A Bayesian Method for Combining Multiple Unreliable Text Annotators

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***Abstract*—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.**

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, $A_j \sim \mathrm{Dir}(\boldsymbol{\beta}_j)$, 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 term, $c_{i,1}^{(k)} \sim \mathrm{Categorical}(\boldsymbol{\alpha}_{t_{i,1},O}^{(k)})$, then subsequent terms $c_{i,\tau}^{(k)} \sim \mathrm{Categorical}(\boldsymbol{\alpha}_{t_{i,\tau},c_{i,\tau-1}^{(k)}}^{(k)})$. 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. We then define the variational factors and expectation terms needed to perform each step of the algorithm. The procedure is as follows:

1) Initialise variational factors for parameters $\boldsymbol{A}_j$, $\forall j$ and $\boldsymbol{\pi}_{j,l}^{(k)}, \forall j, \forall l, \forall k$, e.g. by setting to prior distributions.
2) Calculate $\mathbb{E}[\log \boldsymbol{A}]$ and $\mathbb{E}\left[\log \boldsymbol{\pi}^{(k)}\right], \forall k$ given the current factors $q(\boldsymbol{A}_j)$ and $q(\boldsymbol{\pi}_j^{(k)})$.
3) Update the variational factor for the ground truth labels, $q(\boldsymbol{t})$, given the expectations $\mathbb{E}\left[\log \boldsymbol{\pi}^{(k)}\right], \forall k$, and $\mathbb{E}[\log \boldsymbol{A}]$, using the forward-backward algorithm [3], which will be explained further below.
4) Update the variational factors $q(\boldsymbol{\pi}_j^{(s)}), \forall j, \forall s$ for the confusion matrices given current estimate for $q(\boldsymbol{t})$.
5) Update the variational factor for the transition matrix rows $q(\boldsymbol{A}_j), \forall j$ given the current estimate for $q(\boldsymbol{t})$.
6) Check for convergence in the ground truth label predictions, $\mathbb{E}[\boldsymbol{t}]$, or in the variational lower bound. The latter may be more expensive to compute but gives stronger guarantees of convergence. If not converged, repeat from step 2.
7) Output the predictions for the true labels, $\mathbb{E}[\boldsymbol{t}]$ given the converged estimates of the variational factors.

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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 $\mathbb{E}\left[\log \boldsymbol{A}\right]$ 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 $\mathbb{E}\left[\log \boldsymbol{A}\right]$ 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 $\mathbb{E}\left[\log \boldsymbol{A}\right]$ 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 $\mathbb{E}\left[\log \boldsymbol{A}\right]$ 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 $\mathbb{E}\left[\log \boldsymbol{A}\right]$ 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:

$$\begin{aligned}\log q^*(\boldsymbol{t}) &= \mathbb{E}_q\left[\sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\left\{\log p(t_{i,\tau}|t_{i,\tau-1}, \boldsymbol{A}) \right.\right. \\ &\left.\left. + \sum_{k=1}^{K} p(c_{i,\tau}^{(k)}|t_{i,\tau}, c_{i,\tau-1}^{(k)}, \boldsymbol{\pi}^{(k)})\right\}\right] + \text{const}, \\ &= \sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\mathbb{E}[\log A_{j,t_{i,\tau}}] + \sum_{k=1}^{K}\log\tilde{\pi}_{i,\tau,t_{i,\tau}}^{(k)} + \text{const}, \end{aligned} \tag{3}$$

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:

$$r_{i,\tau,j} = q^*(t_{i,\tau} = j) = \mathbb{E}_q[p(t_{i,\tau} = j|\boldsymbol{c})], \tag{4}$$

$$\begin{aligned} s_{i,\tau,j,j'} &= q^*(t_{i,\tau-1} = j, t_{i,\tau} = j') \\ &= \mathbb{E}_q[p(t_{i,\tau-1} = j, t_{i,\tau} = j'|\boldsymbol{c})]. \end{aligned} \tag{5}$$

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.

