Spammer model (*BSCC-MACE*): proposed for MACE (Hovy et al., 2013), each worker has a parameter encoding $p(workerisspamming)$ and a set of L parameters encoding $p(label|workerisspamming)$.
3. Confusion matrix (*BSCC-IBCC*): as in (Simpson et al., 2013), each worker

has a matrix of parameters containing $p(labell|trueclassj)$.

4. Sequential confusion matrix (*BSCC-Seq*): as described in Section 2, extends the confusion matrix using an HMM to model label transitions.

Secondly, with different feature models:

1. No text features (*NF*): only the crowdsourced 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.

2. Independent text features (*IF*): 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.

3. Integrated LSTM (*intLSTM*): the LSTM is integrated into the variational inference loop as described in Section 2.

9 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. (**?**). 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. (**?**), 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.

9.0.1 Examples of Aggregation

9.1 Prediction using an LSTM Trained by the Crowd

In this task, we use the aggregation methods to train an LSTM sequence tagger (**?**) 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.

10 Active Document Selection

We run an active learning simulation to evaluate whether the proposed Bayesian approach and integrated LSTM can improve the efficiency of the 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 9.1. 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 availble 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 9.1. 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.

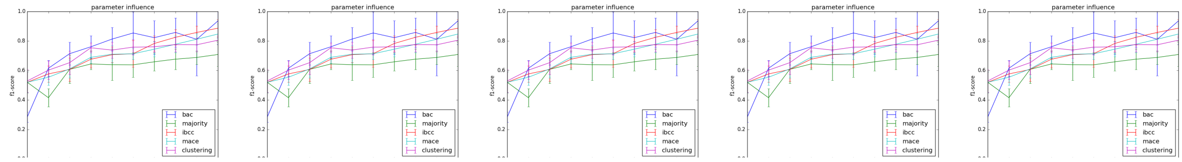
The active learning process tested here employs *uncertainty sampling*, which is a well-established heuristic (**?**). The selection method and batch size could be fine-tuned for future applications – the

NER	Span-level metrics			Token-level metrics					
	Prec.	Recall	F1	F1	AUC	CEE	$N_{invalid}$	Notes	Hyperparams
MV	78.89	56.13	65.59	68.48	.9406	7.72	73		
MACE	67.01	67.16	67.09	66.95	.8385	2.87	69		.1, .1
DS	77.52	71.68	74.49	75.35	.9548	4.10	54		
IBCC	78.02	71.38	74.55	75.41	.9586	0.61	44		.1, 10, .1
HMM-Crowd*	77.67	70.05	73.67	75.33	.9766	1.11	0	Why better than BSCC-Vec-IF?	0, 0.1
HMM-Crowd-then-LSTM*	77.67	70.66	74.00	75.11	.9058	13.92	0		0, .1
BSCC-Seq-NF*	81.30	67.46	73.74	70.35	.9585	0.45	0		100, 100, 36
BSCC-Acc-IF	81.07	53.79	64.67	67.42	.9643	1.41	0		.1, 1, 1
BSCC-MACE-IF	44.42	79.92	57.10	57.93	.9534	1.35	0		.1, 1, .1
BSCC-Vec-IF	78.48	66.63	72.08	72.88	.9747	0.93	0		.1, 10, .1
BSCC-IBCC-IF	73.18	76.48	74.79	74.36	.9739	0.87	0		.1, .1, 1
BSCC-Seq-IF	81.25	71.64	76.14	75.69	.9286	1.06	0		.1, 10, 1
BSCC-IBCC-IF-then-LSTM*	71.53	69.88	70.70	70.61	.9082	16.92	0	Pre bug-fix result	50, 9
BSCC-Seq-IF+LSTM*	81.67	69.64	75.17	71.32	.9707	0.44	0		100, 36
BCC-Seq-IF+LSTM*								Running	100, 36

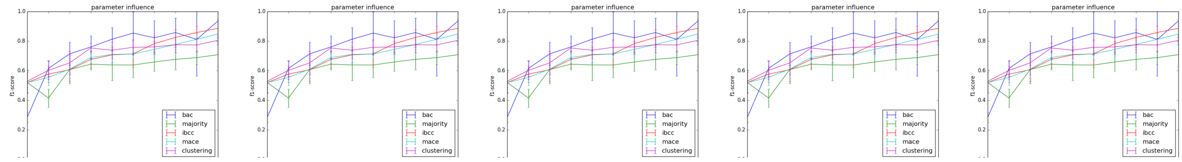
Table 1: Crowdsourced label aggregation performance on NER dataset: estimating true labels given crowdsourced labels.

