Multi-class Multi-annotator Active Learning with Robust Gaussian Process for Visual Recognition

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Abstract

Active learning is an effective way to relieve the tedious work of manual annotation in many applications of visual recognition. However, less research attention has been focused on multi-class active learning. In this paper, we propose a novel Gaussian process classifier model with multiple annotators for multi-class visual recognition. Expectation propagation (EP) is adopted for efficient approximate Bayesian inference of our probabilistic model for classification. Based on the EP approximation inference, a generalized Expectation Maximization (GEM) algorithm is derived to estimate both the parameters for instances and the quality of each individual annotator. Also, we incorporate the idea of reinforcement learning to actively select both the informative samples and the high-quality annotators, which better explores the trade-off between exploitation and exploration. The experiments clearly demonstrate the efficacy of the proposed model.

1. Introduction

Most of the current recognition systems are based on supervised learning with large quantity of labeled training data [15, 29]. In recent years, crowd-sourcing is has been explored to collect large-scale labeled image datasets, such as ImageNet [4] and LabelMe [28].

There are still several issues raised when using the current crowd-sourcing systems like Amazon Mechanical Turk. First of all, the collected labels could be very noisy from irresponsible or low-quality annotators. Secondly, there is no mechanism to control the label quality online. Last but not least, there is no mechanism to prioritize the data to be labeled. To make the most use of the scarce human resource and facilitate more efficient data labeling, active learning has been explored in some previous works [5, 13, 14, 23, 32, 33] to enhance the efficacy of the labeled data for a generalizable model.

However, most previous active learning approaches only investigate the case with a single human oracle on the assumption that the provided labels are noise-free. Theoretically, due to human perception variations, multiple annotators are likely to provide diverse labels for some inherent ambiguous examples even if they are responsible, not to mention random behaviors from the irresponsible annotators. Hence, the problem of active learning with multiple annotators under the condition that multiple annotators may provide noisy labels has not been fully explored, although previous works such as Hua et al. [9] and Long et al. [21, 22] have studied it under the context of binary classification.

Indeed, most existing research works in active learning explore merely on binary classification [7, 9, 10, 21, 27, 40, 42]. Relatively fewer approaches have been investigated for multi-class active learning as discussed in [11] and many of them are direct extension of binary active learning approaches to the multi-class scenario [12]. However, many real visual recognition are multi-class application problems and it is possible that the performance of active learning will be degraded by decomposing a multi-class problem as several independent binary classification subproblems. Therefore, the problem multi-class active learning algorithms with collaborative multiple annotators deserves further exploration.

In this paper, we propose a Bayesian multi-class classification model which explicitly models the expertise level of
each individual annotator from crowds, as shown in Figure 1. Expectation propagation (EP) is adopted for efficient approximate Bayesian inference of our probabilistic model for classification. Based on the EP approximation inference, a generalized Expectation Maximization (GEM) algorithm is derived to estimate both the parameters for instances and the expertise of each individual annotator. Active learning is also explored to select the high-quality annotators and guide them to label the most informative visual examples. We incorporate the ideas of reinforcement learning [5] to determine the optimal strategy to actively select both the samples and higher quality annotators, which effectively strikes for a balance between exploitation and exploration.

Several aspects distinguish our work from previous multi-class active learning based labeling [5, 11, 19, 31, 37, 41]: first of all, our proposed Gaussian process classification model uses a back-up mechanism [8], which is robust when the label errors occur far away from the decision boundaries; Secondly, we enable the active learning with multiple annotators who may label an example incorrectly, a topic which has not been sufficiently explored before. Thirdly, we achieve better exploration-exploitation trade-off for collaborative active learning, which finally leads to a unified Gaussian process model that simultaneously model the noise from multiple annotators.

2. Related work

The related works fall into 4 categories: Crowd-sourcing labels, Multi-class Active learning, Active learning with Gaussian process, and Reinforcement learning.

