Multi-Label Annotation Aggregation in Crowdsourcing

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Abstract

As a means of human-based computation, crowdsourcing has been widely used to annotate large-scale unlabeled datasets. One of the obvious challenges is how to aggregate these possibly noisy labels provided by a set of heterogeneous annotators. Another challenge stems from the difficulty in evaluating the annotator reliability without even knowing the ground truth, which can be used to build incentive mechanisms in crowdsourcing platforms. When each instance is associated with many possible labels simultaneously, the problem becomes even harder because of its combinatorial nature. In this paper, we present new flexible Bayesian models and efficient inference algorithms for multi-label annotation aggregation by taking both annotator reliability and label dependency into account. Extensive experiments on real-world datasets confirm that the proposed methods outperform other competitive alternatives, and the model can recover the type of the annotators with high accuracy. Besides, we empirically find that the mixture of multiple independent Bernoulli distribution is able to accurately capture label dependency in this unsupervised multi-label annotation aggregation scenario.

1 Introduction

Crowdsourcing has emerged as a cost-effective tool to harness the power of human computation to annotate large-scale unlabeled datasets. These tasks, such as image tagging and video annotation, are often too repetitive and time-consuming for individuals to complete [11]. Many crowdsourcing systems, such as Amazon Mechanical Turk (AMT), provide a platform where a large amount of tasks can be distributed to human workers and then the results are aggregated together. Such systems have recently started to play a vital role in industry. For example, Google launched Image Labeler [1] to allow users to annotate random images so as to improve the performance of the image search engine. reCAPTCHA has been adopted by many websites where users are asked to solve captchas to prove they are humans, then the captchas are utilized to digitize scanned articles and books [8].

Academic communities are also increasingly attracted to use crowdsourcing for their research needs. For instance, to create taxonomy for large amount of entities, [3] recruits workers from AMT to label the relationship between entities; [18] relies on AMT to construct a training set for coding the sentiments of online comments, where the results are further utilized to construct reputation measure.

Although promising, crowdsourcing for annotation aggregation still faces many significant challenges. In practice, annotators may come from a diverse pool including experts, novices, spammers,
and even malicious annotators [21]. Moreover, unintentional errors are common because most crowdsourcing tasks are tedious [14]. Hence, a fundamental challenge in crowdsourcing applications is how to accurately and efficiently estimate the ground truth from these noisy labels provided by a set of heterogeneous annotators. Another challenge comes from the evaluation of annotation reliability since the ground truth is often unknown in practice. Annotator evaluation can not only improve the aggregation performance [12], but can also serve as a spammer detector [21] and help design better incentive mechanisms (e.g., performance-based payments [10]).

In the previous literature, the problem of multi-class annotation aggregation has been intensively studied to address the aforementioned challenges [19, 15, 21, 30, 28, 7, 22]. However, there is very little work focusing on multi-label annotation aggregation. In certain application areas, it’s quite common that each instance is associated with a subset of label candidates simultaneously (see [24, 29] and references therein). For instance, a document may contain multiple topics or ideas, and an image can be assigned with multiple tags. Due to combinatorial explosion in the number of possible label combinations, multi-label annotation aggregation is particularly more difficult. One simple heuristic is to treat each label independently and transform the problem into multiple binary tasks. Such heuristic completely ignores the label dependency that is likely to arise in real-world applications (though unknown in the label collection step of crowdsourcing pipeline) and the resulting procedure might lead to sub-optimal or even incorrect estimation. Therefore, it is crucial to take such dependency into account so as to improve the overall performance of multi-label aggregation. For example, a document labeled with military is more likely to be associated with politics rather than education or health, and quiet music is often lonely music as well as being relaxing music.

At the other extreme, we can model dependency among C labels by explicitly using $2^C$ parameters to represent $P = \{p_S|S \subseteq \{1, 2, \cdots, C\}\}$, where $p_S$ is the probability of an instance’s labels being equal to $S$. Some existing approaches include the power set approach [24], the additive model [5], and the multivariate Bernoulli distribution [6]. Though all orders of interactions can be characterized, these approaches are limited in that (1) they are computationally demanding and hence are only applicable when $C$ is fairly small and (2) the estimation of $2^C$ parameters could be highly biased unless the sample size is fairly large. Other intermediate methods between these two extremes, such as Ising model [26], only consider second-order relations to model $P$ with $O(C^2)$ parameters. However, capturing only pairwise dependency is insufficient especially in certain real-world applications where there exist many higher-order interactions.