PICO	Span-level metrics			Token-level metrics					
	Prec.	Recall	F1	F1	AUC	CEE	$N_{invalid}$	Notes	Hyperparams.
MV	82.45	52.75	64.34	76.41	.9232	2.55	80		
MACE*	45.01	88.49	59.63					results from (Nguyen et al., 2017)	
DS	71.32	66.30	68.72	79.33	.9336	0.44	54		
IBCC	72.12	65.99	68.92	79.31	.9349	0.27	37		.1, 10, 10
HMM-Crowd	76.49	66.23	70.99	77.90	.9435	0.79	0	3% lower than (Nguyen et al., 2017) on different split running	
HMM-Crowd-then-LSTM									
BSCC-Seq-NF	81.16	59.18	68.45	59.76	.9218	0.73	0		.1, .1, .1
BSCC-Acc-IF	89.58	45.14	60.04	74.95	.9260	1.06	0	Without strong prior on IF	.1, .1, 10
BSCC-MACE-IF	46.68	84.36	60.10	68.51	.9443	1.98	0		.1, 100, .1
BSCC-Vec-IF	74.90	67.18	70.83	76.95	.9344	0.81	0	Without strong prior on IF	.1, 1, .1
BSCC-IBCC-IF	61.83	76.33	68.32	74.80	.9389	1.37	0	Without strong prior on IF	.1, 100, 1
BSCC-Seq-IF	86.39	61.97	72.17	52.64	.9288	.73	0	Without strong prior on IF	.1, .1, .1
BSCC-Seq-then-LSTM	87.14	61.38	72.02	51.55	.8212	21.62	0		.1, .1, .1
BSCC-Seq+LSTM	75.09	77.33	76.20	51.85	.9336	0.68	0		.1, .1, .1
BCC-Seq+LSTM	52.88	17.06	25.80	46.92	.8446	0.58	587	fail!	.1, .1, .1

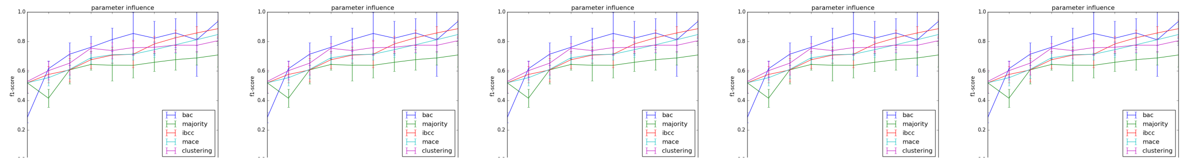
Table 2: Crowdsourced label aggregation performance on PICO dataset: estimating true labels given crowdsourced labels.



