A Bayesian Method for Vetting and Combining Crowds of Text Annotators

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***Abstract*—**

I. Introduction

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 [1], 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 [2], which we use as the basis for our implementation in the current work. This paper provides the following contributions:

- 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
- Compares the approach on real-world NLP datasets with simple heuristic methods (e.g. mode) and alternatives such as weighted combinations
- Demonstrates how using the proposed Bayesian model enables an active learning approach that improves crowdsourcing efficiency

A. Notes on Applications and Datasets

There are several annotation tasks for NLP 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.
- Semantic role labelling (SRL).

II. 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 [1] for combining annotations provided by a crowd of unreliable annotators. We refer to our model as Bayesian annotator combination or BAC. In BAC, 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.

We model the annotators using a confusion matrix similar to that used in [2], 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.

A. Generative Model

In the BAC 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, $A_j \sim \text{Dir}(\boldsymbol{\beta}_j)$, 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 $t_{i,\tau} \sim \text{Categorical}(\boldsymbol{A}_O)$, then for $\tau > 1$, we draw subsequent labels from $t_{i,\tau} \sim \text{Categorical}(\boldsymbol{A}_{t_{i,\tau-1}})$. 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 $\boldsymbol{\pi}_{j,l}^{(k)} \sim \text{Dir}(\boldsymbol{\alpha}_{j,l}^{(k)})$, 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 term, $c_{i,1}^{(k)} \sim \text{Categorical}(\boldsymbol{\alpha}_{t_{i,1},O}^{(k)})$, then subsequent terms $c_{i,\tau}^{(k)} \sim \text{Categorical}(\boldsymbol{\alpha}_{t_{i,\tau},c_{i,\tau-1}^{(k)}}^{(k)})$. As with the true labels, the first annotation in each sequence uses hyperparameters $\boldsymbol{\alpha}_{t_{i,1},O}^{(k)}$ because we assume that the annotation prior to token 1 is equivalent to an O annotation.

B. Variational Bayes (VB) Algorithm

We modify the mean-field variational Bayes algorithm proposed by [2], which assumes an approximate posterior distribution that factorises between the parameters and latent variables. For our proposed model, the variational approximation is given by:

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

Below, we summarise the algorithm used to optimise this distribution to obtain an approximate posterior. The following subsection then defines the variational factors and expectation terms needed to perform each step of the algorithm. The procedure is as follows:

Input: Crowdsourced annotations, $\boldsymbol{c}$
Initialise $\mathbb{E}[\log \boldsymbol{A}]$ and $\mathbb{E}\left[\log \boldsymbol{\pi}^{(k)}\right], \forall k$;
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 $\mathbb{E}[\log \boldsymbol{A}]$ and $\mathbb{E}\left[\log \boldsymbol{\pi}^{(k)}\right], \forall k$ using the forward-backward algorithm;
  Update $q^*(\boldsymbol{A}_j), \forall j$ given current $q^*(t_{i,\tau} = j)$;
  Update $q^*\left(\boldsymbol{\pi}_j^{(k)}\right), \forall j, \forall k$ given current $q^*(t_{i,\tau-1} = j, t_{i,\tau} = j')$;
  Recompute $\mathbb{E}[\log \boldsymbol{A}]$ and $\mathbb{E}\left[\log \boldsymbol{\pi}^{(k)}\right], \forall k$ given current estimates of $q(\boldsymbol{A}_j)$ and $q(\boldsymbol{\pi}_j^{(k)})$;
end
Output: Predictions for the true labels, $\mathbb{E}[t_{i,\tau}]$.

There are several ways to initialise the expectation terms $\mathbb{E}[\log \boldsymbol{A}]$ and $\mathbb{E}\left[\log \boldsymbol{\pi}^{(k)}\right], \forall k$. One possibility is to estimate the means of the distributions using a cheaper method, such as maximum likelihood expectation maximisation, then take logarithms. Values may also be chosen at random. In our experiments we find initialising $\mathbb{E}[\log \boldsymbol{A}]$ and $\mathbb{E}\left[\log \boldsymbol{\pi}^{(k)}\right], \forall k$ to their prior values to be effective as we use weakly informative priors.

The algorithm above iteratively updates each variational factor in turn. Each update 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. We now present equations for the variational factors and expectation terms required by the algorithm, followed by the lower bound, $\mathcal{L}$.

C. Variational Factors

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

$$\log q^*(\boldsymbol{t}) = \mathbb{E}_q\left[\sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\left\{\log p(t_{i,\tau}|t_{i,\tau-1},\boldsymbol{A}) + \sum_{k=1}^{K} p(c_{i,\tau}^{(k)}|t_{i,\tau},c_{i,\tau-1}^{(k)},\boldsymbol{\pi}^{(k)})\right\}\right] + \text{const},$$
$$= \sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\mathbb{E}[\log A_{j,t_{i,\tau}}] + \sum_{k=1}^{K}\log\tilde{\pi}_{i,\tau,t_{i,\tau}}^{(k)} + \text{const}, \quad (2)$$

where for notational convenience we define $\log\tilde{\pi}_{i,\tau,j}^{(k)} = \mathbb{E}\left[\log\pi_{j,c_{i,\tau-1}^{(k)},c_{i,\tau}^{(k)}}^{(k)}\right]$. 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 [3], 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.