$$\begin{aligned}\log r_{i,\tau,j}^{-} &= \mathbb{E}_q\left[\log p(t_{i,\tau} = j|\boldsymbol{c}_{i,1:\tau}^{(1)}, ..., \boldsymbol{c}_{i,1:\tau}^{(K)})\right] \\ &= \frac{1}{Z}\sum_{j'=1}^{L}\left\{\log r_{i,\tau-1,j'}^{-} + \mathbb{E}[\log A_{j',j}]\right\} + \sum_{k=1}^{K}\log\tilde{\pi}_{i,\tau,j}^{(k)}, \end{aligned} \tag{6}$$

where $\boldsymbol{c}_{i,1:\tau}^{(k)}$ is the set of labels from 1 to τ in document i, and Z is the normalisation constant obtained by summing the other terms over j. For the first token in each sequence, we compute $\log r_{i,1,j}^{-}$ as follows:

$$\log r_{i,1,j}^{-} = \mathbb{E}[\log p(t_{i,1})] + \sum_{k=1}^{K}\log\tilde{\pi}_{i,1,j}^{(k)}, \tag{7}$$

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:

$$\begin{aligned}&\log\lambda_{i,T_i,j} = 0 \\ &\log\lambda_{i,\tau,j} = \mathbb{E}_q\left[\log p(\boldsymbol{c}_{i,\tau+1:T_i}^{(1)}, ..., \boldsymbol{c}_{i,\tau+1:T_i}^{(K)}|t_{i,\tau} = j)\right] \\ &= \log\lambda_{i,\tau+1,j} + \sum_{j'=1}^{L}\left\{\mathbb{E}[\log A_{j,j'}] + \sum_{k=1}^{K}\log\tilde{\pi}_{i,\tau+1,j'}^{(k)}\right\}, \end{aligned} \tag{8}$$

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

$$r_{i,\tau,j} = \frac{r_{i,\tau,j}^{-}\lambda_{i,\tau,j}}{\sum_{j'=1}^{L} r_{i,\tau,j'}^{-}\lambda_{i,\tau,j'}} \tag{9}$$

$$s_{i,\tau,j,j'} = \frac{r_{i,\tau-1,j}^{-}\lambda_{i,\tau,j'}\mathrm{e}^{\mathbb{E}[\log A_{j,j'}] + \log\tilde{\pi}_{i,\tau,j'}^{(k)}}}{\sum_{j'=1}^{L}\sum_{j''=1}^{L} r_{i,\tau-1,j'}^{-}\lambda_{i,\tau,j''}\mathrm{e}^{\mathbb{E}[\log A_{j',j''}] + \log\tilde{\pi}_{i,\tau,j''}^{(k)}}}. \tag{10}$$

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:

$$\begin{aligned}
&\log q^*(\boldsymbol{A}_j) \\
&= \sum_{i=1}^{N}\sum_{\tau=1}^{T_i}\sum_{j'=1}^{L} s_{i,\tau,j,j'} \log \boldsymbol{A}_{j,j'} + \log p(\boldsymbol{A}_j|\boldsymbol{\beta}_j) + \text{const} \\
&= \sum_{j'=1}^{L} N_{j,j'} \log \boldsymbol{A}_{j,j'} + \log p(\boldsymbol{A}_j|\boldsymbol{\beta}_j) + \text{const}, \qquad (11)
\end{aligned}$$

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

$$\mathbb{E}[\log A_{j,j'}] = \Psi\left(b_{j,j'}\right) - \Psi\left(\sum_{j'=1}^{L} b_{j,j'}\right), \qquad (12)$$

where Ψ is the digamma function.

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

$$\begin{aligned}
\log q^*\left(\boldsymbol{\pi}_{j,l}^{(k)}\right) = &\sum_{m=1}^{J} N_{j,l,m}^{(k)} \log \pi_{j,l,m}^{(k)} \\
&+ \log p\left(\boldsymbol{\pi}_{j,l}^{(k)}|\alpha_{j,l}^{(k)}\right) + \text{const}, \qquad (13)
\end{aligned}$$

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:

$$\mathbb{E}\left[\log \pi_{j,l,m}^{(k)}\right] = \Psi\left(a_{j,l,m}^{(k)}\right) - \Psi\left(\sum_{m=1}^{L} a_{j,l}^{(k)}\right). \qquad (14)$$

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:

$$\begin{aligned}
\mathcal{L} = &\mathbb{E}_q\left[\log p\left(\boldsymbol{c}, \boldsymbol{t}|\boldsymbol{A}, \boldsymbol{\pi}^{(1)}, ..., \boldsymbol{\pi}^{(K)}\right) - \log q(\boldsymbol{t})\right] \\
&+ \sum_{j=1}^{L}\Bigg\{\mathbb{E}_q\left[\log p\left(\boldsymbol{A}_j|\boldsymbol{\beta}_j\right) - \log q(\boldsymbol{A}_j)\right] \\
&+ \sum_{l=1}^{J}\sum_{k=1}^{K}\mathbb{E}_q\left[\log p\left(\boldsymbol{\pi}_{j,l}^{(k)}|\boldsymbol{\alpha}_{j,l}^{(k)}\right) - \log q\left(\boldsymbol{\pi}_{j,l}^{(k)}\right)\right]\Bigg\}. \qquad (15)
\end{aligned}$$