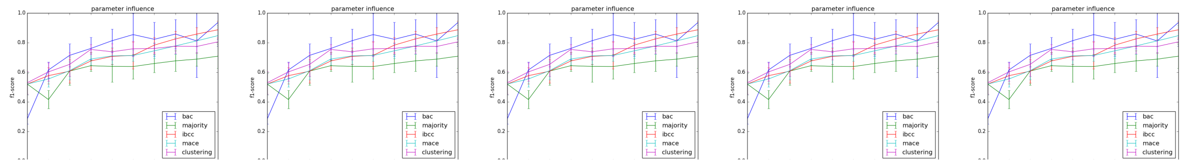
(a) BSCC-Acc-IF



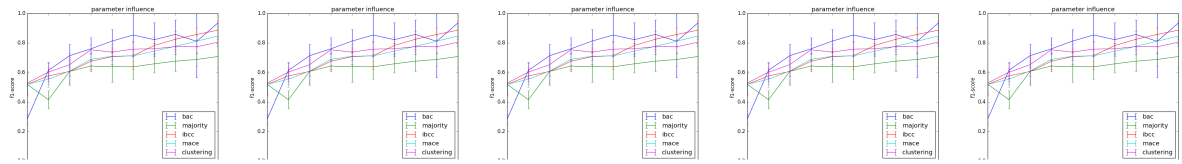
(b) BSCC-Vec-IF



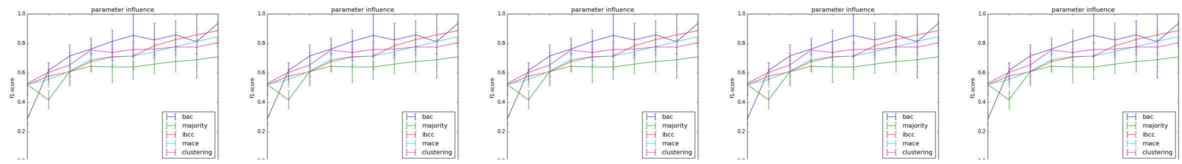
(c) BSCC-MACE-IF



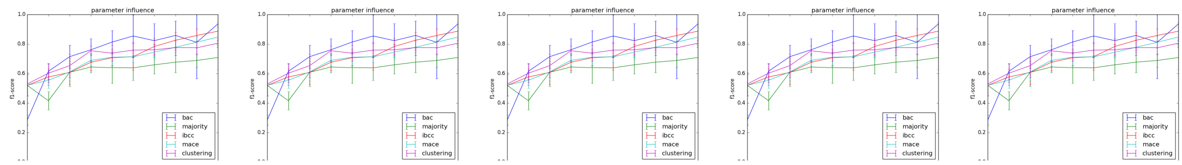
(d) BSCC-IBCC-IF



(e) BSCC-Seq-IF, previous label = I



(f) BSCC-Seq-IF, previous label = O



(g) BSCC-Seq-IF, previous label = B

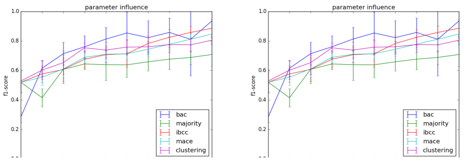
Figure 1: Confusion matrix representations from each BSCC-***-IF variant trained on the PICO datasets showing the different representations of workers.

NER	Span-level metrics			Token-level metrics				
	Prec.	Recall	F1	F1	AUC	CEE	$N_{invalid}$	Notes
HMM-Crowd								
HMM-Crowd-then-LSTM	72.75	68.26	70.43	35.73	.8752	23.45	0	V. close to Nguyen et al. (2017)
LSTM	83.19	57.12	67.73					
LSTM-Crowd	82.38	62.10	70.82					
BSCC-IBCC-IF-then-LSTM	57.67	66.04	61.57	33.60	.8821	32.64	0	
BSCC-Seq-IF+LSTM	51.51	3.79	7.06	12.61	.8120	0.74	0	Failed
BCC-Seq-IF+LSTM								

Table 3: Prediction performance on NER test dataset. Methods trained on crowdsourced labels for training set.

PICO	Span-level metrics (std.)			Token-level metrics (std.)			
	Prec.	Recall	F1	F1	AUC	CEE	$N_{invalid}$
HMM-Crowd							
HMM-Crowd-then-LSTM							
LSTM							
LSTM-Crowd							
BSCC-IBCC-IF							
BSCC-Seq-IF							
BSCC-Seq-IF-then-LSTM							
BSCC-Seq+LSTM							
BSCC-Seq-IF+LSTM							

Table 4: Prediction performance on PICO test dataset. Methods trained on crowdsourced labels for training set.



(a) NER dataset, BSCC-IBCC-IF+LSTM (b) PICO dataset, BSCC-Seq-IF+LSTM

Figure 2: Confusion matrices learned for the integrated LSTM using BSCC-***-IF+LSTm.

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.