Crowd-sourcing labels. To handle the label noises in crowd-sourcing, besides Zhao et al.’s incremental relabeling mechanism [43], there are existing research works that explore to model the annotator’s quality [9, 30, 34, 38, 39]. For modeling multiple annotators’ quality for image labeling from crowds, the most relevant works to our research is Welinder et al.’s Bayesian model for the annotation process [34, 35]. We shall emphasize that they rely on the noisy labels for each images from multiple annotators and never extract visual features. In contrast, our work in this paper is designed directly on visual features extracted from images and models the annotators’ quality to enable the active selection of high-quality annotators to obtain the reliable labels.

Multi-class active learning. The existing multi-class active learning approaches can be divided to two categories. One type of methods decompose the multi-class problem to binary cases [11, 12, 19, 25, 26, 37], and the other type of methods deal with the multi-class scenario directly [1, 31, 41]. Three most recent works are Yang et al.’s a multi-class active learning algorithm [41] that explores the uncertain evaluation with diversity maximization, Aodha et al.’s graph-based active learning framework [1] to effectively explore the potential of Expected Error Reduction (EER), and Vasishth et al.’s non-myopic and near-optimal active learning with sparse Bayesian multi-label graphical model [31]. However, all these existing algorithms haven’t considered the multiple-annotator scenario, which is the focus of this paper.

Active learning with Gaussian process. Regarding active learning with Gaussian processes, Kapoor et al. [13] extended Lawrence et al.’s work [16] by introducing a heuristic confidence criterion for active selection of the informative instance based on the variance of the posterior prediction for active learning. Recently, Long et al. [21] and Rodrigues et al. [27] proposed general Gaussian process classifiers in multiple-annotator settings. However, both of these two active learning algorithms focus only on the binary classification case. In contrast, our approach aims to directly deal with multi-class cases, which integrates the potential diverse opinions from multiple annotators and introduces a new heuristic for actively selecting the high-quality annotators to label the informative instances.

Reinforcement learning. The Markov decision process (MDP) provides the general framework to make a decision with respect to the discrimination dynamics. Ebert et al. [5] formulated the active selection criteria based on the MDP-based reinforcement learning to adapt the trade-off between exploration and exploitation and obtained promising experimental results. In this paper, we extend the MDP-based framework to determine the criteria for active selection of both the informative samples and the high-quality annotators.

3. Formulation, inference, and learning

Given a set of \( N \) data points \( X = \{x_1, x_2, ..., x_N \} \), where \( x_i \in \mathbb{R}^D \). We let \( M \) annotators label each \( x_i \). With \( s_i \) denoting the latent random variable with a Gaussian process prior, \( s_i \) can be interpreted intuitively as the soft score for the corresponding data point \( x_i \). We denote the hidden true label of \( x_i \) as \( y_i \), and the observed label of \( x_i \) from annotator \( j \) as \( t_{ij} \). Note that \( t_{ij} \) could be noisy, i.e., \( t_{ij} \) may not be consistent with the hidden true label \( y_i \). We denote \( t_i = \{t_{ij}\}_{j=1}^M \) as the set of labels from the \( M \) annotators for \( x_i \).

Assuming there are \( C \) categories and \( S = \{S^k|k = 1, ..., C\} \), then the Gaussian process prior of the overall function value \( S^k \) is defined as a normal distribution. For notation convenience, we denote \( S = \{s_1, s_2, ..., s_N\} \), \( Y = \{y_1, y_2, ..., y_N\} \) and \( T = \{t_1, t_2, ..., t_N\} \).

3.1. Probabilistic Model

As illustrated in the graphical model in Figure 1, the conditional joint probability of our proposed probabilistic mod-
el is defined as
\[ p(S, Y, T, \rho, z|X, \Theta) \]

\[ \propto p(S|X)p(\rho)p(z|\rho) \prod_{i=1}^{N} \left\{ p(y_i|s_i, z_i) \prod_{j=1}^{M} p(t_{ij}|y_i, \epsilon_j) \right\}, \]

(1)

where \( \Theta \) is the hyperparameter and \( z = \{z_1, \ldots, z_N\} \) is a set of binary latent variables for each visual instance to indicate whether \( s_i^{y_i} \geq s_k \) for any \( k \neq y_i \) (\( z_i = 0 \)) or not (\( z_i = 1 \)).