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:

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

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. 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 [6], which are based on the approach by [7]. 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 [**?**], [2], [8]. Recent extensions follow the Bayesian treatment of [**?**], called IBCC, to deal with specific problems in crowdsourcing with large numbers of workers: [**?**], [9] identify clusters of crowd workers with shared confusion matrices to improve performance when information about individual workers is sparse; [**?**] account for the time each worker takes to complete a task; [6], [10] 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 [11] 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.

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], [12]. 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. [13]. To reduce costs, the human resolution step could be applied only to text with large amounts of disagreement.

IV. Experiments

A. Synthetic Data

We use synthetic data to illustrate the strengths and weaknesses of different methods by varying one independent dataset and tracking the performance metrics of each method:

1) When do other methods outperform simple majority voting? Show performance against worker accuracy. Similar experiments were carried out with a different set of baselines in [14], Section 2.5.2, with all workers having similar accuracies, and Section 2.5.4, where some workers are noisy and others are highly accurate. Here, we vary the average accuracy of workers, with lower average accuracy leading to more diversity between workers. Analyse whether the full IBCC confusion matrix offers benefits over MACE due to worker accuracy varying between classes when accuracy is lower.
2) How well do MACE, IBCC, and BAC handle worker bias? Show performance against worker bias toward one class. This is a comparable experiment to [14], Section 2.5.3, which notably does not include MACE.
3) How well does each method handle data sparsity? (a) Vary the amount of observations per worker. Expect MACE to perform well, BAC may suffer from the larger confusion matrix. (b) Vary the number of observations per data point.
4) Do MACE and IBCC still work with unbalanced datasets? Test with unbalanced class distributions, i.e. starting from $p(B) = p(I) = p(O) = 0.3$, decrease $p(B)$ and $p(I)$ until $p(O) = 0.99$.

In each case, we use a set of default values for the variables that are not currently being tested. These are chosen so that all methods perform well (e.g. 90% accuracy) under the best conditions of the test. E.g. for the test where we vary worker accuracy, we set bias and sparsity to be low so that the performance of all methods is good when workers are 80% accurate.

For all methods except BAC, we compute performance metrics both before and after the valid annotation post-processing step, which is required to ensure that I tokens do not follow O tokens.

Performance metrics:

1) Metrics that evaluate the quality of the most probable class labels: recall, precision and F1-score (of B class and I class separately), accuracy (mean over classes)
2) Metrics that evaluate the confidence values output by the models: area under ROC curve or AUC (separate for B and I classes), and cross entropy error
3) Annotation count error: the mean difference between the number of annotations produced by the model and the true number.
4) Number of invalid labels that must be corrected by post-processing.
5) Mean length of annotations compared to the ground truth: show whether some methods find annotation fragments.

We also evaluate the competence scores estimated by each method. First, we compute the ground truth from the synthetic confusion matrices. We use a weighted average over classes (weighted by class frequency) to produce the overall worker accuracy. Then, we compute accuracy from BAC, MACE and IBCC using similar methods. For each method, we can compute the mean and STD of cross entropy error between the estimated and the ground truth confusion matrices. We then reproduce the plots described above, but showing the cross entropy error for the competence estimates.

B. Real-world Data

We investigate the performance on some real datasets to show how well the methods work when combining real workers. Besides the performance metrics mentioned above, we also quantitatively analyse examples of where BAC outperforms other methods to show where they may have trouble forming valid or grammatically correct annotations, e.g. where the starting token is incorrect. Ideally, we would also analyse whether the annotations produced are grammatically sensible, e.g. if there is conflict between workers about where an annotation should start, the method should choose one valid start point, not an invalid start point that lies in between. These points can be evaluated by computing:

1) The percentage of "sensible" annotations, as judged by an expert for the task. For tasks where this data is not available, we can use the following metrics to gauge annotation quality.
2) The percentage of each method's annotations that have an exact match in the gold standard (exact annotation precision)
3) The percentage of gold standard annotations that have an exact match in the method's output (exact annotation recall)
4) Mean and variance of no. tokens difference to nearest annotation; this is averaged over the annotations, rather than the number of tokens, so gives a greater indication of how well they matched the gold standard.

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