TrueLabel + Confusions: A Spectrum of Probabilistic Models in Analyzing Multiple Ratings

Anonymous Author(s)
Affiliation
Address
email

Abstract

This paper revisits the problem of analyzing multiple ratings given by different judges. Different from previous work that focuses on distilling the true labels from noisy crowdsourcing ratings, we emphasize gaining diagnostic insights into our in-house well-trained judges. We generalize the well-known DAWIDSKENE model [1] to a spectrum of probabilistic models under the same "TrueLabel + Confusion" paradigm, and show that our proposed hierarchical Bayesian model, called HYBRIDCONFUSION, consistently outperforms DAWIDSKENE on both synthetic and real-world data sets.

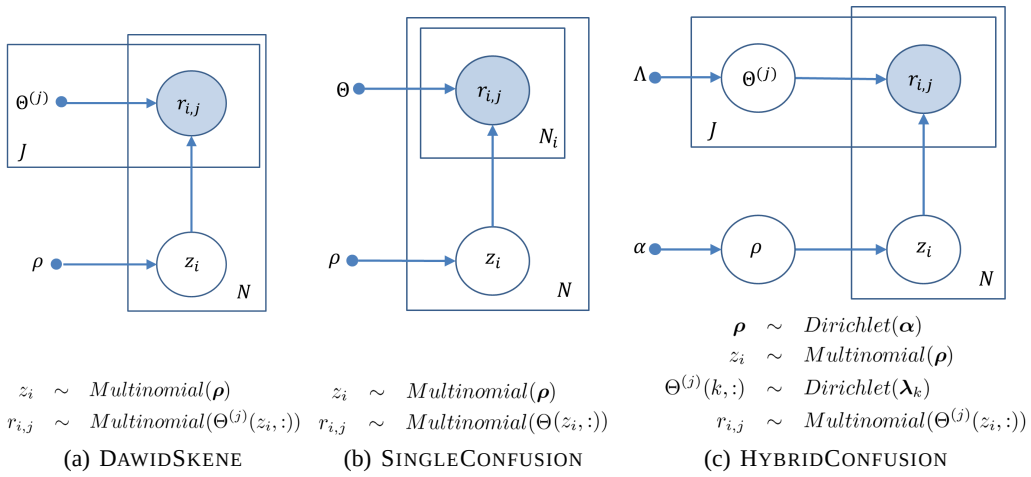
1 Motivation

Recent advent of online crowdsourcing services (*e.g.,* Amazon's Mechanical Turk) excites the machine learning community by making large amount of labeled data practically feasible. Because of the low cost, crowdsourcing labels are usually given by anonymous lowly-paid non-experts, which sparks recent interest in recovering the true labels from noisy (or even malicious) labels [11, 10, 5, 6]. In this paper, we study the same problem of analyzing multiple ratings, but in quite a different setting.

We are in a major Web search engine company, training search rankers based on human ratings on the relevance of tens of millions of (query, URL) pairs using learning-to-rank algorithms. As it is too risky to bet the search engine on crowdsourcing ratings, we have to carefully recruit human judges, rigorously train them, and continually monitor their quality during the work. Since these judges are well-trained and the rating task is considerably hard, the cost of each label becomes so expensive that even two ratings per (query, URL) pair are economically infeasible, given that we have tens of millions of pairs to rate and the number keeps increasing. Instead, we hope that a human judge would function satisfactorily once qualified, and each (query, URL) pair is only rated by one judge.

A key component in controlling the judge quality is to blend a small set of "monitoring" (query, URL) pairs into judges' regular work without their knowledge. This set of (query, URL) pairs are rated by all judges under monitoring. By analyzing the multiple ratings on (query, URL) pairs in this monitoring set, we hope to correctly score the quality of each judge, and more importantly, to gain insights into what confusions each judge makes so that we could plan targeted tutoring and/or clarify/revise the rating guidelines. Therefore, different from previous work that focuses on recovering the true labels from low-cost noisy labels, we are more interested in diagnostic information about judge confusions. For this reason, this paper emphasizes on probabilistic models that use a confusion matrix to quantify the competency of each judge.

The DAWIDSKENE model [1] is a good candidate. It pioneers the "TrueLabel + Confusion" paradigm: each item has a true label, and the rating each judge assigns to it is the true label obfuscated through the judge's confusion matrix. Suppose the rating is on a K-level scale, a confusion matrix is a $K \times K$ matrix with the (k, t) element being the probability that the judge would rate the