In this paper, we propose to use the mixture of multiple Bernoulli distribution [16, 2], with the hope that only a fairly small number of mixture components need to be combined to capture intrinsic label dependency. Mixture of multiple Bernoulli distribution has been utilized to model label dependency for supervised multi-label classification task; see [17] and references therein. However, to the best of our knowledge, there is no work on demonstrating its role in the context of unsupervised multi-label annotation aggregation, in which only noisy labels are available.

Overall, we make the following contributions in this work: (a) Building on top of the mixture of multiple Bernoulli distribution, we develop a flexible Bayesian model for observed annotations by taking both annotator reliability and label dependency into account; (b) We propose an efficient inference algorithm to perform annotation aggregation from possibly noisy labels in an unsupervised manner; (c) Results on three real-world datasets confirm that our new approaches outperform other competitive alternatives in terms of recovering ground truth labels. The methods are also able to capture the observed label dependency and recover the type of annotators with high accuracy.
2 Bayesian Modeling Framework

2.1 Problem Setup

Suppose that there are $L$ annotators, $N$ instances, and $C$ labels in a crowdsourcing system. In the multi-label setting, each instance $i$ can be associated with any subset of all labels $\{1, 2, \ldots, C\}$. For convenience, we use a binary vector of length $C$ to represent the labels of an instance. In practice, an annotator $l$ usually only labels a subset of all instances, denoted as $N(l) \subseteq \{1, 2, \ldots, N\}$. Hence, the labels collected from the system are a set of possibly noisy annotations $Y = \{y^1, y^2, \ldots, y^L\}$, with $y_i^l \in \{0, 1\}^{|N(l)| \times C}$ provided by the annotator $l$. The element $y_i^l j \in \{0, 1\}$ indicates whether the instance $i$ receives the label $j$ from the annotator $l$. An equivalent representation is $Y = \{y_1, y_2, \ldots, y_N\}$, where $y_i \in \{0, 1\}^{L(i) \times C}$ and $L(i) \subseteq \{1, 2, \ldots, L\}$ is the set of annotators who have labeled the instance $i$. Such notation will be used in the sequel.

Our goal is to infer the ground truth $z \in \{0, 1\}^{N \times C}$ of $N$ instances based on their observed annotations $Y$, where $z_{i,j}$ indicates whether the instance $i$ has the label $j$. We take a probabilistic approach and propose two unsupervised Bayesian models to perform multi-label annotation aggregation in such crowdsourcing setting. Both models take annotator reliability into account, and the second model is also able to capture correlations among multiple labels.

2.2 BNC Model

First, we introduce the Bayesian model with No label Correlation (BNC), in which each of $C$ labels is treated independently. Its graphical model representation is shown in Figure 1a.

We use the notation $\Psi^l \in [0, 1]^C$ to denote the reliability of the annotator $l$, where $\Psi^l j$ is the probability that the annotator $l$ makes a correct annotation regarding the presence of the $j$-th label\(^1\). Due to the heterogeneity of annotators, we assume that each annotator has his own reliability, though more complicated models with a clustering structure could be considered. The component

\(^1\)For simplicity, we assume that the probability of being reliable is symmetric, i.e., $P(y_{i,j} = 1 \mid z_{i,j} = 1) = P(y_{i,j} = 0 \mid z_{i,j} = 0)$. It is straightforward to extend to the asymmetric case, such as in [22].
τ_j of \( \tau \in [0, 1]^C \) specifies the probability of an instance having the label \( j \). Conditioning on \( \tau \), the ground truth \( z_{i,j} \) follows
\[
  z_{i,j} \mid \tau_j \sim \text{Bernoulli}(\tau_j).
\]  

(1)

Given the ground truth \( z \) and annotator reliability \( \Psi \), we have the following model for observed annotations \( Y \):
\[
y_{i,j}^l \mid \Psi, z \sim \text{Bernoulli}(\Psi_j^l z_{i,j} + (1 - \Psi_j^l)(1 - z_{i,j})).
\]

(2)

We also introduce priors over the parameters \( \Psi_j^l \) and \( \tau_j \). In particular, we use conjugate prior distributions
\[
  \Psi_j^l \mid a, b \sim \text{Beta}(a, b),
  \tau_j \mid \alpha, \beta \sim \text{Beta}(\alpha, \beta).
\]

(3)

Here, the hyperparameters \( a, b \) indicate how strong our prior belief is about the reliability of annotators, while \( \alpha, \beta \) specify our prior belief about the number of present labels. The choice of those hyperparameters is often context-dependent. See experimental section for more details.