In this paper, \( p(S|X) \) is defined as a Gaussian process prior [36] with kernel trick, i.e.,
\[ p(S|X) = \sum_{k=1}^{C} \mathcal{N}(S^{k}|0, K^{k}), \]

(2)

where \( K^{k} = [k(x_i, x_j)]_{i,j=1}^{N} \) is a kernel matrix defined over the set of all N data samples. This treatment ensures that similar data samples to have similar prediction scores. Usually, any valid kernel can be used in our formulation.

\( p(y_i|s_i, z_i) \) is a back-up mechanism to deal with label noises and is defined as
\[ p(y_i|s_i, z_i) = \prod_{k \neq y_i} H(s_i^{y_i} - s_k) \left[ \frac{1}{C} \right]^{z_i}, \]

(3)

where \( H(x) = 1 \) if \( x > 0 \) and \( H(x) = 0 \), otherwise. Note that the first term directly depends on the accuracy of \( y_i^{y_i} \). In particular, it takes value 1 when the corresponding instance is correctly classified and 0 otherwise. Our model is robust when the observed data contain labeling errors far from the decision boundaries, and the prior kernel function described in Equation 3 considers only the total number of prediction errors made by \( y_i^{y_i} \), rather than the distance of these errors to the decision boundary.

The conditional probability \( p(t_{ij}|y_i, \epsilon_j) \) is assumed as a flipping noise model [24], i.e.,
\[ p(t_{ij}|y_i, \epsilon_j) = \epsilon_j H(y_i = t_{ij}) + (1 - \epsilon_j) H(y_i \neq t_{ij}). \]

(4)

The intuition here is that we assume that \( t_{ij} \) will be a flipped version of \( y_i \) with probability \( (1 - \epsilon_j) \). Obviously, the larger \( \epsilon_j \) leads to the higher the probability that \( t_{ij} \) will agree with the true label \( y_i \), and vice versa. Therefore, we can use \( \epsilon_j \) to naturally represents the quality of the labels given by annotator \( j \). Note that different from [24], we parameterize the flip model based on label quality, which equals one minus the label noise.

The prior \( p(z|\rho) \) is defined as a factorizing multivariate Bernoulli distribution
\[ p(z|\rho) = \text{Bern}(z|\rho) = \prod_{i=1}^{N} \rho^{z_i}(1 - \rho)^{1-z_i}, \]

(5)

where \( \rho \) is the prior fraction of training instances expected to be outliers. And the prior for \( \rho \) is set to be a conjugate beta distribution, i.e.,
\[ p(\rho) = \text{Beta}(\rho|\alpha, \beta) = \frac{\rho^{\alpha-1}(1 - \rho)^{\beta-1}}{B(\alpha, \beta)}, \]

(6)

where \( B(\cdot, \cdot) \) is the the beta function and \( \alpha \) and \( \beta \) are hyperparameters.

3.2. Inference

By integrating \( y_i \) out, we can reach the probability on Equation 3 and 4 as,
\[ p(t_{ij}|s_i, z_i, \epsilon) = \sum_{y_i} p(y_i|s_i, z_i) \prod_{j} p(t_{ij}|y_i, \epsilon_j) \]

(7)

and then the joint probability in Equation 1 can be rewritten as
\[ p(T, S, \rho|X, \epsilon) \propto p(S|X)p(\rho)p(z|\rho) \prod_{i} p(t_{ij}|s_i, z_i, \epsilon). \]

(8)

Such a collapsed joint probability enable us to conveniently derive the EP inference algorithm.