(a) DAWIDSKENE (b) SINGLECONFUSION (c) HYBRIDCONFUSION

Figure 1: Graphical Model Representation of the Spectrum of Probabilistic Models

item t when the true label is k. Because each confusion matrix entails $K * (K-1)$ free parameters, DAWIDSKENE possesses at least $J * K * (K-1)$ free parameters when J judges are involved. While this large number of free parameters renders big model capacity, it could also lead to overfitting easily, as will be seen in the experiments. For this reason, we propose a simplified model, called SINGLECONFUSION, which forces all judges to share the same confusion matrix. It significantly reduces the dimension of freedom, but unfortunately proves too rigid for real-world data, *i.e.*, underfitting. As a tradeoff between the two, we further propose a hierarchical Bayesian model, called HYBRIDCONFUSION, which allows each judge to have her own confusion matrix, but at the same time regularizes these matrices through Bayesian shrinkage. Effectively, the three models form a spectrum of probabilistic models under the "TrueLabel + Confusion" paradigm. In summary, we make the following two contributions in this paper: (1) we study the problem of analyzing multiple ratings with an emphasis on the diagnostic aspect of different models, a different setting from previous work, (2) we generalize the well-known DAWIDSKENE model to a spectrum of probabilistic models under the same paradigm, and show the newly proposed model, HYBRIDCONFUSION, consistently outperforms DAWIDSKENE and SINGLECONFUSION on both synthetic and real-world data sets.

The rest of this paper is organized as follows. We elaborate on the spectrum of probabilistic models in Sections 2, and report on experiments on synthetic and real-world data in Sections 3 and 4, respectively. With related work discussed in Section 5, Section 6 concludes this study.

2 A Spectrum of Probabilistic Models

Suppose we have N items rated by J judges on a K-level metric. The metric can be either ordinal or categorical. Let $r_{i,j}$ be the rating of the ith item assigned by the jth judge: $r_{i,j} \in \{1, 2, \cdots, K\}$ if the jth judge indeed rates the ith item and $r_{i,j} = 0$ otherwise. We use $t_i \in \{1, 2, \cdots, K\}$ to denote the true label of the ith item. The competency of the jth judge is modeled by a confusion matrix $\Theta^{(j)} \in R^{K \times K}$ with its (k,t) element $\Theta^{(j)}_{k,t}$ being the probability that the jth judge will give a rating of t when $t_i = k$. Collectively, we denote $\mathbf{r}_i = \{r_{i,j}\}_{j=1}^{J}$, $\mathbf{r} = \{\mathbf{r}_i\}_{i=1}^{N}$, $\mathbf{t} = \{t_i\}_{i=1}^{N}$, and $\boldsymbol{\Theta} = \{\Theta^{(1)}, \Theta^{(2)}, \cdots, \Theta^{(J)}\}$, and use the hat notation ($\widehat{\ }$) to denote the estimated value of the corresponding parameter.

The spectrum of probabilistic models are plotted in Figure 1. We start with a brief review of the DAWIDSKENE model (Figure 1(a)). It assumes that the true rating of each item is sampled from a multinomial distribution parameterized by $\boldsymbol{\rho}$. Suppose the sampled true label is k, then the rating assigned by the jth judge is regarded as being sampled from another multinomial distribution parameterized by the kth row of the jth judge's confusion matrix, namely, $\Theta^{(j)}(k,:)$, using the Matlab notation. The goal of the inference is to recover the model parameters ($\boldsymbol{\Theta}$ and $\boldsymbol{\rho}$) and the true rat-

Algorithm 1 : Inference for DAWIDSKENE

Input: Observed ratings $\mathbf{r}$

Output: Estimated $\widehat{\boldsymbol{\Theta}}, \widehat{\boldsymbol{\rho}}$ and $\widehat{\mathbf{t}}$

Initialize:

$$\widehat{\boldsymbol{\rho}}_k = 1/K,\ \widehat{\boldsymbol{\Theta}}^{(j)}_{k,t} = \begin{cases} \lambda/(\lambda+K) \text{ if } k=t \\ 1/(\lambda+K) \text{ otherwise} \end{cases}$$

Iterate until convergence:

E-step:

$$Z_{i,k} = \frac{\boldsymbol{\rho}_k \prod_{j=1}^{J} \mathbb{I}(r_{i,j} \neq 0) \Theta^{(j)}_{k,r_{i,j}}}{\sum_{k=1}^{K} \boldsymbol{\rho}_k \prod_{j=1}^{J} \mathbb{I}(r_{i,j} \neq 0) \Theta^{(j)}_{k,r_{i,j}}}$$

M-step:

$$\widehat{\boldsymbol{\Theta}}^{(j)}_{k,t} = \frac{\sum_{i=1}^{N} Z_{i,k} \mathbb{I}(r_{i,j}=t)}{\sum_{t=1}^{K}\sum_{i=1}^{N} Z_{i,k} \mathbb{I}(r_{i,j}=t)}$$

$$\widehat{\boldsymbol{\rho}}_k = \frac{\sum_{i=1}^{N} Z_{i,k}}{\sum_{k=1}^{K}\sum_{i=1}^{N} Z_{i,k}}$$