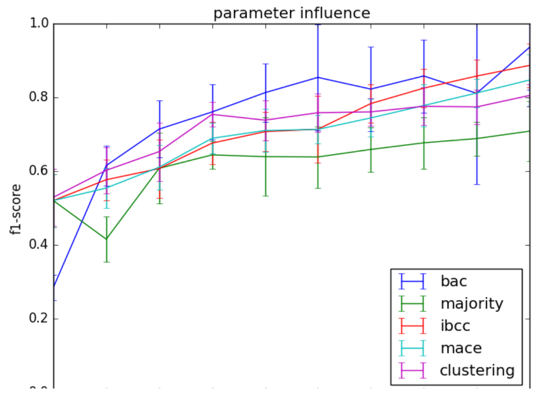
11 Discussion

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 number 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...¿

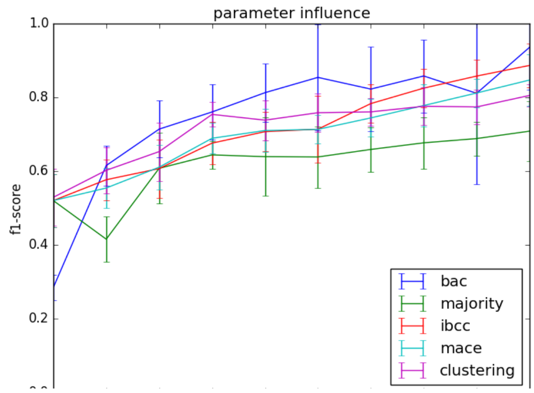
12 Future Work

The model can also be applied to other sequential classification tasks beside span annotation. For example, the order of tasks that are intended to be exchangeable may affect the likelihood of the labels provided by the annotators(Mathur et al., 2017). Seq-BCC could be applied to model the propensity of the workers to choose certain labels given their previous labels, while the ground truth sequence may be ignored.

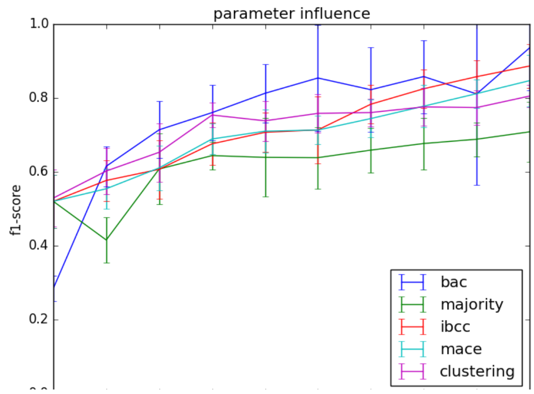
It may be possible to improve the performance of BLSTM by refining the model through attention layers. However, similar refinements could also be applied to the Bayesian approach, although it remains to be seen whether more complex models would be suitable for scenarios with limited data. It may be possible to take advantage of neural network models in combination with a Bayesian approach by learning argument embeddings in domains using neural networks trained in domains with sufficient data, then using them to embed arguments in new domains to produce input data for a GP. This could be more successful than simply using word or sentence embeddings, as the embeddings would be tailored to the task of modelling



(a) Example 1

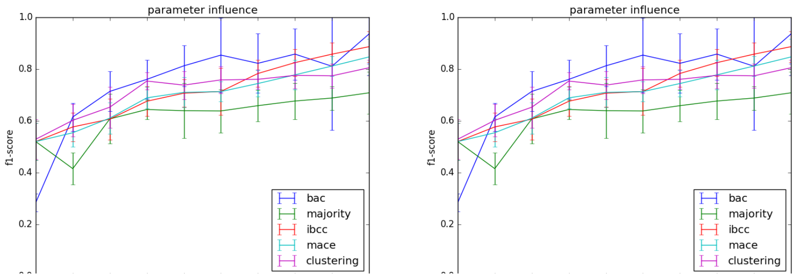


(b) Example 2



(c) Example 3

Figure 3: Examples of different handling of annotator disagreement on PICO. Lines above the text show the crowd's annotations. Lines below show the aggregated annotations from MV, IBCC, HMM-Crowd and BSCC-Seq-IF. The sequential methods are able to resolve some issues, while non-sequential methods can lead to invalid annotations.



(a) NER dataset (b) PICO dataset

Figure 4: Active learning simulation: prediction performance after each labelled batch is received. Mean scores over 10 repeats.

arguments. At the same time, these embeddings would be at a low level so that the GP could learn an appropriate model over the target domain.

In our experiments we used a single type of kernel for each feature and combined the kernels using a simple product or sum function. While this makes it feasible to include thousands of features, in future work we plan to investigate other ways to incorporate textual features, such as string kernels, which map strings of varying lengths to vectors and may be used to improve semantic representation of word embeddings(Lodhi et al., 2002).

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