Given a set of labeled data samples \( X_L = \{x_1, \ldots, x_L\} \), the set of labels are denoted as \( T_L = \{t_{ij} | 1 \leq i \leq N, 1 \leq j \leq M \} \) and an unlabeled data sample \( x_u \), we need to solve the following Bayesian inference problem to predict the label \( y_u \) of a \( x_u \). We denote \( D_L = \{X_L, T_L\} \), \( S = \{S_L, s_u\} \), and \( X = \{X_L, x_u\} \), and then we arrive at,
\[ p(y_u|x_u, D_L) = \sum_{z_u} \int_S p(y_u|s_u, z_u)p(z_u|\rho)p(S|D_L, x_u)d\rho dS \]

(9)

where
\[ p(S|D_L, x_u) \propto p(S|X)p(\rho) \prod_{s_i \in S_L} p(z_i|\rho)p(t_{ij}|s_i, z_i, \epsilon). \]

(10)

Let \( \Psi \) be the set that contains all these exact factors, and then we can rewrite \( p(S|D_L, x_u) \) in Equation 10 as
\[ \left[ \prod_{k=1}^{C} \psi_k \right] \left[ \prod_{s_i \in S_L} \psi_i \right] \]
We resort to Expectation Propagation [24] to obtain an approximate integral by approximating each $\psi \in \Psi$ using a corresponding simple factor $\hat{\psi}$ such that

$$\psi_p \left[ \prod_{s_i \in S_L} \psi_{s_i} \right] \approx \hat{\psi}_p \left[ \prod_{s_i \in S_L} \hat{\psi}_{s_i} \right]$$

with the constraint that all the approximate factors $\hat{\psi}$ belong to the same family of exponential distributions. And then we can approximate the posterior distribution of as the normalized product of the approximate factors, i.e.,

$$Q(S, z, \rho) = \frac{1}{Z} \left[ \prod_{k=1}^{C} \left( \psi_{s_k} \right) \right] \left[ \prod_{s_i \in S_L} \hat{\psi}_{s_i} \right]$$

where $Z$ is a normalization constant that approximates $p(S|D_L, x_u)$. Note that exponential distributions are preserved with product and division operations. Since all the approximate factors belong to the exponential family, $Q$ has the same form as the approximate factors and $Z$ can be readily computed.

In implementation, we select the form of $Q$ first and then constrain the approximate factors to reach the same form as $Q$. The relation between each approximate factor $\hat{\psi}$ and the corresponding exact factor $\psi$ is defined $Q(\hat{\psi}) \propto Q/\hat{\psi}$. By minimizing the Kullback-Leibler (KL) divergence between $\psi Q/\hat{\psi}$ and $\psi Q/\hat{\psi}$, all the $\hat{\psi}$ can be iteratively updated one by one. The steps of the EP algorithm are summarized in Algorithm 1.

**Algorithm 1** The Expectation Propagation Algorithm

1: Initiate each approximate factor $\hat{\psi}$ and the posterior approximation $Q$.
2: repeat
3: Choose one $\hat{\psi}$ to refine and compute $Q(\hat{\psi}) \propto Q/\hat{\psi}$.
4: Update $\hat{\psi}$ by minimizing $KL(\hat{\psi} Q/\hat{\psi})$.
5: Update the posterior approximation $Q$ to the normalized version of $\hat{\psi} Q/\hat{\psi}$.
6: until convergence
7: Evaluate $Z \approx p(Y|X)$ as the integral of the product of all the approximate factors.

EP obtains a Gaussian approximation $Q(S)$ to the posterior distribution $p(S|D_L, x_u)$. Hence the integral over $S_L$ in Equation 9 can also be approximated by a Gaussian distribution over $s_u$, i.e., $N(s^u_m, m^u_m, v^u_m)$, where $m^u_m$ and $v^u_m$ are mean and variance, respectively. Then the predictive distribution of $x_u$ can be approximated as:

$$p(y_u|x_u, D_L) \approx \frac{\tilde{\rho}}{C} + (1 - \tilde{\rho}) \int N(s^u_m, m^u_m, v^u_m) \prod_{k \neq y_u} \Phi(\frac{s^u_m - m^k_u}{\sqrt{v^k_u}}) ds_u$$

where $\tilde{\rho} = \sum_{j=1}^{K} \frac{\epsilon_j}{\sum_{j=1}^{K} \epsilon_j}$, $m^u_m$ and $v^u_m$ indicate the corresponding predictive mean and variance, respectively, and $\Phi(.)$ is the step function.