2.3 BMMB Model

In the BNC model, the label correlations are ignored and hence the problem reduces to \( C \) independent binary annotation aggregation tasks (one per label). However, as we have already pointed out, label dependency is likely to arise in practice and it is important to be incorporated to improve the performance of multi-label related tasks (multi-label aggregation [9] and multi-label learning [29]). We propose to use the mixture of multiple independent Bernoulli distribution, which offers a flexible and powerful framework for modeling label dependency.

Specifically, in our Bayesian model with Mixture of Multiple Bernoulli distribution (BMMB), we assume that there are \( K \) clusters with each cluster \( k \) being a multiple independent Bernoulli distribution, which is parameterized by \( \tau_k \in [0, 1]^C \). The mixing coefficient \( \pi_k \) indicates the probability of an instance belonging to the cluster \( k \). Under this setup, in contrast to the independent assumption in the BNC model (1), the ground truth \( z_i \in \{0, 1\}^C \) has the following probability distribution:
\[
p(z_i \mid \pi, \tau_k) = \sum_{k=1}^{K} \pi_k \prod_{j:z_{i,j}=1}^{C} \tau_{k,j} \prod_{j:z_{i,j}=0}^{C} (1 - \tau_{k,j}).
\]

(4)

The graphical model representation of the BMMB model is shown in Figure 1b, where we introduce a latent variable \( x_i \in \{1, 2, \cdots, K\} \) to represent the cluster index of the instance \( i \). In summary, we have the following observational model:
\[
y_{i,j}^l \mid \Psi, z \sim \text{Bernoulli}(\Psi_j^l z_{i,j} + (1 - \Psi_j^l)(1 - z_{i,j})),
  z_{i,j} \mid x_i, \tau \sim \text{Bernoulli}(\tau_{x_i,j}),
  x_i \mid \pi \sim \text{Discrete}(\pi).
\]

(5)

Similarly, we impose conjugate priors over the parameters \( \Psi_j^l \), \( \tau_{k,j} \), and \( \pi \) as follows:
\[
  \Psi_j^l \mid a, b \sim \text{Beta}(a, b),
  \tau_{k,j} \mid \alpha, \beta \sim \text{Beta}(\alpha, \beta),
  \pi \mid \gamma \sim \text{Dirichlet}(\gamma).
\]

(6)
The inference procedure for the BNC model is similar. See Appendix B for more details.

An illustrative example. We use an illustrative example to demonstrate how exploiting label dependency in the BMMB model can improve the performance. The Emotions [23] dataset consists of hundreds of music pieces with 6 pre-defined labels. We generate random noisy annotations that are provided by annotators with varying reliability (see Section 4 for details). For one particular music piece with true labels \{3, 4, 5\} ("relaxing-calm", "quiet-still", "sad-lonely"), the probabilities of having these labels estimated by the BNC model are 1.0000, 0.0643, and 0.9998, respectively. As a consequence, the label "quiet-still" is missed by the BNC estimate. In contrast, the corresponding probabilities estimated by the BMMB model with \(K = 6\) components are 1.000, 0.996, and 1.000, respectively, which shows the effectiveness of modeling label dependency. We can gain more insight by examining the estimated mixture components. As shown in Figure 2, the major components all characterize certain type of label dependency. For instance, (1) the first component indicates that quiet music tends to be relaxing, calm, and lonely; (2) intuitively, happy and pleased music is quite likely to be relaxing and calm (the second component); (3) when one piece of music is emotional, it may have labels "amazed-surprised" and "angry-aggressive" together (the third component). Interestingly, the BMMB estimate concludes that the selected sample is extremely likely from the first mixture component (with probability being almost 1.0), which is the one that mainly captures the dependency among the true labels \{3, 4, 5\}.