Compute:

$$\widehat{\mathbf{t}}_i = \underset{k=1,2,\cdots,K}{\arg\max}\ Z_{i,k}$$

(a) DAWIDSKENE

Algorithm 2 : Inference for SINGLECONFUSION

Input: Observed ratings $\mathbf{r}$

Output: Estimated $\widehat{\Theta}, \widehat{\boldsymbol{\rho}}$ and $\widehat{\mathbf{t}}$

Initialize:

$$\widehat{\boldsymbol{\rho}}_k = 1/K,\ \widehat{\Theta}_{k,t} = \begin{cases} \lambda/(\lambda+K) \text{ if } k=t \\ 1/(\lambda+K) \text{ otherwise} \end{cases}$$

Iterate until convergence:

E-step:

$$Z_{i,k} = \frac{\boldsymbol{\rho}_k \prod_{t=1}^{K} (\Theta_{k,t})^{\sum_{j=1}^{J} \mathbb{I}(r_{i,j}=t)}}{\sum_{k=1}^{K} \boldsymbol{\rho}_k \prod_{t=1}^{K} (\Theta_{k,t})^{\sum_{j=1}^{J} \mathbb{I}(r_{i,j}=t)}}$$

M-step:

$$\widehat{\Theta}_{k,t} = \frac{\sum_{j=1}^{J}\sum_{i=1}^{N} Z_{i,k} \mathbb{I}(r_{i,j}=t)}{\sum_{t=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{N} Z_{i,k} \mathbb{I}(r_{i,j}=t)}$$

$$\widehat{\boldsymbol{\rho}}_k = \frac{\sum_{i=1}^{N} Z_{i,k}}{\sum_{k=1}^{K}\sum_{i=1}^{N} Z_{i,k}}$$

Compute:

$$\widehat{\mathbf{t}}_i = \underset{k=1,2,\cdots,K}{\arg\max}\ Z_{i,k}$$

(b) SINGLECONFUSION

Figure 2: Inference Algorithms for DAWIDSKENE and SINGLECONFUSION

ings $\mathbf{t}$. To be self-contained, the inference algorithm is reproduced in Figure 2(a) from [1], which facilitates comparisons across models. The particular way of initialization in Figure 2(a) is merely meant to be consistent with HYBRIDCONFUSION, as to be discussed soon.

DAWIDSKENE model imposes no regularization on the individual confusion matrices, and hence possesses $(J * K + 1) * (K - 1)$ free parameters. In the first place, the large number of free parameters endows DAWIDSKENE with high model capacity, but in the second place, it means DAWIDSKENE could easily overfit and suffer from not having enough data to fit. This observation, as supported by experimental results, prompts us to reduce the capacity by reducing the number of free parameters. We therefore propose the SINGLECONFUSION model, which forces all judges share the same confusion matrix. Its graphical model and inference algorithm are presented in Figure 1(b) and Figure 2(b)[1], respectively. SINGLECONFUSION effectively reduces the number of free parameters to $K^2 - 1$, but unfortunately, proves to be too rigid to model the variations across judges.

We can view DAWIDSKENE and SINGLECONFUSION as two extremes under the same "TrueLabel + Confusion" paradigm: one has too many parameters while the other has too few. We therefore propose the HYBRIDCONFUSION model, whose graphical model is depicted in Figure 1(c). HYBRIDCONFUSION makes tradeoffs between DAWIDSKENE and SINGLECONFUSION by allowing each judge to still have her own confusion matrix but at the same time regularizing them through Bayesian shrinkage. Explicitly, HYBRIDCONFUSION imposes that the kth row of all confusion matrices are sampled from a Dirichlet distribution parameterized by $\boldsymbol{\lambda}_k$. In this paper, we let

$$\Lambda = \mathbf{1}_{K\times K} + \lambda I_{K\times K} = \begin{pmatrix} \lambda+1 & 1 & \dots & 1 \\ 1 & \lambda+1 & \dots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \dots & \lambda+1 \end{pmatrix} = \begin{pmatrix} \boldsymbol{\lambda}_1 \\ \boldsymbol{\lambda}_2 \\ \vdots \\ \boldsymbol{\lambda}_K \end{pmatrix},$$

which explains the choice of initialization in Figure 2. To complete the Bayesian model, a Dirichlet prior is imposed on $\boldsymbol{\rho}$ as well with parameter $\boldsymbol{\alpha}$. We used Markov Chain Monte Carlo (Gibbs sampling in particular) to perform the inference on HYBRIDCONFUSION using the BUGS software

[1]The derivation, inference code and Matlab implementations for all the models are available in the supplement material