### 3.3. Learning $\Theta$ with Expectation Maximization

In order to online evaluate the quality of multiple annotators, we need to estimate the parameters $\Theta = \{\alpha, \beta, \{\epsilon_j\}_{j=1}^{M}\}$. We further introduce a generalized Expectation-Maximization algorithm for estimating it. With the lower bound $F$ of the log likelihood defined as

$$\log p(T_L, S_L|X_L, \Theta) \geq \sum_{z_i} \int_{S_L} Q(S_L) \log \frac{p(z_i|\rho)p(\rho)p(T_L, S_L|X_L, \Theta)}{Q(S_L)} dS_L$$

$$= C + \sum_{z_i} \sum_{t=1}^{L} \int q(s_i) \log \{p(z_i|\rho)p(\rho)p(t_i|s_i, z_i, c)\} ds_i,$$

where $C$ is a constant, the EM algorithm is formed with the following two iterative steps:

1. **E-Step:** Given the current parameter $\Theta_p$, conduct the EP inference to obtain an approximate inference of $Q(S_L) \sim p(S_L|X_L, T_L, \Theta_p)$.

2. **M-Step:** Maximize the lower bound of $\log p(T_L, S_L|X_L, \Theta)$ over $\Theta$ to obtain a new parameter $\Theta$. $\Theta_p \leftarrow \Theta$, goto the **E-Step** and iterate until convergence.

For the M-Step, since closed-form solution of $\Theta$ is not tractable, we resort to the L-BFGS-B algorithm [44] to find a numerical estimation of them to maximize the lower bound $F$ by gradient ascent, which is guaranteed to obtain a local optimal solution.

### 4. Reinforcement Learning for Active selection

To fully explore the trade-off between exploitation and exploration, we adopt the entropy (Ent) and margin (Mar) as two exploitation criteria, Graph density (Gra) as the exploration criterion. For the exact definitions of these criteria, we refer the readers to look into [5] due to the limit of space. Regarding the annotator selection, we provide two criteria as follows.

**Label rate (LR).** $\epsilon_j$ directly models the annotator $j$’s quality, which can be interpreted as the probability that annotator $j$ would label the data correctly. In other words, the higher $\epsilon_j$ is, the better quality the annotator has. In our active learning process, we can naturally select the top $K(K < M)$ annotators with the top $K$ $\epsilon_j$ to label a selected data sample. The joint active selection of both annotators and data samples greatly facilitates to obtain higher quality labels.

**Label correct likelihood (LCL).** We identify the annotators who are more likely to label correctly given our current
state of knowledge, i.e., given the predictive probability of the selected unlabeled sample and the levels of expertise of the different annotators. Therefore, we pick the top $K$ annotators based on the measurement $\epsilon_p(y^n_s | x^n_s, D_L) + (1 - \epsilon_p)(1 - p(y^n_s | x^n_s, D_L))$, where $p(y^n_s | x^n_s, D_L)$ is the predictive probability of the selected unlabeled sample.

Inspired by [5], we formulate the active learning as a Markov decision process to incorporate the accumulated feedback to deal with multiple selection criteria. The 4-tuple $(S, A, Q, R)$ is defined as follows: (a) $S = \{U + D + L\}$ with $U \in \{Mar, Ent\}$, $D \in \{Gra\}$ and $L \in \{LR, LCL\}$ is a mixture of two sampling criteria and one annotator selection criterion; (b) $A = \{\beta_1(t) = a_1, \ldots, \beta_n(t) = a_n\} \times S$ with $a_i \in [0, 1]$, represents $n$ different fixed trade-offs among $U$ and $D$ to fully explore the trade-off between exploitation and exploration; (c) $R$ is the reward for executing action $a_i$ in state $s_j$; and (d) $Q$ are the transition weights that action $a_i$ is selected in state $s_j$.