3 Inference Algorithm

In this section, we develop a mean-field variational inference algorithm [13, 26] for performing approximate inference under our BMMB model. The true posterior of latent variables \(p(\Psi, z, \tau, x, \pi | Y, a, b, \alpha, \beta, \gamma)\) is approximated by a fully factorized variational distribution \(q(\Psi, z, \tau, x, \pi)\) where

\[
q(\Psi, z, \tau, x, \pi) = q(\Psi | g, h)q(z | \lambda)q(\tau | e, f)q(x | r)q(\pi | m).
\]  

(7)

Specifically, the posteriors \(\Psi_j\) and \(\tau_{k,j}\) follow the distributions Beta\((g_j, h_j)\) and Beta\((e_{k,j}, f_{k,j})\), respectively; the posterior \(q(z_{i,j})\) is parameterized as \(q(z_{i,j}) = \text{Bernoulli}(\lambda_{i,j})\); the posterior \(q(x_i)\) is parameterized as \(q(x_i) = \text{Discrete}(r_i)\); and the posterior \(q(\pi)\) follows the Dirichlet\((m)\). For ease of presentation, we denote all variational parameters as \(\theta_v = \{g, h, \lambda, e, f, r, m\}\) and all hyperparameters as \(\theta_h = \{a, b, \alpha, \beta, \gamma\}\).

\(^2\)The inference procedure for the BNC model is similar. See Appendix B for more details.
The variational inference aims to minimize the KL divergence \( KL(q\|p) \) between the approximating distribution \( q \) and the true but unknown posterior \( p \). It is well-known that the log marginal likelihood \( \log(Y \mid \theta_h) \) can be decomposed in the form of \( \log(Y \mid \theta_h) = \mathcal{L}(\theta_v) + KL(q\|p) \), where

\[
\mathcal{L}(\theta_v) = \mathbb{E}_q[\log p(Y, \Psi, z, \tau, x, \pi \mid \theta_h)] - \mathbb{E}_q[\log q(\Psi, z, \tau, x, \pi)]
\]

is known as the Evidence Lower Bound (ELBO). Therefore, minimizing the KL divergence is equivalent to maximizing the ELBO with respect to the variational parameters \( \theta_v \). The exact form of the ELBO \( \mathcal{L}(\theta_v) \) for the BMMB model is provided in Appendix A. Applying coordinate ascent algorithm iteratively to maximize \( \mathcal{L}(\theta_v) \), we obtain the following update rules.

- Updates for \( g, h \): for \( j = 1, \ldots, C \) and \( l = 1, \ldots, L \),

\[
g_j^l = a + \sum_{i \in N(l)} \{ \lambda_{i,j} y_{i,j}^l + (1 - \lambda_{i,j})(1 - y_{i,j}^l) \}, \quad h_j^l = b + \sum_{i \in N(l)} \{ \lambda_{i,j} (1 - y_{i,j}^l) + (1 - \lambda_{i,j}) y_{i,j}^l \}. \tag{9}
\]

- Updates for \( \lambda \): for \( i = 1, \ldots, N \) and \( j = 1, \ldots, C \),

\[
\lambda_{i,j} \propto \exp \left\{ \sum_{k=1}^{K} r_{i,k} \mathbb{E}_q[\log \tau_{k,j}] + \sum_{l \in L(i)} \{ y_{i,j}^l \mathbb{E}_q[\log \Psi_j^l] + (1 - y_{i,j}^l) \mathbb{E}_q[\log (1 - \Psi_j^l)] \} \right\},
\]

\[
1 - \lambda_{i,j} \propto \exp \left\{ \sum_{k=1}^{K} r_{i,k} \mathbb{E}_q[\log (1 - \tau_{k,j})] + \sum_{l \in L(i)} \{ (1 - y_{i,j}^l) \mathbb{E}_q[\log \Psi_j^l] + y_{i,j}^l \mathbb{E}_q[\log (1 - \Psi_j^l)] \} \right\}. \tag{10}
\]

- Updates for \( e, f \): for \( k = 1, \ldots, K \) and \( j = 1, \ldots, C \),

\[
e_{k,j} = \alpha + \sum_{i=1}^{N} r_{i,k} \lambda_{i,j}, \quad f_{k,j} = \beta + \sum_{i=1}^{N} r_{i,k} (1 - \lambda_{i,j}). \tag{11}
\]

- Updates for \( r \): for \( i = 1, \ldots, N \) and \( k = 1, \ldots, K \),

\[
r_{i,k} \propto \exp \left\{ \mathbb{E}_q[\log \pi_k] + \sum_{j=1}^{C} \{ \lambda_{i,j} \mathbb{E}_q[\log \tau_{k,j}] + (1 - \lambda_{i,j}) \mathbb{E}_q[\log (1 - \tau_{k,j})] \} \right\}. \tag{12}
\]