	A	B	C
A	0.8	0	0.2
B	0.1	0.8	0.1
C	0.1	0	0.9

(a) Confusion Matrix $\Theta^{(1)}$

	A	B	C
A	0.7	0.2	0.1
B	0.1	0.7	0.2
C	0.1	0.1	0.8

(b) Confusion Matrix $\Theta^{(2)}$

	A	B	C
A	0.6	0.3	0.1
B	0.1	0.5	0.4
C	0.1	0.4	0.5

(c) Confusion Matrix $\Theta^{(3)}$

Figure 3: Confusion Matrices in the Simulation

package [4]. We run 3 Gibbs sampler with 1000 built-in and obtain 100 examples with a thinning interval of 10 in all experiments. After collecting the samples, we take the mode rating from the samples of the true labels as the recovered true label, and the mean values of samples about $\boldsymbol{\rho}$ and $\boldsymbol{\Theta}$ as the estimates $\widehat{\boldsymbol{\rho}}$ and $\widehat{\boldsymbol{\Theta}}$. As the K labels are mutually exchangeable, all of the three models need to deal with the un-identifiability issue, and we tackle this using a method similar to [9]. In all the experiments, $\boldsymbol{\alpha} = [1, 1, \cdots, 1]$ and $\lambda = 3$ unless otherwise noted.

The usage of $\lambda = 3$ imposes a moderate prior that judges tend to identify the true label. Depending on the applications, one could put a stronger prior by using a bigger λ or impose confusion patterns based on prior knowledge (*e.g.*, a bigger value for $\Lambda_{1,3}$ if judges tend to misjudge "1" as "3"). In the case of ordinal rating, one could even put on a diagonal-decaying prior (*i.e.*, $\Lambda_{i,j_1} > \Lambda_{i,j_2}$ if $|j_1 - i| < |j_2 - i|$), indicating the belief that a judge is more likely to confuse adjacent levels than nonadjacent ones. In short, HYBRIDCONFUSION provides a flexible way to encode different prior knowledge, but the best setting, as always, depends on the application and prior knowledge.

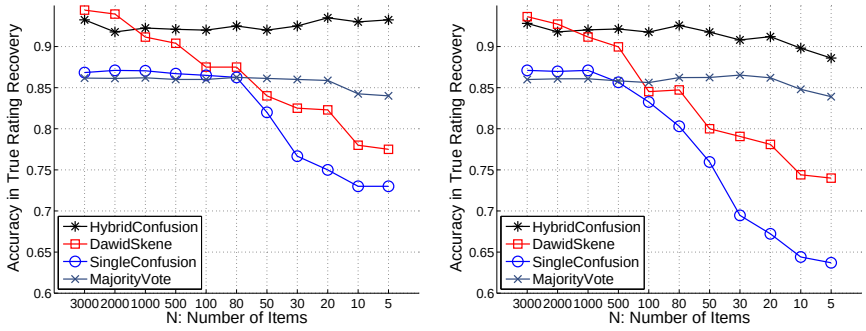
3 Experiments on Synthetic Data

In this section, we use synthetic data to examine how accurately different models would recover the ground truth, *i.e.*, true model parameters and true labels. We synthesize the data using the DAWIDSKENE model for three judges ($J = 3$) on a three-level metric ($K = 3$). For convenience, we denote the three levels by "A", "B", and "C", whose prior probabilities are assumed to be 0.05, 0.15 and 0.8, respectively. The three confusion matrices are shown in Figure 3. As can be seen, the three matrices are not chosen to favor any models, and in fact, $\Theta^{(1)}$ (as shown in Figure 3(a)) actually disfavors HYBRIDCONFUSION because HYBRIDCONFUSION never estimates any cells to be 0.

Throughout the experiments in this subsection, we examine the accuracy of recovering the ground truth for different models by varying the number of items. Intuitively, the more items to rate, the more accurately these models would recover the ground truth. The number of items is varied from 3000 down to 5, which would render a complete view of the model efficacy when the data size changes. The data is synthesized in each run, and all the reported numbers are the average across 100 runs. We also include the majority voting (denoted by MAJORITYVOTE) algorithm in the comparison. MAJORITYVOTE takes the mode rating as the true rating, and breaks ties randomly when there are multiple modes. Once the true label is determined, $\widehat{\boldsymbol{\rho}}$ and $\widehat{\boldsymbol{\Theta}}$ are obtained through simple counting.