We resort to a fast and adaptive reinforcement learning algorithm, i.e., Q-Learning, to learn our transition table $Q \in R^{|S| \times |A|}$ online during the active learning process. After each transition $s(t-1) \rightarrow a \rightarrow s(t)$, we update $Q$ given the current reward, i.e.,

$$Q(s(t-1), a) \leftarrow Q(s(t-1), a) + \lambda(\gamma(s(t), a_i) - Q(s(t-1), a)),$$

where $\lambda$ is the learning rate that controls the influence of the current reward $r(t)$, and $\gamma$ is the discount factor that weights the future reward. $r(t)$ is defined as the difference of the overall entropy (alternatively, either the mean predicted output or the KL-divergence) of the class posteriors between two consecutive steps during the learning process.

During the active learning process, the optimal action $a = \max_i Q(s(t-1), a_i)$ leads to the adaptive trade-off. Then we can combine the current state $U + D + L$ and the obtained trade-off between $U$ and $D$ to determine which unlabeled samples to select and which $K$ annotators to query. In this paper, we set $K = 3$.

5. Experiments

Our experiments are carried out on three image collections, i.e., the E-Album [3] and the G-Album [6], and the ImageNet dataset [4]. We measure our proposed method and the competing methods with the recognition accuracy in both the active learning pool and the hold-out testing dataset with the progress of the learning process, and the results reported in this paper are average over multiple rounds.

5.1. Datasets

The E-Album consists of 108 photos taken with 15 different people in 145 detected faces. The G-Album has 312 photos taken with 13 different people in 441 detected faces. The detected faces in both albums are labeled by 7 nonprofessional annotators. For each annotator, we measure the annotator quality with the label accuracy which is defined as the percentage of his/her labels which are correct. In the E-Album, the label accuracies of the 7 annotators are 95.17%, 75.17%, 84.83%, 94.48%, 96.55%, 92.41% and 91.72%, respectively. And in the G-Album, the corresponding label accuracies are 98.41%, 79.37%, 94.33%, 75.06%, 97.96%, 87.07% and 94.10%, respectively.

The third dataset is composed of 3 classes of images from the ImageNet grand challenge [4], which includes 2 categories of dogs, i.e., “Yorkshire terrier”, “English setter” plus the “Meerkat, meerkat” category. These three classes are among the top 10 in the ImageNet grand challenge in terms of number of labeled images, with 3047, 2426 and 2341 images, respectively. We put these images back to Amazon Mechanical Turk and obtained 7 copies of labels for each image. The label accuracies of the 7 annotators are 92.03%, 92.62%, 91.89%, 92.41%, 92.68%, 92.08% and 92.50%, respectively.

For the readers’ convenience, we summarize the above-mentioned information in Table 1.

| Dataset   | $|\text{classes}|$ | $|\text{instances}|$ | Annotator Quality          |
|-----------|-----------------|-----------------|---------------------------|
| E-Album   | 15              | 145             | 84.83% - 95.17%           |
| G-Album   | 13              | 441             | 75.06% - 98.41%           |
| ImageNet  |                 | 7814            | 91.89% - 92.68%           |

5.2. Visual features and kernels

On both the E-Album and the G-Album, we use the 100-dimensional feature with the Eigen-PEP representation [17] extracted from detected faces after resizing the images to 150 pixels by 150 pixels. To make it simple, we adopt the RBF kernel. As for the similarity or distance measurements, we adopt the similarity score from the Joint-Bayesian classifier [18].

The features we use in the ImageNet dataset is the local coordinate coding (LCC) [20] on densely extracted HoG features with 4096 codewords. The LCC features are pooled in 10 spatial cells, resulting a 40960 dimensional feature. We use the dot-product kernel.

5.3. Experiments with synthetic label noise

The simulated experiments we conducted is on the G-Album. We randomly select 60% of all the detected faces to form the active learning pool, and the rest of faces are put together as the hold-out testing dataset. To demonstrate the effectiveness of our model in the situation when there are irresponsible annotators, we simulated the case that there are
with a combination of other learning strategies, i.e., samples and annotators. We compare MARMGPC-ASAA classifier (MARMGPC) with active selection of both stands for multi-annotator robust multi-class Gaussian pro-
labels for the actively selected samples.

annotators. The top 3 annotators are selected to provide the selection of both informative data samples and high-quality annotators. The top 3 annotators are selected to provide the labels for the actively selected samples.