- Updates for \( m \): for \( k = 1, \ldots, K \),

\[
m_k = \gamma + \sum_{i=1}^{N} r_{i,k}. \tag{13}
\]

For the beta distribution, the expectation of \( \log \Psi_j^l \) and \( \log (1 - \Psi_j^l) \) under \( q \) in (10) is:

\[
\mathbb{E}_q[\log \Psi_j^l] = \psi(g_j^l) - \psi(g_j^l + h_j^l), \quad \mathbb{E}_q[\log (1 - \Psi_j^l)] = \psi(h_j^l) - \psi(g_j^l + h_j^l), \tag{14}
\]

where \( \psi(\cdot) \) is the digamma function. Similarly, we have \( \mathbb{E}_q[\log \tau_{k,j}] = \psi(e_{k,j}) - \psi(e_{k,j} + f_{k,j}) \), \( \mathbb{E}_q[\log (1 - \tau_{k,j})] = \psi(f_{k,j}) - \psi(e_{k,j} + f_{k,j}) \), and \( \mathbb{E}_q[\log \pi_k] = \psi(m_k) - \psi(\sum_{i=1}^{K} m_k) \) in (12).
The per-iteration computational complexity of the algorithm is $O(C(KN + LT))$, which scales linearly with $C, K, N, L, T$ ($T$ is the number of annotations that each annotator provides). Once the algorithm converges, our estimation of the ground truth $z_{i,j}$ is given by $\lambda_{i,j}$, which indicates the posterior probability of the instance $i$ having the label $j$. Moreover, the reliability of annotators $\Psi_j$ can be estimated by $g_j^l/(g_j^l + h_j^l)$ and the distribution $P$ over $2^C$ distinct label combinations can be estimated by

$$
\hat{P} = \left\{ p_S \mid p_S = \sum_{k=1}^{K} \prod_{j \in S} \mathbb{E}_q[\pi_k] \prod_{j \in \{1,2,\ldots,C\}\backslash S} (1 - \mathbb{E}_q[\tau_{k,j}]), S \subseteq \{1,2,\ldots,C\} \right\},
$$

where $\mathbb{E}_q[\pi_k] = m_k$ and $\mathbb{E}_q[\tau_{k,j}] = \frac{e_{k,j}}{e_{k,j} + f_{k,j}}$. In the next section, we will show how well $\hat{P}$ serves as an estimator of $P$ (see Figure 5c for an illustration).

4 Experiments

We show that our proposed BMMB model outperforms the BNC model and several other competitive alternatives in terms of recovering ground truth labels. The experiments also reveal that the mixture of multiple independent Bernoulli distribution is able to accurately capture most of label interactions observed in the real dataset.

4.1 Datasets and Annotation Setup

Our experiments are based on three real-world multi-label datasets, as described in the follows:

- **Emotions.** The Emotions [23] dataset contains 593 pieces of music, each of which is associated with six possible pre-defined emotional tags, such as "happy-pleased" and "sadly-lonely".

- **Enron.** The Enron [25] is a dataset of emails. Each email is assigned with a subset of pre-defined categories based on genre, content, topic, or tone. There are 1,702 instances and 53 categories.

- **NUS-WIDE-SCENE.** The NUS-WIDE-SCENE [4] is a collection of images with real-world scenes, such as airport, ocean, and valley. It consists of 33 scene categories. We randomly sample 3,500 instances from the entire dataset.

To demonstrate the advantage of taking heterogeneous user reliability into account for annotation aggregation, as well as to verify how well our proposed models can recover their reliability, we generate noisy annotations of data samples from multiple annotators with varying quality. Following the setup in [20], we assume that there are three types of annotators: reliable, normal, and random. For reliable annotators, their reliability score $\Psi_j$ is sampled from $\text{Uni}(0.85, 0.99)$. The reliability score of normal annotators is sampled from $\text{Uni}(0.66, 0.85)$. Finally, those random annotators have $\Psi_j = 0.5$. Moreover, we are interested in analyzing the behavior of different methods with respect to the sparsity of annotations. In particular, we allow each annotator to label varying number of instances. In the sequel, we use $R$ to denote the ratio of three types of annotators (heterogeneity ratio) and $T$ as the number of instances annotated by each user.
4.2 Experimental Settings

Hyperparameters. In both BNC and BMMB models, we choose the hyperparameters $a$ and $b$ based on the average number of annotations received by each instance. If the average number is less than two, we set $a = 12, b = 1$; otherwise, if it is less than four, we choose a weaker prior with $a = 6, b = 1$; in all other cases, $a = 4, b = 1$. We put a weak prior over $\tau$ with $\alpha = 0.06, \beta = 0.84$. Finally, for the BMMB model, we set $\gamma = 1/K$.