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

where $\boldsymbol{c}_{i,1:\tau}^{(k)}$ is the set of labels from 1 to τ in document i. We assume that the label at position, $t_{i,0} = O$, is always an 'outside' label. 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 $t_{i,\tau}$.

$$\log\lambda_{i,T_i,j} = 1$$
$$\log\lambda_{i,\tau,j} = \mathbb{E}_q\left[\log p(\boldsymbol{c}_{i,\tau+1:T_i}^{(1)},...,\boldsymbol{c}_{i,\tau+1:T_i}^{(K)}|t_{i,\tau}=j)\right]$$
$$= \log\lambda_{i,\tau+1,j} + \sum_{j'=1}^{L}\left\{\mathbb{E}[\log A_{j,j'}] + \sum_{k=1}^{K}\log\tilde{\pi}_{i,\tau+1,j'}^{(k)}\right\} \quad (6)$$

By taking the exponents and applying Bayes' rule we arrive at the terms $r_{i,\tau,j}$ and $s_{i,\tau,j,j'}$:

$$r_{i,\tau,j} \propto r_{i,\tau,j}^{-}\lambda_{i,\tau,j} \quad (7)$$
$$s_{i,\tau,j,j'} \propto r_{i,\tau-1,j}^{-}\lambda_{i,\tau,j'}\exp\Big(\mathbb{E}[\log A_{j,j'}] + \log\tilde{\pi}_{i,\tau,j'}^{(k)}\Big). \quad (8)$$

The $r_{i,\tau,j}$ terms are normalised by a sum over j, and the $s_{i,\tau,j,j'}$ terms are normalised by a sum over j and j'. We also use the $r_{i,\tau,j}$ terms to produce the output predictions from the VB algorithm.

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

$$\log q^*(\boldsymbol{A}_j)$$
$$= \sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\sum_{j'=1}^{L} s_{i,\tau,j,j'}\log\boldsymbol{A}_{j,j'} + \log p(\boldsymbol{A}_j|\boldsymbol{\beta}_j) + \text{const}$$
$$= \sum_{j'=1}^{L} N_{j,j'}\log\boldsymbol{A}_{j,j'} + \log p(\boldsymbol{A}_j|\boldsymbol{\beta}_j) + \text{const}, \quad (9)$$

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

$$\mathbb{E}[\log A_{j,j'}] = \Psi\left(b_{j,j'}\right) - \Psi\left(\sum_{j'=1}^{L} b_{j,j'}\right), \quad (10)$$

where Ψ is the digamma function.

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

$$\log q^*\left(\boldsymbol{\pi}_{j,l}^{(k)}\right) = \sum_{m=1}^{J} N_{j,l,m}^{(k)}\log\pi_{j,l,m}^{(k)} + \log p\left(\boldsymbol{\pi}_{j,l}^{(k)}|\alpha_{j,l}^{(k)}\right) + \text{const}, \quad (11)$$

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

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

$$\mathbb{E}\left[\log\pi_{j,l,m}^{(k)}\right] = \Psi\left(a_{j,l,m}^{(k)}\right) - \Psi\left(\sum_{m=1}^{L} a_{j,l}^{(k)}\right). \quad (12)$$

D. 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:

$$\mathcal{L} = \mathbb{E}_q\left[\log p\left(\boldsymbol{c},\boldsymbol{t}|\boldsymbol{A},\boldsymbol{\pi}^{(1)},...,\boldsymbol{\pi}^{(K)}\right) - \log q(\boldsymbol{t})\right]$$
$$+ \sum_{j=1}^{L}\left\{\mathbb{E}_q\left[\log p\left(\boldsymbol{A}_j|\boldsymbol{\beta}_j\right) - \log q(\boldsymbol{A}_j)\right]\right.$$
$$\left. + \sum_{l=1}^{J}\sum_{k=1}^{K}\mathbb{E}_q\left[\log p\left(\boldsymbol{\pi}_{j,l}^{(k)}|\boldsymbol{\alpha}_{j,l}^{(k)}\right) - \log q\left(\boldsymbol{\pi}_{j,l}^{(k)}\right)\right]\right\}. \quad (13)$$

The lower bound computation uses the equations described above 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 $\mathbb{E}\left[\log \boldsymbol{A}_j\right]$ and $\mathbb{E}\left[\log \boldsymbol{\pi}_{j,l}^{(k)}\right]$. The first term of $\mathcal{L}$ makes use of auxiliary variables from the forward-backward algorithm:

$$\mathbb{E}_q\left[\log p\left(\boldsymbol{c}, \boldsymbol{t} | \boldsymbol{A}, \boldsymbol{\pi}^{(1)}, .., \boldsymbol{\pi}^{(K)}\right)\right] = \sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\sum_{j=1}^{L} r_{i,\tau,j} \log r_{i,\tau,j}^{-} \tag{14}$$

III. 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.

A. 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 [4],.... 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. [5]). 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.

B. Worker Accuracy-Based Methods

Determine worker accuracy from a number of gold-standard tasks. Weight the workers' votes by accuracy and apply the majority voting approach above to produce a *weighted majority voting* method.

An interesting approach is used by [6] that takes into account amibiguity in sentiment classifications. It is unclear whether this can be generalised to other types of annotation such as argument components.

The weights can also be obtained using unsupervised and semi-supervised learning. In this case we use an EM algorithm, in which we initialise the true annotations using the majority voting method, then use these to compute worker accuracies. The true annotations are then re-estimated using a weighted majority vote. The process repeats until convergence. This method is labelled *weighted majority voting (EM)*.

C. 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?

D. 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. [4], [6]. 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. [7]. To reduce costs, the human resolution step could be applied only to text with large amounts of disagreement.

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