We name our algorithm as MARMGPC-ASAA, which stands for multi-annotator robust multi-class Gaussian process classifier (MARMGPC) with active selection of both samples and annotators. We compare MARMGPC-ASAA with a combination of other learning strategies, i.e., active selection of samples but random selection of annotators, random selection of samples but active selection of annotators, and random selection of both samples and annotators. We call these algorithms MARMGPC-ASRA, MARMGPC-RSAA and MARMGPC-RSRA, respectively. All theses online learning algorithms are based on the same classification model and we select 3 annotators to provide the labels using the corresponding criterion for the annotator selection.

One algorithm we compare against is an active learning algorithm with the RMGPC classification model [8]. At each round, the method is performed on a single copy of labels which is obtained via majority voting among all 7 copies labels. In brief, we name such an active learning R-

MGPC with majority voting labels as RMGPC-MVAS. And the random learning counterpart as RMGPC-MVRS.

We report the results in Figure 2. As we can observe, (1) in all the cases, our proposed MARMGPC-ASAA outperforms all the competing algorithms in both the active learning pool and the hold-out testing dataset; (2) MARMGPC-
ASRL performs better than MARMGPC-RSAA at the early stage and then it works worse than MARMGPC-RSAA, which suggests the active selection of both samples and high quality annotators benefits the improvement of recognition accuracy; and (3) with the increasing number of irresponsible annotators, the performance of all the competing algorithms are affected, but our MARMGPC-ASAA still performs the best. All these demonstrate that our proposed MARMGPC-ASAA is robust to deal with label noises in the learning progress.

5.4. Experiments with real crowd-sourced labels

We further run experiments with all real crowd-sourced labels on the E-Album, G-Album and ImageNet dataset. On both two albums, we use 60% of all the detected faces to form the active learning pool, and the rest of faces as the hold-out testing dataset. While on the ImageNet dataset, the active learning pool and the hold-out testing pool consist of the same number of images. Besides the above-mentioned competing methods, we also compare our method with a reinforced active learning formulation proposed by Ebert et
multiple copies of labels from multiple annotators and make

\[ \text{(1) our proposed MARMGPC has the ability to jointly treat} \]

\[ \text{MARMGPC-ASAA achieves the better performance are:} \]

\[ \text{ples selection strategies. The reasons why our proposed} \]

\[ \text{trade-off between exploration and exploitation active sam-} \]

\[ \text{the idea of reinforcement learning to obtain the adaptive} \]

\[ \text{posed method with the active selection of both the informa-} \]

\[ \text{ber of labeled examples. Again, all the observations on} \]

\[ \text{ral-MVRS, which demonstrates the advantage of Gaus-} \]

\[ \text{peting methods both in the active learning pool and in the} \]

\[ \text{results are summarized in Figure 3, 4 and 5, respectively. As we can observe, (1) on the} \]

\[ \text{G-Album, the results are consistent with the observations} \]

\[ \text{5.3. Furthermore, our proposed MARMGPC-} \]

\[ \text{MARMGPC-ASAA also performs better than RALF-MVAS and RALF-} \]

\[ \text{ral-MVAS, and its random learning counterpart is named as} \]

\[ \text{ral-MVRS; (2) in both the E-Album and the ImageNet dataset,} \]

\[ \text{our proposed MARMGPC-ASAA outperforms all the com-} \]

\[ \text{full use the diverse opinion among them, while the majority} \]

\[ \text{voting strategy ignore such informative and useful diverse} \]

\[ \text{opinions; and (2) the active selection of annotators with} \]

\[ \text{the active selection of samples in the joint reinforcement} \]

\[ \text{learning framework can prevent the low-quality annotators} \]

\[ \text{from participating in the labeling process for a long time so} \]

\[ \text{that we can obtain the relatively more reliable labels in the} \]

\[ \text{progress.} \]

\[ \text{5.5. Discussion} \]