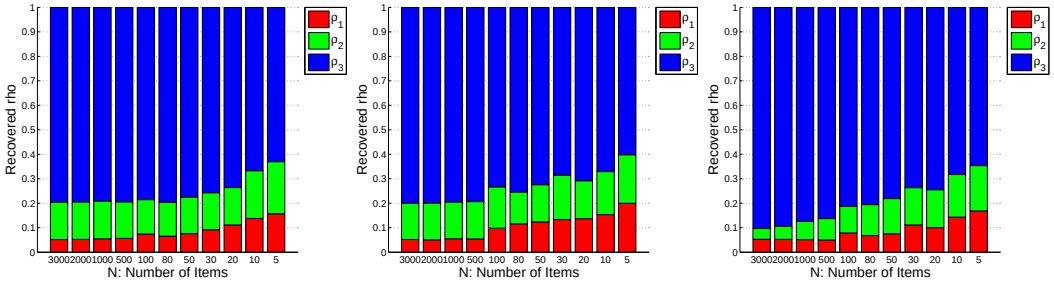
3.1 Experimental Results

Figure 4(a) plots the accuracy in recovering the true labels when the number of items decreases from 3000 to 5, using the default parameter $\lambda = 3$. First, we observe that since the data is synthesized through DAWIDSKENE, the best recovery is indeed achieved by DAWIDSKENE, provided abundant data is available. But when data becomes smaller, DAWIDSKENE quickly deteriorates, as a result of overfitting. On the other hand, we see that HYBRIDCONFUSION is consistently above 0.9, only being slightly weaker than DAWIDSKENE when $N = 2000, 3000$, and significantly outperforming DAWIDSKENE otherwise. This consistent performance should be attributed to the Bayesian shrinkage. Third, we see MAJORITYVOTE is pretty flat, and effectively saturates after $N \geq 20$. Finally, SINGLECONFUSION is the weakest and twisted with MAJORITYVOTE when $N \geq 50$. The inferior



(a) True Label Recovery ($\lambda = 3$) (b) True Label Recovery ($\lambda = 10$)

Figure 4: Accuracy in Recovering the True Label with Different λ's



(a) HYBRIDCONFUSION (b) DAWIDSKENE (c) SINGLECONFUSION

Figure 5: Accuracy in Recovering $\boldsymbol{\rho}$ by Different Models

performance of SINGLECONFUSION is likely due to its strict constraint to have all judges share the same confusion matrices whereas in fact they are quite different (see Figure 3). Figure 4(b) presents the same experiments with $\lambda = 10$, and we observe the same trend.

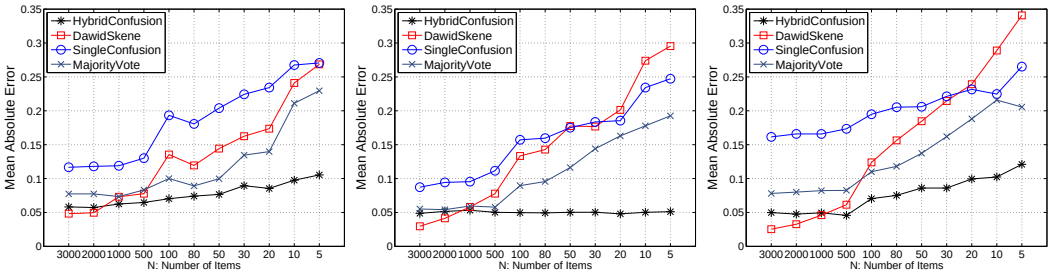
The recovered $\boldsymbol{\rho}$ by HYBRIDCONFUSION, DAWIDSKENE, and SINGLECONFUSION with varying numbers of items are plotted in Figure 5. The recovered $\boldsymbol{\rho}$ by MAJORITYVOTE is consistently around (0.1, 0.15, 0.75) regardless of the number of items, and hence not plotted in Figure 5. We see that both HYBRIDCONFUSION and DAWIDSKENE can exactly recover the true $\boldsymbol{\rho}$ with enough data whereas SINGLECONFUSION misses the target even when 3000 items are provided.

Finally, Figure 6 plots the accuracy in recovering the true confusion matrices, as measured by the Mean Absolute Error (MAE),

$$MAE(\widehat{\Theta}^{(i)}, \Theta^{(i)}) = \frac{1}{K^2} \sum_{k=1}^{K} \sum_{t=1}^{K} |\widehat{\Theta}_{k,t}^{(i)} - \Theta_{k,t}^{(i)}|.$$

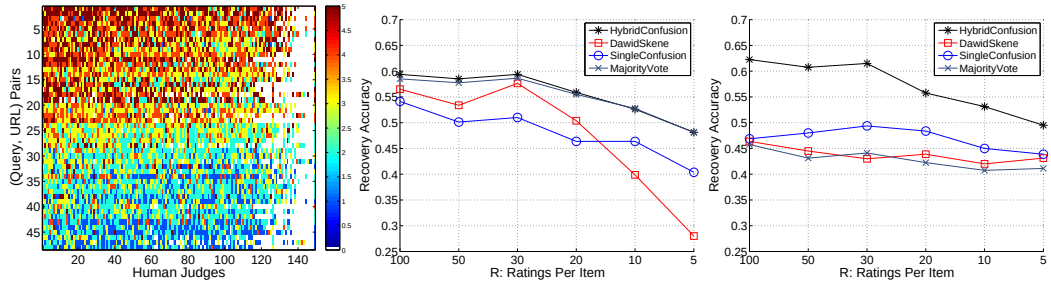
Figure 6(a) plots the MAE of different models in recovering $\Theta^{(1)}$ when the number of items varies. Again, we have seen that DAWIDSKENE gives the best recovery, but only when enough items are provided, and it clearly deteriorates with fewer and fewer data. HYBRIDCONFUSION, on the other hand, is very accurate, and barely decays when N gets smaller. SINGLECONFUSION remains the worst performing model but MAJORITYVOTE appears very competitive. The same trend on relative performance of different models is confirmed in Figures 6(b) and 6(c) as well.