Termination Criterion. We run the inference algorithms until the relative improvement in the ELBO is less than a threshold $\eta = 0.0001$ or the program reaches the maximum number of iterations (MAXITER = 500).

Competing Algorithms. We compare our methods with the following algorithms:

- Majority voting (MV). If a label appears in more than half of annotations received by an instance, then we predict the instance to have that label. Although MV is easy to implement, it suffers from those random and adversarial annotators.

- Power set+iBCC. The iBCC model [15] is a Bayesian method to perform multi-class annotation aggregation. To apply the iBCC in the multi-label setting, a direct approach would be to treat each label combination as a class, resulting in $2^C$ distinct classes. We only run this algorithm when $C$ is small due to the exponential number of label combinations.

- Pairwise+iBCC. It is a method that applies the iBCC to the subsets of label combinations formed from pairing labels [9]. The algorithm doesn’t scale well either due to the exponential number of pairing schemes.

4.3 Results

Impact of annotator reliability. First, we vary the heterogeneity ratio $R$ from 7:7:0 (no random annotators) to 4:4:6 (more than 40% are random annotators), and evaluate the performance of different algorithms in terms of recovering ground truth labels. As shown in Figure 3, BMMB outperforms all competing methods across all values of $R$, with BNC being the second best algorithm. Moreover, as expected, the performance gap between our proposed methods and majority voting tends to increase with the ratio of unreliable annotators. Finally, on the Emotions dataset where it is possible to run Powerset+iBCC and Pairwise+iBCC, the performance gap increases less significantly because iBCC also models the annotator reliability.

Impact of annotation sparsity. Next, we vary the number of instances annotated by each user from $T = 1$ to $T = 6$, and evaluate the behavior of the different algorithms with respect to annotation sparsity. The results are reported in Figure 4. Overall, the proposed models still have better performance across different levels of annotation sparsity, with the best performance achieved at the least sparsity level ($T = 6$). Again, the gap between BMMB and BNC demonstrates the effectiveness of modeling label dependency.

3The values of $\alpha, \beta$ don’t have strong influence on the results as long as they are small enough.
Figure 3: Impact of annotator reliability on recovering ground truth labels (evaluated by F1-score) of three datasets. The number of annotators $L$ is 700, 2100, and 2100, respectively. The number of mixture components $K$ is 6, 8, and 6, respectively. Each annotator provides $T = 5$ annotations.

Figure 4: Impact of annotation sparsity on recovering ground truth labels (evaluated by F1-score) of three datasets. The number of annotators $L$ is 900, 2700, and 4500, respectively. The number of mixture components $K$ is 6, 8, and 6, respectively. The heterogeneity ratio of annotators $R = 1:1:1$.

**Estimation of label dependency.** All orders of label dependency can be captured if we have access to the ground truth probability $P = \{p_S \mid S \subseteq \{1, 2, \cdots, C\}\}$ for each label combination. Given that $|P| = 2^C$, we can only use the Emotions dataset ($C = 6$) to demonstrate how well the BMMB estimator $\hat{P}$ (15) can approximate the ground truth. Figure 5a and 5b present the KL divergence between $P$ and $\hat{P}$ with different values of $K$ and $L$, and Figure 5c shows the element-wise difference between $P$ and one $\hat{P}$ estimated with $K = 6$ and $L = 900$. It is clear from Figure 5a that the performance gain from increasing $K$ is quite marginal once $K$ goes beyond 5. This is because not all label interactions are salient when the sample size is limited, as shown in Figure 5c. In this case, a fairly small number of mixture components is enough to capture most of label interactions observed in the dataset.