\[ \text{To obtain a quantitative evaluation of the effectiveness of} \]

\[ \text{our proposed MARMGPC, we run experiments with all the} \]

\[ \text{labeled examples on both the E-Album and the G-Album.} \]

\[ \text{We compare the proposed model with the multi-class sup-} \]

\[ \text{port vector machine (SVM) [2] and the standard multi-} \]

\[ \text{classes Guassian process classifier (SMGPC) with majority} \]

\[ \text{voting labels. Both SVM and SMGPC conduct the multi-} \]

\[ \text{classes classifications by reducing it into the binary cases.} \]

\[ \text{We also compare the proposed model with the robust multi-} \]

\[ \text{class Gaussian process classifier (RMPGC) with majority} \]

\[ \text{voting labels and the ground truth labels. In brief, we call} \]

\[ \text{them SVM-MV, SMGPC-MV, RMGPC-MV and RMGPC-GRD,} \]

\[ \text{respectively.} \]

\[ \text{It is worth paying attention that the performance of} \]

\[ \text{RMPGC-GRD is the upper bound for both MARMGPC and} \]

\[ \text{RMPGC-MV. As apparent in Table 2, our proposed MAR-} \]
MGPC obtains the comparable recognition performance to RMGPC-GRD and outperforms SVM-MV, SMGPC-MV and RMGPC-MV. On one hand, this demonstrates that MARMGPC is robust to multi-classes classification directly instead of decomposing into binary subproblems. On the other hand, MARMGPC jointly treats the labels from multiple annotators and can make full use of the diverse opinions to achieve higher recognition accuracy than the majority voting. All these further validate the efficacy of our proposed model.

Table 2: Comparison of recognition performance with different classification models

<table>
<thead>
<tr>
<th></th>
<th>E-Album</th>
<th>G-Album</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM-MV</td>
<td>70.05%</td>
<td>71.93%</td>
</tr>
<tr>
<td>SMGPC-MV</td>
<td>71.64%</td>
<td>73.42%</td>
</tr>
<tr>
<td>RMGPC-MV</td>
<td>71.99%</td>
<td>74.30%</td>
</tr>
<tr>
<td>RMGPC-GRD</td>
<td>72.29%</td>
<td>75.69%</td>
</tr>
<tr>
<td>MARMGPC</td>
<td>72.08%</td>
<td>75.34%</td>
</tr>
</tbody>
</table>

To better understand the active selection of high quality annotators, we draw two pie charts in Figure 6 to display the fractions of the used labels from 7 annotators in the active learning progress on the two albums. As we can observe, on the E-Album, the top 3 annotators are Annotator 1, 4 and 5. On the G-Album, the corresponding top 3 annotators are Annotator 1, 3 and 5. Not surprisingly, the top 3 annotators in our experiments agree with the label accuracies of the 7 annotators as described in Section 5.1. The most likely explanation to Figure 6 is that 3 high-quality annotators are selected to provide labels in each iteration so that the top 3 annotators are consistent as expected. This validates the ability of our proposed method to actively select high quality annotators to obtain more reliable labels.

We also visualize the selected samples in the active learning process on the G-Album. Figure 7 presents some examples that are selected actively in the early stages. As we can see, the results are sensible as a lot of examples picked up in the early stage have cluttered background, heavy blurring, and several of them are baby faces. It is well known that it is not easy to recognize the identities of the baby from their facial images.

6. Conclusion

In this paper, we propose a novel multi-annotator Gaussian process model to deal with multi-class visual recognition in the collaborative active learning framework with multiple annotators. A generalized EM-EP algorithm is derived to estimate the parameters and approximate Bayesian inference. We also fully employ the idea of reinforcement learning and use Markov decision process to determine the optimal joint selection strategy of both the samples and annotators, and fully explore the trade-off between exploitation and exploration. The advantage of the proposed method over the state-of-the-art methods has been sufficiently validated through the experiments. Our future work includes extending the MARMGPC model to deal with the large-scale labeled data and further better exploring exploration-exploitation in the multi-annotator scenarios.

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