As a short conclusion, we have observed that HYBRIDCONFUSION is comparable to DAWIDSKENE when abundant data is available even if the data is synthesized by DAWIDSKENE. While DAWIDSKENE quickly deteriorates when data becomes scarce, HYBRIDCONFUSION remains very accurate in recovering the ground truth, which clearly demonstrates the efficacy of Bayesian shrinkage. But DAWIDSKENE is roughly 5 times as fast as HYBRIDCONFUSION.



(a) Accuracy in Recovering $\Theta^{(1)}$ (b) Accuracy in Recovering $\Theta^{(2)}$ (c) Accuracy in Recovering $\Theta^{(3)}$

Figure 6: Accuracy in Recovering $\boldsymbol{\Theta}$ using Mean Absolute Error



(a) Data Visualization (b) "Memoryless" Mode (c) "Memory" Mode

Figure 7: Experiments on Real-World Data Set

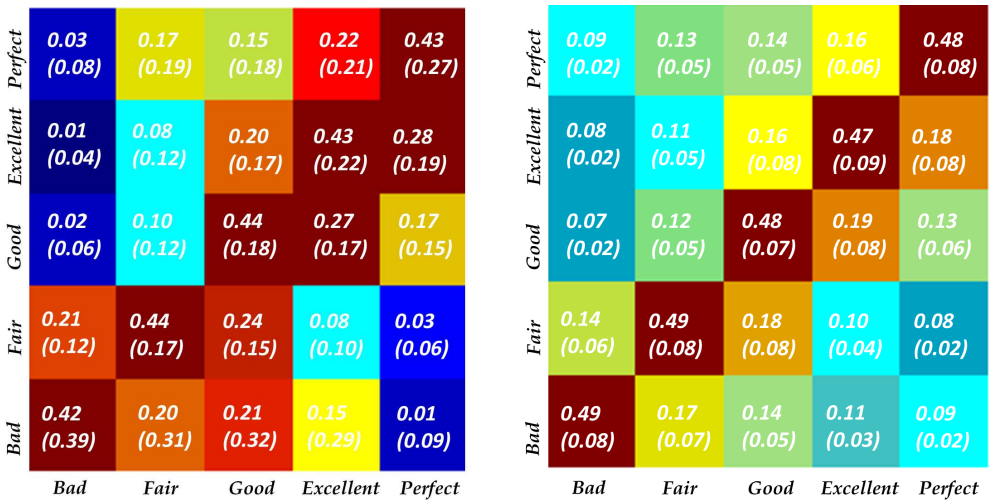
4 Experiments on Real-World Data

In this section, we report on the experimental results on a real-world data set that motivates the study. As explained in Section 1, we use a set of "monitoring" (query, URL) pairs to gauge judge quality. For each (query, URL) pair, a judge is expected to assign it into one of the five categories *Bad*, *Fair*, *Good*, *Excellent*, *Perfect* (denoted by 1 to 5, respectively), based on her assessment of the relevance according to a 20-page written guideline. This "monitoring" set is chosen to be "hard" to maximally differentiate judge qualities. A "super-judge", who supposedly best understands the judgment guideline provides the gold rating to each pair in the set, and the quality of each judge is determined based on the gold ratings. Because only a few super-judges are available, quality calibration based on existing gold labels usually suffers from data scarcity, for example, a lot of cells in the confusion matrices would be zero. Therefore, in this section, we explore to what extent each model would recover the gold rating based on individual ratings from regular judges, and furthermore whether the estimated parameters by each model could help further lift the prediction accuracy.

One monitoring set consists of 6008 ratings from 148 judges on 48 (query, url) pairs, as visualized in Figure 7(a)[2]. Each row corresponds to a distinct (query, url) pair, and each column to a distinct human judge. For eligibility, (query, url) pairs and judges are sorted based on the average rating across judges and items, respectively. The gold labels are listed in the last column. There are only 6 colors of interest in the colorbar: blue for 1 (*Bad*) to red for 5 (*Perfect*) with white for 0 denoting unrated item by certain judges. As can be seen, some judges only rated a few (query, URL) pairs, and they are generally new judges hired into the system. They are not excluded in order to keep the fidelity to real-world data.