**Estimation of annotator reliability.** In this part, we evaluate the estimation of annotator reliability by examining if our proposed methods can successfully recover the type of annotators (reliable, normal, and random). To assign an annotator type for the user $l$, we average the estimated reliability score $\Psi_{lj}$ across all labels. As shown in Figure 6, the recovery rate of our methods rapidly increases with the number of annotated instances.
Figure 5: Estimation of label dependency on the Emotions dataset. The heterogeneity ratio of annotators $R = 1:1:1$ and each annotator provides $T = 5$ annotations. (a) We vary $K$ from 1 to 20 with $L = 900$. (b) We vary $L$ from 150 to 1650 with $K = 6$. (c) The element-wise difference between $P$ and one $\hat{P}$ estimated with $K = 6$ and $L = 900$. For clarity of presentation, we have sorted the elements of $\hat{P}$ according to their ranking in $P$.

Figure 6: Recovery rate of the annotator type with $R = 1:1:1$. The number of annotators $L$ is 900, 2700, and 4500, respectively. For the BMMB model, $K$ is 6, 8, and 6, respectively.

**Impact of $K$.** We have already demonstrated that a sufficiently large value of $K$ would be enough to capture the label dependency. In this part, we show further evidence that the performance gain in terms of recovering ground truth labels (measured by F1-score) becomes marginal once $K$ goes beyond some moderate value (Figure 7).

**5 Conclusions and Implications**

In this paper, we have shown how to exploit both annotator reliability and label dependency to perform multi-label annotation aggregation in a crowdsourcing scenario. Specifically, we propose flexible Bayesian models and efficient inference algorithms that make use of the mixture of multiple independent Bernoulli distribution. Experiments on real datasets confirm that our approaches outperform other competitive alternatives in terms of recovering ground truth labels. In addition, our method is able to recover the type of annotators with high accuracy, and the estimated model can well capture the observed label dependency. Encouraged by our results, in the future we plan to also
consider the clustering structure of annotators with similar behaviors [19] and use such information to further improve the performance.

Our research has several business implications. First, the proposed approach serves as a cost-effective tool to perform multi-label annotation aggregation. Although multi-class annotation aggregation has been well studied in the literature, the multi-label scenario still remains an important issue to be addressed. As demonstrated by the experimental results, our proposed model BMMB can improve the annotation accuracy by 10% – 30% (compared with majority voting) and 1% – 6% (compared with treating each label independently). This improvement will immediately translate into large differences in expense, given that certain big firms rely on such service on a daily basis [27] and that annotation collection is often the first step in the business process. Second, the crowdsourcing platforms can potentially utilize the estimated annotator reliability to build incentive mechanisms (e.g., performance-based payments [10]) so as to motivate workers to provide higher-quality annotations.

Figure 7: Impact of $K$ on recovering ground truth labels (evaluated by F1-score) of three datasets with $R = 1:1:1$ and $T = 4$. The number of annotators $L$ is 900, 2700, and 4500, respectively.

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Appendix

A Details of Inference for the BMMB model

The exact form of the ELBO for the BMMB model is:

\[
\mathcal{L}(\theta_v) = \sum_{l=1}^{L} \sum_{j=1}^{C} \sum_{i \in N(l)} \left\{ \lambda_{i,j} y_{i,j} [\log \Psi_j^l] + (1 - y_{i,j}) [\log (1 - \Psi_j^l)] \right\} \\
+ \sum_{j=1}^{C} \sum_{l=1}^{L} \left\{ \log \Gamma(g_j^l + h_j^l) - \log \Gamma(g_j^l) - \log \Gamma(h_j^l) \right\} - LC [\log \Gamma(a + b) - \log \Gamma(a) - \log \Gamma(b)] \\
+ \sum_{j=1}^{C} \sum_{l=1}^{L} (a - g_j^l) [\log \Psi_j^l] + \sum_{j=1}^{C} \sum_{l=1}^{L} (b - h_j^l) [\log (1 - \Psi_j^l)] \\
+ \sum_{j=1}^{C} \sum_{k=1}^{K} \sum_{i=1}^{R} \left\{ \lambda_{i,j} \log \lambda_{i,j} + (1 - \lambda_{i,j}) \log (1 - \lambda_{i,j}) \right\} + \sum_{i=1}^{N} \sum_{k=1}^{K} r_{i,k} [\log \pi_k] - \log r_{i,k} \\
+ \log \Gamma(K \gamma) + \sum_{k=1}^{K} \log \Gamma(m_k) - K \log \Gamma(\gamma) - \log \Gamma(\sum_{k=1}^{K} m_k) + \sum_{k=1}^{K} \log \pi_k.
\]

B Details of Inference for the BNC model

The true posterior of latent variables \( p(\Psi, z, \tau | Y, a, b, \alpha, \beta) \) is approximated by a fully factorized distribution \( q(\Psi, z, \tau) \) where

\[
q(\Psi, z, \tau) = q(\Psi | g, h) q(z | \lambda) q(\tau | e, f).
\]

(17)
The ELBO for the BNC model is:

\[
\mathcal{L}(\theta_v) = \sum_{l=1}^{L} \sum_{j=1}^{C} \sum_{i \in N(l)} \lambda_{i,j} [g_{i,j}^l \mathbb{E}_q[\log \Psi_j^l] + (1 - g_{i,j}^l) \mathbb{E}_q[\log(1 - \Psi_j^l)]]
+ (1 - \lambda_{i,j}) [g_{i,j}^l \mathbb{E}_q[\log(1 - \Psi_j^l)] + (1 - g_{i,j}^l) \mathbb{E}_q[\log \Psi_j^l]]
+ \sum_{j=1}^{C} \sum_{l=1}^{L} \{ \log \Gamma(g_j^l + h_j^l) - \log \Gamma(g_j^l) - \log \Gamma(h_j^l) \} - LC[\log \Gamma(a + b) - \log \Gamma(a) - \log \Gamma(b)]
+ \sum_{j=1}^{C} \sum_{l=1}^{L} (a - g_j^l) \mathbb{E}_q[\log \Psi_j^l] + \sum_{j=1}^{C} \sum_{l=1}^{L} (b - h_j^l) \mathbb{E}_q[\log(1 - \Psi_j^l)]
+ \sum_{j=1}^{C} \{ \log \Gamma(e_j + f_j) - \log \Gamma(e_j) - \log \Gamma(f_j) \} - C[\log \Gamma(\alpha + \beta) - \log \Gamma(\alpha) - \log \Gamma(\beta)]
+ \sum_{j=1}^{C} (\alpha - e_j) \mathbb{E}_q[\log \tau_j] + \sum_{j=1}^{C} (\beta - f_j) \mathbb{E}_q[\log(1 - \tau_j)]
+ \sum_{i=1}^{N} \sum_{j=1}^{C} \{ \lambda_{i,j} \mathbb{E}_q[\log \tau_j] - \log \lambda_{i,j} \} + (1 - \lambda_{i,j}) \{ \mathbb{E}_q[\log(1 - \tau_j)] - \log(1 - \lambda_{i,j}) \}.
\]

The update rules are as follows:

- The update equations for \( g, h \) are the same as the ones (9) in the BMMB model.
- Updates for \( \lambda \): for \( i = 1, \ldots, N \) and \( j = 1, \ldots, C \),

\[
\lambda_{i,j} \propto \exp \left\{ \mathbb{E}_q[\log \tau_j] + \sum_{l \in L(i)} \{ y_{i,j}^l \mathbb{E}_q[\log \Psi_j^l] + (1 - y_{i,j}^l) \mathbb{E}_q[\log(1 - \Psi_j^l)] \} \right\},
1 - \lambda_{i,j} \propto \exp \left\{ \mathbb{E}_q[\log(1 - \tau_j)] + \sum_{l \in L(i)} \{ (1 - y_{i,j}^l) \mathbb{E}_q[\log \Psi_j^l] + y_{i,j}^l \mathbb{E}_q[\log(1 - \Psi_j^l)] \} \right\}.
\]

- Updates for \( e, f \): for \( j = 1, \ldots, C \),

\[
e_j = \alpha + \sum_{i=1}^{N} \lambda_{i,j}, \quad f_j = \beta + \sum_{i=1}^{N} (1 - \lambda_{i,j}).
\]

Similar to the BMMB model, we have \( \mathbb{E}_q[\log \Psi_j^l] = \psi(g_j^l) - \psi(g_j^l + h_j^l), \mathbb{E}_q[\log(1 - \Psi_j^l)] = \psi(h_j^l) - \psi(g_j^l + h_j^l), \mathbb{E}_q[\log \tau_j] = \psi(e_j) - \psi(e_j + f_j) \), and \( \mathbb{E}_q[\log(1 - \tau_j)] = \psi(f_j) - \psi(e_j + f_j) \), where \( \psi(\cdot) \) is the digamma function.