Again we report experiment results using the average across 100 runs. In each run, we first sample R ratings for each item, and then randomly partition the 48 (query, URL) pairs into training and testing sets with a ratio of 2:1. We compare the accuracy of predicting the gold label on the testing set with different models. In order to see if any models could recover the unknown true parameters to some extent from the training set, we test the prediction accuracy in two different modes. The

[2]The same visualization with better legibility is available in the supplement material



(a) Confusion Matrix: DAWIDSKENE (b) Confusion Matrix: HYBRIDCONFUSION

Figure 8: A Peek into the Average Confusion Matrix

first is the "Memoryless" mode where the true label is predicted solely based on the testing set, and the second is the "Memory" mode where each (query, URL) pair is predicted using the estimated parameters obtained from the training set. Explicitly, the "Memory" mode computes the posterior of the rating based on $\widehat{\mathbf{\Theta}}, \widehat{\boldsymbol{\rho}}$ and $\mathbf{r_i}$ using

$$p(z_i = k|\mathbf{r_i}; \widehat{\mathbf{\Theta}}, \widehat{\boldsymbol{\rho}}) \quad = \quad \frac{\widehat{\boldsymbol{\rho}}_k \prod_{j=1}^{J} \mathbb{I}(r_{i,j} \neq 0) \widehat{\Theta}^{(j)}_{k,r_{i,j}}}{\sum_{k=1}^{K} \widehat{\boldsymbol{\rho}}_k \prod_{j=1}^{J} \mathbb{I}(r_{i,j} \neq 0) \widehat{\Theta}^{(j)}_{k,r_{i,j}}},$$

and assigns the ith item to the most probable rating.

The "Memoryless" model corresponds to the cold-start scenario where no knowledge about the judges is available, whereas the "Memory" mode mimics the case where the confusion matrices and label distributions are known a priori from previous data. However, in neither mode is the gold label of the training set used, and the gold label of testing data is merely used in measuring the prediction accuracy. The goal of this study aims at comparing the recovery accuracy of the true label using different models, and to what extent the estimated parameters could help; the goal is not to build a state-of-the-art prediction model for true label.

Figures 7(b) and 7(c) plot the prediction accuracy w.r.t. the number of ratings per item in the two modes, respectively. In the "Memoryless" mode (Figure 7(b)), all models deteriorate as fewer ratings are available to each item, and DAWIDSKENE deteriorates the most, yet another piece of evidence of overfitting. In contrast, HYBRIDCONFUSION performs very well and does not deteriorate much even when $R = 5$. Surprisingly, MAJORITYVOTE is very close to HYBRIDCONFUSION, and the performance gap is no longer as wide as that shown in Figure 4. A likely reason for the strong performance of MAJORITYVOTE is the fact that all our judges are well-trained and understand that their quality is continually monitored; hence their consensus should be strong. Nevertheless, we still see HYBRIDCONFUSION beats MAJORITYVOTE with a small but consistent margin with 30 or more ratings per item (p-value < 0.05 using one-sided Fisher Sign Test).

Figure 7(c) compares the performance in the "Memory" mode, where we see that HYBRIDCONFUSION significantly beats all other three models and is visibly better than HYBRIDCONFUSION in the "Memoryless" mode. This suggests that HYBRIDCONFUSION indeed recover the true parameters to some extent, which helps lift the prediction accuracy. In contrast, we see the accuracy of MAJORITYVOTE drops significantly from the "Memoryless" mode, indicating the inferior quality of the estimated parameters due to data sparsity.

Finally, we peek into the estimated confusion matrices by DAWIDSKENE and HYBRIDCONFUSION to understand what the estimates look like. Figure 8 plots the average confusion matrices for DAWIDSKENE and HYBRIDCONFUSION, as averaged across all judges over the 100 runs with

$R = 5$. At first glimpse, we see the confusion matrix from DAWIDSKENE is much more chaotic than that from HYBRIDCONFUSION, which visually demonstrates the efficacy of Bayesian shrinkage in HYBRIDCONFUSION. Within each cell, we also mark out the probability value with the standard deviation in the parenthesis. Clearly, we see that confusion matrices from DAWIDSKENE are more divergent from each other (big standard deviations as shown in Figure 8(a)). In contrast, the confusion matrix from HYBRIDCONFUSION (Figure 8(b)) exhibits natural diagonal-decaying phenomena, and the standard deviations are generally much smaller. Now that our judges are well-trained, we believe the latter is closer to the truth than the former, although we have no way to solicit the truth.

5 Related Work

The need of large amount of labeled data, as inherent in many machine learning algorithms and applications, cultivates the advent of online crowdsourcing services (*e.g.*, Amazon's MechanicTurk). Readers interested in a detailed survey in this area are referred to [3]. While the low cost of crowdsourcing renders multiple labels on numerous items practically feasible, it also calls for principled approaches to distilling true labels from the less-than-expert ratings, among other issues [7]. Because of the importance of this problem, recent years have seen increasing interests in this problem, *e.g.*, [11, 10, 5, 6]. Specifically, Whitehill et al. [11] models the probability that a judge would rate an item correctly as a logistic function of the product between the quality of the judge and the difficulty of the item. This leads to a model that not only recovers the true label, but estimates the judge quality (represented by a single number) and item difficulty at the same time. But since the model deals with the probability that a judge hits the right rating, it does not provide detailed diagnostic information about judge confusions. Welinder et al. [10, 5] generalizes [11] by introducing a high-dimensional concept of item difficulty, and shows a small but consistent improvement over [11] in true label recovery rate, but again fails to provide the confusion matrices. In this paper, we focus on models under the "TrueLabel + Confusion" paradigm for diagnostic insights into judge confusion. In addition to the different focus, the judges in our setting are also different from previous work: our in-house judges are well trained, decently paid, and benign in general, which directly contrasts to the anonymous non-expert or even malicious judges in crowdsourcing services. This entails two consequences: first, we do not worry about malicious judges, and second, MAJORITYVOTE becomes much more competitive, although it is still inferior to our proposed model.

The spectrum of models as presented here are not restricted to ratings from human judges, and in fact they can be effectively used to combine any ratings from any sources, be it human judges or predictive models. To some extent, this setting is closer to ours in that the predictive models are generally reasonable and benign. Previously, Ghahramani and Kim presented some preliminary results using a model similar to HYBRIDCONFUSION [2], but failed to examine how the performance varies when the numbers of items and judges change. This paper fills in the gap, and to the best of our knowledge, this is the first piece of work generalizing DAWIDSKENE to a spectrum of models with a comparative study of their pros and cons. Finally, another piece of work worth mentioning is by Raykar et al. [6], which performs supervised learning with the true labels recovered as a by-product. The method is shown to be superior to first recover the true labels and train the supervised learning model next, as practiced in [8]. Their focus is on building accurate predictive models rather than diagnosing judge qualities.

6 Conclusion

In this paper, we generalize the DAWIDSKENE model into a spectrum of probabilistic models under the "TrueLabel+Confusion" paradigm. Our proposed models, SINGLECONFUSION and HYBRIDCONFUSION, complement the well-known DAWIDSKENE model that could easily overfit. We study their pros and cons using both synthetic and real-world data, and clearly demonstrate the advantages of HYBRIDCONFUSION under different settings. Although we have observed some evidence of the capability of HYBRIDCONFUSION in recovering the true confusion matrices, a quantitative study on how the recovered confusion matrices help optimize the whole judging pipeline lies on top of our future work. For example, would it lead to more effective judge training and/or guideline revision and refinement? These are critical questions with high monetary values, but unfortunately not studied yet in literature.

References

[1] A. P. Dawid and A. M. Skene. Maximum likelihood estimation of observer error-rates using the em algorithm. *Applied Statistics*, 28(1):20–28, 1979.

[2] Z. Ghahramani and H. chul Kim. Bayesian classifier combination. Technical report, University College London, 2003.

[3] P. G. Ipeirotis and P. K. Paritosh. Managing crowdsourced human computation: a tutorial. In *Proceedings of the 20th international conference companion on World wide web*, WWW '11, pages 287–288, New York, NY, USA, 2011. ACM.

[4] D. J. Lunn, A. Thomas, N. Best, and D. Spiegelhalter. Winbugs a bayesian modelling framework: Concepts, structure, and extensibility. *Statistics and Computing*, 10:325–337, October 2000.

[5] P. P. P. Welinder. Online crowdsourcing: rating annotators and obtaining cost-effective labels. In *CVPR*, 2010.

[6] V. C. Raykar, S. Yu, L. H. Zhao, A. Jerebko, C. Florin, G. H. Valadez, L. Bogoni, and L. Moy. Supervised learning from multiple experts: Whom to trust when everyone lies a bit. In L. Bottou and M. Littman, editors, *Proceedings of the 26th International Conference on Machine Learning*, pages 889–896, Montreal, June 2009. Omnipress.

[7] V. S. Sheng, F. Provost, and P. G. Ipeirotis. Get another label? improving data quality and data mining using multiple, noisy labelers. In *Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, KDD '08, pages 614–622, New York, NY, USA, 2008. ACM.

[8] P. Smyth, U. M. Fayyad, M. C. Burl, P. Perona, and P. Baldi. Inferring ground truth from subjective labelling of venus images. In G. Tesauro, D. S. Touretzky, and T. K. Leen, editors, *NIPS*, pages 1085–1092. MIT Press, 1994.

[9] M. Stephens. Dealing with multimodal posteriors and non-identifiability in mixture models. Technical report, Department of Statistics, University of Oxford, March 1999.

[10] P. Welinder, S. Branson, S. Belongie, and P. Perona. The multidimensional wisdom of crowds. In *Neural Information Processing Systems Conference (NIPS)*, 2010.

[11] J. Whitehill, P. Ruvolo, T. fan Wu, J. Bergsma, and J. Movellan. Whose vote should count more: Optimal integration of labels from labelers of unknown expertise. In Y. Bengio, D. Schuurmans, J. Lafferty, C. K. I. Williams, and A. Culotta, editors, *Advances in Neural Information Processing Systems 22*, pages 2035–2043. 2009.